Contributions to Economics

Wei Tian
Miaojie Yu

Input Trade Liberalization in China

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Wei Tian · Miaojie Yu

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Springer

Wei Tian
School of Economics
Peking University
Beijing, China

Miaojie Yu
Office of President
Liaoning University
Shenyang, China

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Preface

Today China is the largest economics in foreign trade. In 2021, China's trade volume reaches more than USD 6 trillion, registering more than 11% of global trade. How can China makes such an achievement?

Chapter "Processing Trade, Trade Liberalisation, and Opening Up: China's Miracle of International Trade" argues that the realisation of this foreign trade miracle can be broken into four steps: the extensive margin of opening up (before 2001), the intensive margin of opening up (2001–08), deeper opening up against financial crises (2008–17), and all- around opening up (since 2017). The first stage was the extensive margin of opening up. During this period, the main feature of China's international trade was the utilisation of the country's huge labour force, which provides China with comparative advantages in labour-intensive industries and processing trade. The second stage was the intensive margin of opening up. The main feature of this period was trade liberalisation in China and dramatic changes in Chinese firms' performance, product market, and more importantly, the intermediate market. The third stage was deeper opening up against the financial crisis. Chinese firms began to find new advantages, including quality, brand, service, and so on. The fourth stage is the all-around opening up. The fourth stage is the all-around opening up. In 2017, China decided to shift from a high-speed increase stage to a high-quality development stage, and improving the supply quality has become a top priority. At the same time, trade protectionism and anti-globalisation forces are on the rise. Against this background, the government proposes to build a new pattern featuring all-around opening up, thus promoting the development of both the Chinese and global economies. This chapter is collaborate with Mr. Huihuang Zhu, one of my former graduate students and currently a Ph.D. candidate at UCLA.

This paper takes product complexity into account to study the impact of imported intermediate inputs on firms. Highly disaggregated Chinese transaction-level trade data and firm-level production data from 2002 to 2006 are used to construct firm-level imported intermediate inputs. After controlling for the endogeneity of imported intermediate inputs and taking industrial imports of final goods into account, the analysis finds that firm productivity increases with increased imported intermediate inputs. The impact of imported intermediate inputs on firm productivity is weaker as firms produce more complex products. This paper was published with Jin Li on *Japanese Economic Review.*

This paper investigates the effect of trade liberalisation on Chinese firms' productivity. In the past three decades, China has experienced dramatic trade liberalisation as well as productivity gains. The average unweighted tariffs decreased from around 55 per cent in the early 1980s to about 13 per cent in 2002. At the same time, China's average annual increase in total factor productivity (TFP) in the first two decades since economic reform in 1978 was around 4 per cent, although this pace seems to have slowed down after that (Zheng et al., 2009). It is interesting to see whether or not China's trade liberalisation has boosted its productivity. Although economists have paid some attention to this issue, the research is far from conclusive and deserves further exploration. In this paper, the effect of China's trade liberalisation on its productivity was estimated by precisely measuring TFP, by taking into account the difference in complex goods and simple goods, by choosing an appropriate indicator of trade liberalisation and by using the most disaggregated firm-level data. The estimation results suggest that trade liberalisation significantly increases productivity for firms that produce complex goods. In contrast, we find that trade liberalisation has the opposite effect on the productivity of producers of simple goods. These findings are robust after controlling for potential endogeneity. We further find that the effect of trade liberalisation on firm productivity to exporting firms is smaller than non-exporting firms. This paper was published with Guangliang Ye and Baozhi Qu on *The World Economy.*

How do reductions in input trade costs affect firm's sales decision between domestic and foreign markets? By using Chinese firm-level production data and transaction- level trade data during 2000–2006 to construct firm-specific input trade costs, we find rich evidence that a reduction in input trade cost for large trading firms leads to an increase in export intensity (i.e., exports over total sales). The impact is more pronounced for ordinary firms than that for hybrid firms which engage in both processing and ordinary trade since ordinary import enjoys the free-duty treatment in China. The declining input trade costs not only increase the probability of firm's being new exporters (i.e., extensive margin) but also lead to higher export intensity (i.e., intensive margin). Such results are robust to different empirical specification and econometric methods. This paper was published with Wei Tian on *Journal of Asia-Pacific Economy.*

This article explores how reductions in tariffs on imported inputs and final goods affect the productivity of large Chinese trading firms, with the special tariff treatment that processing firms receive on imported inputs. Firm-level input and output tariffs are constructed. Both types of tariff reductions have positive impacts on productivity that are weaker as firms' share of processing imports grows. The impact of input tariff reductions on productivity improvement, overall, is weaker than that of output tariff reductions, although the opposite is true for non-processing firms only. Both tariff reductions are found to contribute at least 14.5% to economy-wide productivity growth. This paper was published on *Economic Journal.*

The nexus between firm innovation and trade liberalisation is an important research subject in the empirical trade literature, as firm innovation is an important channel for firms to realise productivity gains from trade. The present paper examines the effect of input trade liberalisation on firm R&D by taking into account China's special treatment on imported intermediate inputs. This paper contributes to the literature in three important ways. First, it enriches our under- standing of China's innovation activity in the new century. Second, the paper contributes to understanding the channels and mechanisms of the effects of trade liberalisation on firm performance. Third, the paper makes a contribution to the issue of empirical identification. Firm R&D activity may be endogenous to import tariffs. This paper was published with Wei Tian on *The World Economy.*

This paper investigates how input liberalization affects firm import behavior. Using comprehensive production and trade data of Chinese firms, the paper shows that firms switch import sources from developing countries to developed countries as Chinese input tariffs fall. This finding is evident for import value and import scope. The observation holds after excluding the possible influence of reducing processing trade. The paper further demonstrates that the mechanism can be attributed to quality upgrading and innovation led by input cost reductions. The analysis handles the possible endogeneity problem, and the findings are robust and significant to different empirical methodologies and measurements. This paper was published with Wei Tian on *Review of International Economics.*

The conventional trade theorem predicts that a country will export goods that use its abundant factor intensively. However, as tariffs decline, trade grows not only between countries with different levels of intensity of factors of production, but also between countries with similar levels. Furthermore, as suggested by Bernard et al. (2003), the increase of North–South trade generates more trade between developing countries as countries in different developing stages engage in different stages of global value chains. The main findings of this paper are threefold. First, Chinese manufacturing firms with a significant import share from Indonesia perform better in terms of productivity, export value, number of employees and sales, and they are more likely to engage in processing exports. Second, all aspects of trade liberalisation foster firm export value, and the impact is stronger for firms with more import from Indonesia. Last, we investigate how trade liberalisation affects export and import scopes differently for firms with a different extent of imports from Indonesia. The empirical study shows that trade liberalisation (tariff rate reductions) on inputs increases both import and export scopes. The impacts on import scopes are more pronounced for firms with higher import shares from Indonesia. This paper was written with Lili Yan Ing and Wei Tian, forthcoming on *The World Economy.*

Using Chinese firm-level production data, this paper developed a Mincer (1974)-type approach to investigate the impact of input trade liberalization on firms' wage inequality between skilled and unskilled workers (or skill premium). When controlling for product-market tariffs in a firm's industry, we find robust evidence that reduced input tariffs in a firm's industry are associated with a higher skill premium at firms with more skilled workforces. This effect is more pronounced at ordinary (non-processing) firms. We also provide evidence that reduced input tariffs in a firm's industry are associated with higher value added and profits at firms with more skilled workforces. This paper was published with Chen Bo and Zhihao Yu on *Journal of International Economics.*

Chinese firms faced an all-around trade liberalization process during the early 2000s: lower barriers from other countries on Chinese goods, and lower Chinese barriers on other countries' goods and inputs. This paper disentangles the effects of each type of trade liberalization on Chinese firm-level employment. We find that reductions in Chinese and foreign final-good tariffs are associated with job destruction in low and mid-low productivity firms and job creation in high-productivity firms. Chinese final-good trade liberalization produces the largest firm-level employment responses, whereas the employment effects of Chinese input-trade liberalization are limited to job destruction in the least productive firms. This paper was published with Antonio Rodriguez-Lopez on *Review of International Economics.*

Beijing, China Wei Tian
Shenyang, China Miaojie Yu

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Contents

Processing Trade, Trade Liberalisation, and Opening Up: China's Miracle of International Trade

Miaojie Yu and H. Zhu

1 Introduction

China began to reform its economy in 1978, and that economy has continued to grow rapidly over the past four decades. That such a large economy can achieve such long-term sustainable development has been seen as a miracle. One obvious feature of this miracle is that China has participated deeply and extensively in the global international trading system. Due to its opening-up policies, China has become the largest trading country in the world. In 2018, its foreign trade was valued at $4.62 trillion, with exports of $2.48 trillion and imports of $2.14 trillion. China replaced Germany as the largest exporter in the world in 2009, and the United States (US) as the largest importer in 2015. Over the past four decades, China's foreign trade volume has increased 204-fold, whereas its gross domestic product has only increased 34-fold. In this regard, China has already successfully achieved a miracle of foreign trade. Thus, to understand the miracle of China's economic growth, it is necessary to understand what role international trade has played in this process.

The realisation of this foreign trade miracle can be broken into four steps: the extensive margin of opening up (before 2001), the intensive margin of opening up (2001–08), deeper opening up against financial crises (2008–17), and all- around opening up (since 2017) after China's Communist Party announced the establishment of a new era of all-around opening up in China in its 19th National Congress.

The first stage was the extensive margin of opening up. During this period, the main feature of China's international trade was the utilisation of the country's huge labour force, which provides China with comparative advantages in labour-intensive industries and processing trade. Along with the decline of trade barriers between countries all over the world, the development of transportation and communication

M. Yu (✉) · H. Zhu
National School of Development, China Center for Economic Research, Peking University, Beijing, China
e-mail: mjyu@ccer.pku.edu.cn

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technologies, and the separation of production processes, China began integrating into the global value chain and taking advantage of its abundant labour force. A typical example of this integration was China's preferential trade policy of importing intermediate goods with zero tariffs to encourage processing trade production. Firms who participated in processing trade specialised in tasks requiring labour-intensive production. At the same time, by participating in processing trade and importing intermediate goods and capital goods, Chinese firms gradually became familiar with production technology and gained experience from foreign companies, which further improved their production and operation efficiency.

The second stage was the intensive margin of opening up. The main feature of this period was trade liberalisation in China and dramatic changes in Chinese firms' performance, product market, and intermediate market. On the one hand, opening up brought intensive import competition, compelling domestic firms and companies to reduce inefficiency and improve product quality to become more competitive. On the other hand, the reduction of import tariffs allowed domestic companies to purchase high- quality intermediate goods and capital goods, allowing them to save costs and upgrade technology. At the same time, export trade liberalisation (for example, the removal of the Multi-Fiber Arrangement) expanded Chinese firms' foreign markets. These market-scale effects can stimulate enterprises to increase investment, research and development (R&D), innovation, and export. Furthermore, along with the increased labour costs, the proportion of processing trade (a relatively low value-added trade mode) gradually decreased, and ordinary trade began to dominate.

The third stage was deeper opening up against the financial crisis. The global financial crisis in 2008 had significant negative impacts on the economic development of the global economy, especially in developed economies. Demand from major developed economies was weak, and the mode of relying mainly on exports to drive China's economic growth was no longer feasible. Thus, Chinese firms began to find new advantages, including quality, brand, service, and so on. On the other hand, the Government of China also implemented several actions to encourage local firms to improve product quality, provide first-class service to their customers, and, at the same time, attract multinational companies to invest in China.

The fourth stage is the all-around opening up. In 2017, the 19th National Congress of the Communist Party of China pointed out that China's economy has shifted from a high-speed increase stage to a high-quality development stage, and improving the supply quality has become a top priority. At the same time, trade protectionism and anti-globalisation forces are on the rise. Against this background, the government proposes to build a new pattern featuring all-around opening up, thus promoting the development of both the Chinese and global economies. Specific measures to be undertaken include (i) further widening market access, (ii) improving the investment environment for foreign investors, (iii) strengthening protection of intellectual property rights, and (iv) taking the initiative to expand imports. In doing so, China will send a message to the world that China's door will not be closed and will only open even wider.

2 Comparative-Advantage-Following and Processing Trade

Before opening up its policy, China adopted a heavy industry-oriented development strategy—a comparative-advantage-defying development strategy. Lin and Yu (2015) found that a development strategy that prioritised heavy industry (which is a comparative-advantage-defying strategy) distorted product and factor prices, and had to rely on a highly centralised planned resource allocation mechanism. Thus, before the reform China adopted a distorted macroeconomic policy, which included suppressing interest rates, over-valuing domestic currency, adopting an import-substitution strategy, setting up 'price-scissors' against peasants, and restricting labour migration. After the 1978 economic reform, China abandoned the heavy industry-oriented development strategy, adopting the comparative-advantage-following (CAF) development strategy based on its factor endowments.

Where does China's comparative advantage lie? Yao and Yu (2009) found that a low dependent rate[1] and low urbanisation rate contribute significantly to China's large labour force and low wages. This provides China with a long-term advantage in labour-intensive industries. Tian et al. (2013) used cross-country data and a gravity model to show that a large labour population has a positive effect on a country's imports and exports. Ma et al. (2014) found that firms become less capital-intensive but more productive after exporting, compared to non-exporters with similar ex-ante characteristics.

After its economic reform, China adopted a CAF development strategy. The government realised that processing trade is an ideal way to implement the CAF strategy given that China is a labour-abundant country. Indeed, processing trade is one of the main causes of the high level of intra-industry trade among the capital-intensive industries mentioned above (Lin & Yu, 2015). The General Administration of Customs reports 16 specific types of processing trade in China. Of these, the two most important are processing with assembly and processing with inputs. Both types of processing trade are duty-free but they are characterised by an important difference. For processing with assembly, a domestic Chinese firm obtains raw materials and parts from its foreign trading partners without any payment. However, after local processing, the firm must sell its products to the same foreign trading partner by charging an assembly fee. By contrast, for processing with inputs, a domestic Chinese firm pays for raw materials from a foreign seller. After local processing, the Chinese firm can then sell its final goods to other foreign countries (Yu, 2015).

Compared with ordinary imports, processing imports in China accounted for just a small proportion of total imports in the early 1980s. However, as shown in Fig. 1, China's processing imports increased dramatically in the early 1990s and began to dominate ordinary imports in 1992, when China officially announced the adoption of a market economy. In 1995, processing imports accounted for more than 50%

[1] According to the Chinese statistical yearbook (2008), the dependent rate of China in 2007 was only 0.4. This number was not only lower than the average dependent rate in east Asia, but also one of the lowest dependent rates all over the world (Yao & Yu, 2009).

of the country's total imports (now decreased to one-third of total trade). Interestingly, processing imports with assembly were more popular in the 1980s because most Chinese firms lacked the capital needed to import. Since the 1990s, processing imports with inputs have become more prevalent.

Due to the prevalence of processing trade, the literature has revisited some international trade theory, one of the main findings of which is the paradox of Chinese exporters' productivity. The firm-level trade literature finds that ex- porters are exceptional performers for a wide range of countries and measures (Melitz, 2003). Paradoxically, the one documented exception is the world's largest exporter, China. Dai et al. (2016) showed that this puzzling finding is entirely driven by firms that engage only in export processing—the activity of assembling tariff-exempted imported inputs into final goods for resale in foreign markets. They document that processing exporters are less productive than non-processing exporters and non-exporters, and perform more poorly in many other aspects such as profitability, wages, R&D, and skill intensity. Furthermore, accounting for processing exporters explains the abnormality in exporter performance in China documented in the previous literature. Although processing trade accounts for half of China's exports, processing firm productivity is lower than that of non-processing (i.e. ordinary) firms and even lower than that of non-exporters. Once they drop processing firms, Chinese exporters are more productive than non-exporters, meaning that the paradox disappears. Low fixed costs of processing exporting and trade and industrial policies favouring processing exporters are both responsible for the low productivity of processing exporters. Tian and Yu (2015) found rich evidence that a reduction in input trade costs for large trading firms leads to an increase in export intensity (i.e. exports over total sales). This impact is more pronounced for ordinary firms than for hybrid firms that engage in both processing and ordinary trade since ordinary imports enjoy duty-free treatment in China. Declining input trade costs not only increase the probability of a firm's being a new exporter (i.e. extensive margin) but also lead to higher export intensity (i.e. intensive margin).

Another main finding is how input and output tariffs affect a firm's productivity. Yu (2015) showed that reducing output tariffs has had a greater effect on productivity improvement than has reducing input tariffs for large Chinese trading firms in the twenty-first century. Such results are primarily attributable to the special tariff treatment afforded to imported inputs by processing firms as op- posed to non-processing firms in China. Processing imports, which account for half of the total imports in China, have zero tariffs. He documents that further tariff reductions on imported intermediate inputs have no impact on firms that engage entirely in processing trade but still have some impact on firms that engage in both processing and non-processing trade. As the firm's processing share grows, input tariff reductions have a smaller impact on productivity gains. Similarly, as a firm's processing share increases, the share of domestic sales de- creases accordingly; and the pro-competition effects from the reductions in output tariffs are hence weaker.

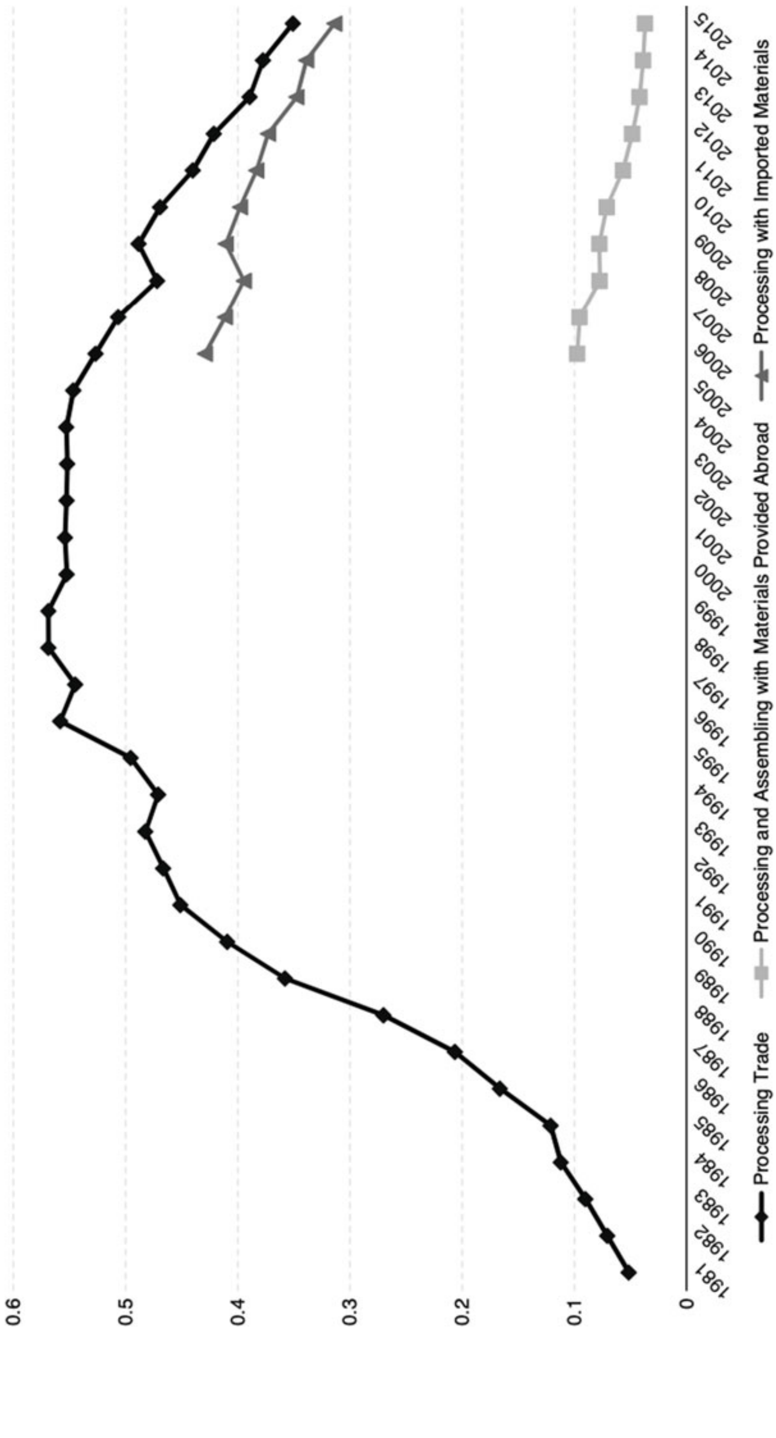


Fig. 1 Ratio of processing trade export in total export. *Source* National Bureau of Statistics, Department of Trade and External Economic Relations Statistics (2017), China Trade and External Economic Statistical Yearbook. Beijing: China Statistics Press

3 Trade Liberalisation and Firm Performance

China's accession to the World Trade Organization (WTO) has had a profound influence on the world economy. However, this step took China far longer than it did other economies. As one of the 23 contracting parties to the General Agreement on Tariffs and Trade (GATT), it took China 15 years, from 1986 to 2001, to accede to the WTO. Wong and Yu (2015) observe this interesting phenomenon and argue that the level of democracy of an applicant country affects the time it takes to gain GATT/ WTO accession. They find that most GATT/WTO members are democratic. More interestingly, democratic regimes seem to take less time to accede to the GATT/WTO than do non-democratic regimes. For example, Hong Kong acceded to GATT in 1986 immediately after its application. In contrast, Congo took more than 26 years to accede to the WTO. In addition, democratising countries also suffer from the length of time spent in attempting to accede to this large global trading organisation. Democracy also has an impact on economic performance and export. Giavazzi and Tabellini (2005) provided evidence that countries that liberalise and then democratise perform much better than countries that do the reverse. Eichengreen and Leblang (2008) argued the existence of two-way positive causality between trade openness and democracy using historical data from 1870 to 2000. Yu (2010a) documents that democracy affects trade through different channels. First, democratisation in the exporting country can improve product quality and reduce trade costs, increasing bilateral trade. Second, democratization in the importing country may increase trade barriers and thus reduce imports.

After China's accession to the WTO, along with the significant reduction in applied tariff rate (Fig. 2), China's exports, firm performance, industrial structure, and factor market have undergone huge developments. According to the empirical findings of other countries, import trade liberalisation mainly affects firms in one country through two following channels: one is the intense competition caused by trade liberalisation in the final goods market; the other is the effect of tariff reductions on imported intermediate inputs (Amiti & Konings, 2007; Goldberg et al., 2010; Topalova & Khandelwal, 2011). On the one hand, import trade liberalisation and tariff reductions make it easier for foreign companies and their products to enter the domestic market, leading to greater competition for domestic companies and products. This will force domestic firms to reduce inefficiency in operations, markup and product price to better cope with the competition. On the other hand, tariff cuts have enabled many companies to purchase better quality intermediates at lower prices, which permits cost savings and quality upgrades.

Amiti and Konings (2007) analysed Indonesian firm-level data and find that firms gain at least twice as much from the reduction of input tariffs as from the reduction of output tariffs. Furthermore, Topalova and Khandelwal (2011) found that Indian firms could gain 10 times as much from input tariff reduction as from output tariff reduction in several industries. They argue forcefully that the primary reason for this result is that access to better intermediate inputs through the reduction of input tariffs is more important than the procompetitive effect of the reduction of output tariffs.

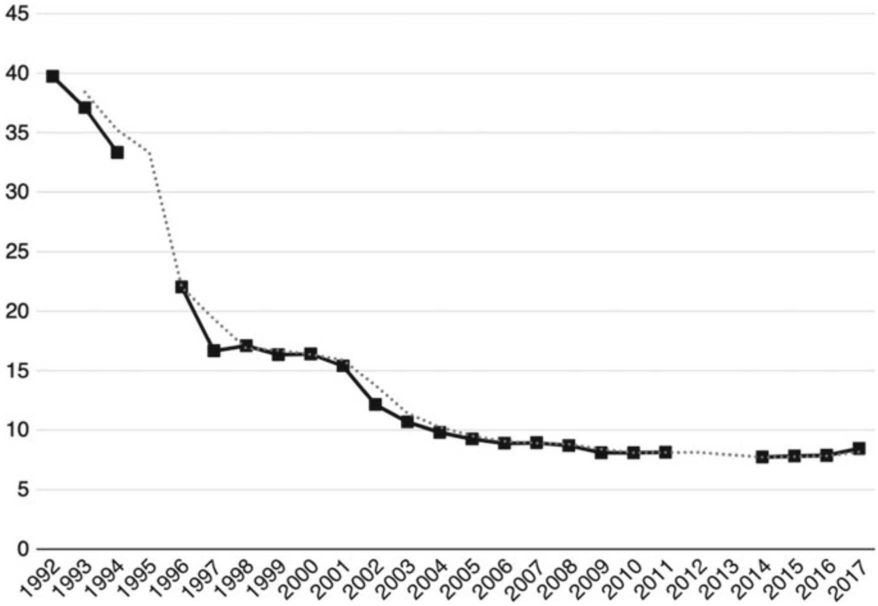


Fig. 2 Applied tariff rate, simple mean, all products (%). *Source* The World Bank, World Bank Open Data, retrieved 15 November 2019 from: https:// data.worldbank.org/indicator/ TM.TAX.MRCH.SM.AR.ZS

In addition to the commonality with the trade liberalisation process in other developing countries, many studies use Chinese firm-level data to study how trade liberalisation affects firm productivity. Firstly, trade liberalisation can boost firm productivity through different channels. Yu et al. (2013) investigated the linkage between firm productivity and product complexity. First, they adopt the Olley-Pakes (1996) approach to address two empirical challenges: simultaneity bias and selection bias caused by ordinary least squares. Then, the estimation results suggest that trade liberalisation significantly increases productivity for firms that produce complex goods. In contrast, they find that trade liberalisation has the opposite effect on the productivity of producers of simple goods. Secondly, trade liberalisation can boost firm total factor productivity through R&D and innovation. Dai and Yu (2013) argue that absorptive capacity developed through pre-export R&D investment is crucial for learning to occur. They estimate the instantaneous and long-term productivity effects of starting to export on the universe of Chinese manufacturing firms during 2001–07 using propensity score-matching techniques. The baseline results show that, while the productivity effect of exporting is weak and transient for all firms on average, it is large and lasting for firms with pre-export R&D. For firms without pre-export R&D, exporting has no significant productivity effect, even instantaneously. In addition, the productivity effect of exporting increases with the number of years of pre-export R&D investment, suggesting that firms involved in intentional and persistent R&D activities enjoy greater learning effects than do firms only accidentally involved in R&D

activities. They suggest that policies that encourage firm R&D and other absorptive capacity-building activities should be combined with trade liberalisation to reap the full growth benefits of openness. Tian and Yu (2017) also find strong evidence that input trade liberalisation due to the WTO accession significantly fosters firm R&D activity.

Furthermore, trade liberalisation can boost firm total factor productivity by increasing import variety. Feenstra et al. (2014) use Chinese firm-level data to confirm the positive effect of imported intermediate goods on firm productivity. The results are primarily attributable to spillover and competition effects from imported goods. However, they find that the impact of imported intermediate inputs on firm productivity becomes weaker as firms produce more complex products. Differentiated products, which account for four-fifths of total products, to some extent bear less pressure from severe competition but enjoy fewer benefits from foreign imports penetrating the domestic market than do homogeneous products. However, the growth in productivity of firms that produce heterogeneous goods is slower than that of firms that produce homogeneous goods when product complexity requires more imported intermediate goods. If a homogeneous intermediate input is imported, firms will find it easier to adopt its up-to-date technology because homogeneous products are less technology-specific than heterogeneous products.

Finally, Yu and Yuan (2016) have also found that the reduction of final tariffs has led to a decline in firms' production cost, and the reduction of tariffs on intermediate goods has led to an increase in firms' production cost. As a firm's processing share increases, the impact of the reduction in tariffs on firms' markup will be smaller. Yu and Li (2016) investigate the impact of trade liberalisation on the quality of imported inputs within narrow product categories. They follow the model in Khandelwal (2010) to estimate the quality of inputs imported to China. To estimate the impact of both input tariff reductions and output tariff reductions, they choose processing trade, which is free from both tariffs, as a control group. By implementing the difference-in-difference method, they find evidence to support the argument that trade liberalisation promotes the quality of imported inputs in ordinary trade relative to processing trade. Yu and Jin (2015) study the impact of imported intermediate inputs and imports of final goods on the firm by taking product complexity into account. After controlling for the endogeneity of imported intermediate inputs, they confirm that firms could benefit from imports. Further, they find that imports could improve the productivity of firms that produce homogeneous goods, but have little effect on those produce complex goods. To explain this heterogeneous effect, market concentration is introduced, and the result reveals that the import competition effect weighs more in homogeneous industry while the import spillover effect is more important to heterogeneous industry. The low impact of imports on firm productivity in heterogeneous industry could be explained by a weak import spillover effect due to low R&D efficiency. Yu and Zhi (2016) find that, in the short term, import liberalisation of final goods allows more foreign firms to export to the domestic market, intensifying domestic market competition and thus reducing the profitability of pure domestic selling firms. However, in the long term, since firms can choose whether to enter or exit the market, some domestic reigning firms will choose to exit, allowing the firms that remain in the market to enjoy higher profitability in equilibrium.

Trade liberalisation also affects within-firm income inequality. Chen et al. (2017) develop a Mincer (1974)-type approach to investigate the impact of input trade liberalisation on firms' wage inequality between skilled and unskilled workers (or skill premium). When controlling for product-market tariffs in a firm's industry, they find robust evidence that reduced input tariffs in a firm's industry are associated with a higher skill premium at firms with more skilled workforces. This effect is more pronounced at ordinary (non-processing) firms. They also provide evidence that reduced input tariffs in a firm's industry are associated with higher value added and profits at firms with more skilled work-forces. Rodriguez-Lopez and Yu (2017) also find a link between trade liberalisation and firm employment. They document a phenomenon where reductions in Chinese and foreign final-good tariffs are associated with job destruction in low-productivity firms and job creation in high-productivity firms. In contrast, the net effect of reductions in Chinese input tariffs is limited to job destruction in low-productivity ordinary exporters.

Moreover, Loren et al. (2017) observe the effects of the trade liberalisation that accompanied China's WTO accession on the evolution of markups and productivity of Chinese manufacturing firms. They show that cuts in output tariffs reduce markups but raise productivity, while cuts in input tariffs raise both markups and productivity. They highlight several mechanisms operating in liberalised sectors that help explain our findings in the Chinese context. Liberalised sectors saw an increase in the exit of private firms and more frequent replacement of management in badly performing state-owned firms. Lim et al. (2019) use both econometrics and a calibrated structural model to disentangle the mechanisms via which trade affects innovation, focusing on scale effects (impact on market size) and competition effects (impact on markups). They find that both scale and competition effects are important for understanding how trade affects innovation in China. In particular, scale effects of trade on in- novation are positive in the aggregate, whereas competition effects are negative. However, when firms can innovate to escape competition, greater competition induced by lower trade barriers can lead firms to increase innovation rather than reduce it.

In addition to trade liberalisation and reductions in import tariffs, Chinese firms also experienced export trade liberalisation, which has greatly expanded the international market faced by Chinese firms. Khandelwal et al. (2013) examine Chinese textile and clothing exports before and after the elimination of externally imposed export quotas. Both the surge in export volume and the decline in export prices following quota removal are driven by net entry. This outcome is inconsistent with a model in which quotas are allocated based on firm productivity, implying the misallocation of resources. Removing this misallocation accounts for a substantial share of the overall gain in productivity associated with quota removal. Feng et al. (2017) study how a reduction in trade policy uncertainty affects firm export decisions. Using a firm- product level dataset on Chinese exports to the US and the European Union in the years surrounding China's WTO accession, they provide strong evidence that the reduction in trade policy uncertainty simultaneously induced firm entries to and exits from export activity within fine product-level markets. In addition, they uncover accompanying changes in export product prices and quality that coincided with this reallocation: firms that provided higher quality products at lower prices entered the export market, while firms that provided lower quality pro- ducts at higher prices prior to the changes exited. To explain the simultaneous export entries and exits, as well as the fact that new entrants are more productive than exiters, they provide a model of heterogeneous firms that incorporates trade policy uncertainty, tracing the effects of the changes in policy uncertainty on firm-level payoffs and the resulting selection effects.

Despite the substantial reduction in tariff rates, recent literature notices a new aspect—non-tariff measures (NTMs)—that is gaining more importance than ever before, sometimes hampering the flow of international trade. NTMs are defined as 'policy measures, other than ordinary customs tariffs, that can potentially have an economic effect on international trade in goods, changing quality traded, or prices or both' (United Nations Conference on Trade and Development [UNCTAD], 2013). Ing et al. (2019) have identified and collected all currently enforced NTMs in China, and provide a brief overview of the diverse types of NTMs that exist in China based on national laws and regulations.

4 Deeper Opening Up Against Financial Crisis

The global financial crisis has had far-reaching repercussions on cross-border economic activity. After a sharp and sudden collapse in international trade in the last quarter of 2008, world trade flows declined by about 12% in 2009 according to the WTO (Chor & Manova, 2012). This exceeded the estimated loss of 5.4% of world gross domestic product during the same period. The contraction in exports was especially acute for small open economies, several of whom saw their trade volumes in the second half of 2008 fall by up to 30% year-on-year.

This trade decline contributed to the spread of recessionary pressures to countries which had little direct exposure to the US subprime mortgage market where the crisis originated. By exploiting the variation in the cost of capital across countries and over time, as well as the variation in financial vulnerability across sectors, Chor and Manova (2012) show that credit conditions were an important channel through which the crisis affected trade volumes. They notice that countries with higher interbank rates and thus tighter credit markets exported less to the US at the peak of the crisis. This effect was especially pronounced in sectors that require extensive external financing, have limited access to trade credit, or have few collateralisable assets. Exports of financially vulnerable industries were thus more sensitive to the cost of external capital than exports of less vulnerable industries, and this sensitivity rose during the financial crisis.

In the context of China, credit constraints faced by exporters played a significant role in the fall in exports. Manova et al. (2015) use China's customs data to provide firm-level evidence that credit constraints restrict international trade and affect the pattern of multinational activity. They show that foreign affiliates and joint ventures in China have better export performance than private domestic firms in sectors that are more financially vulnerable. These results are stronger for destinations with higher trade costs, and are not driven by firm size or other sector characteristics. These findings are consistent with multinational subsidiaries being less constrained by liquidity because they can access foreign capital markets or funding from their parent company.

Feenstra et al. (2014) examine why credit constraints for domestic and exporting firms arise in a setting where banks do not observe firms' productivities. To maintain incentive compatibility, banks lend below the amount that firms need for optimal production. The longer time needed for export shipments induces a tighter credit constraint on exporters than on purely domestic firms. Using Chinese firm-level data, they find that the credit constraint becomes more stringent as a firm's export share grows, as the time to ship for exports is lengthened, and as there is greater dispersion of firms' productivities, reflecting more incomplete information.

Accompanied by the export pressure caused by the global financial crisis, the increase in China's labour cost and appreciation of the renminbi also eroded China's export competitiveness significantly, especially in labour-intensive industries. We focus on three main solutions to expand trade volume. The first of these is to increase the firm's R&D. Dai et al. (2018) find that com- petition plays an important role in providing incentives for firm innovation. They use the appreciation of the renminbi exchange rate during 2005–07 as a natural experiment and exploit its differential impact on Chinese manufacturing firms with different export exposures. The appreciation reduced exports and imposed greater competitive pressure on exporters relative to non-exporters. In response, exporters increased innovation activities more than did non-exporters. Using a difference-in-difference approach, they find that the R&D expenditure of ex- porters increased by 11% more than that of non-exporters during the appreciation period, and the new product development of exporters increased by nearly 1.5 times more than that of non-exporters.

The second solution is to upgrade the quality of exported goods. First, it is necessary to examine how Chinese manufacturers' export quality has evolved since 2000. Yu and Zhang (2017) developed a new method to estimate export quality and avoid pitfalls in the literature. Using China's manufacturing firm data and customs data from 2000 to 2006, they estimate firm-product-destination- year level export quality and find that the overall export quality of Chinese manufacturers has increased by 15%. The quality gap between foreign and domestic firms has narrowed, with domestic firms exhibiting quality convergence.

Export quality increases for most industries are higher in high-income destinations and are negatively associated with both export and import tariffs. Surviving varieties contribute to most of the aggregate export quality upgrading, while low-quality existing varieties facilitate the aggregate export quality upgrading. Ing et al. (2018) estimated micro-level firm-product-destination-year export quality for China (2000–13).

As shown in Table 1, from 2000 to 2013, the quality of Chinese exports increased by 30%. Their findings show that a firm will produce and export a higher quality product to a place with higher consumer preferences when the relative cost of shipping is higher than the unit production costs. They also show that better quality goods are more likely to be sold to high-income destinations. When they decompose the aggregate weighted-average export quality into the intensive and extensive margins, they find that the intensive margin plays a major role in Indonesia's exports, while the extensive margin plays a major role in China's exports. Cui and Yu (2018) studied the effect of the exchange rate on the domestic value-added ratios of processing exports via two channels: substitution and markup. First, home currency depreciation leads to an increase in domestic value-added ratios by affecting each firm's imported and domestic intermediate inputs (the substitution channel). Second, home currency depreciation improves exporters' profitability and results in higher domestic value-added ratios of processing firms (the markup channel), as exports become more competitive with depreciation. Using Chinese firm-level production data and product-level trade transaction data, they find that processing firms' domestic value-added ratios increase significantly through the two channels in response to firm-level nominal effective exchange rate depreciation. The markup channel contributes almost 39% of the variation in domestic value-added ratios in response to changes in the exchange rate.

The third solution is to increase outward foreign direct investment (FDI). Since 2010, the sharp increase in outward FDI from developing countries has been phenomenal, and this is especially true for China. The UNCTAD World Investment Report (UNCTAD, 2015) shows that outward FDI flows from developing economies have already accounted for more than 33% of overall FDI flows, up from 13% in 2007. Furthermore, despite the fact that global FDI flows plummeted by 16% in 2014,

Table 1 Quality distribution, China 2000–13

Year	Mean	Median	75th percentile	25th percentile
2000	1.217	1.072	1.677	0.550
2001	1.242	1.111	1.714	0.579
2002	1.242	1.105	1.704	0.588
2003	1.247	1.111	1.724	0.587
2004	1.293	1.151	1.772	0.621
2005	1.335	1.191	1.817	0.664
2006	1.383	1.232	1.882	0.684
2007	1.371	1.210	1.881	0.650
2008	1.444	1.267	1.968	0.689
2009	1.449	1.275	2.007	0.666
2010	1.470	1.297	2.038	0.689
2011	1.493	1.303	2.063	0.684
2012	1.558	1.351	2.184	0.687
2013	1.588	1.360	2.218	0.702

Source Ing et al. (2018)

multinational corporations (MNCs) from developing economies invested almost $468 billion abroad in 2014, an increase of 23% over the previous year. As the largest developing country in the world, China has seen an astonishing increase in its outward FDI flows. In 2015, China's outward FDI reached the level of 9.9% of the world's total FDI flows, making China the second largest home country of FDI outflows globally. In addition, manufacturing outward FDI from China is becoming more important in China's total outward FDI flows, having increased from 9.9% in 2012 to 18.3% in 2016.

Chen et al. (2019) examine how domestic distortions affect firms' production strategies abroad by documenting two puzzling findings using Chinese firm-level data from manufacturing firms. First, private MNCs are less productive than state-owned MNCs, but more productive than state-owned enterprises overall. Second, there are disproportionately fewer state-owned MNCs than private MNCs. They also built a model to rationalise these findings by showing that domestic discrimination against private firms incentivises them to produce abroad. The model shows that selection reversal is more pronounced in industries with more severe discrimination against private firms, a theory that receives empirical support. Liu et al. (2017) use unique data on Chinese manufacturing firms over the sample period 2002–08. They find that MNCs are generally more productive after they conduct outward FDI, but this productivity effect varies depending on the parent firm and investment strategy heterogeneity. Their results suggest that MNCs without state ownership but with stronger absorptive capability gain higher and more sustainable productivity effects, and such gains are higher for MNCs investing in countries in the Organisation for Economic Co-operation and Development than elsewhere.

5 All-Around Opening Up and Trade Globalization

Since the 2008 global financial crisis, there has been a new wave of trade protectionism headed by the US, casting a shadow on the world economy. The current situation arises from the stagnation of the Doha negotiations, the failure of the Transatlantic Trade and Investment Partnership, negotiations among Western countries, the Brexit negotiations, the Trump regime's abolition of the Trans-Pacific Partnership, renegotiation of the North American Free Trade Agreement, and the recent trade war between the US and China, which has resulted in a tremendous shock to world markets. Widespread protectionism could lower global output, making worldwide economic recovery difficult.

One the one hand, Trump's trade war will have a huge impact on the world economy. Guo et al. (2018) used Eaton and Kortum's 2002 multi-sector, multi-country general equilibrium model with inter-sectional linkages to forecast how exports, imports, output, and real wages would change if Trump's threat of 45% tariffs is carried out. To consider plausible scenarios, they evaluate the case of unilateral action on the part of the US, as well as a scenario where China retaliates by imposing an equally high 45% tariff on its imports from the US. In all of the scenarios, the calibration exercise suggests that a trade war triggered by high US import tariffs will lead to a collapse in US–China bilateral trade. In all of the scenarios, the US will experience large social welfare losses, while China may lose or gain slightly depending on the effect of the trade war on the US–China trade balance. Globally, some small open economies may experience small benefits, while other countries may suffer collateral damage.

On the other hand, China has implemented multiple methods to minimise the impact of Trump's trade war and to continue to open up to the outside world. The first of these is the construction of free trade ports. By definition, a free trade port is a port area within the territory of a country or region that is not subject to the usual customs control, with free access to overseas goods and funds. The main feature of a free trade port is that it is outside the control of the customs authority of a country. It has the features of a port and a free trade zone, with many trade- related functions, including product processing, logistics, and warehousing.

Geographically, a free trade port is part of the territory of a country, but from the perspective of administrative supervision, it is outside the customs jurisdiction of the country. As shown in Fig. 3, there are 13 free trade pilot zones and twelve pilot cities in China. Tian et al. (2018) suggested three areas to promote the development of free trade ports. First, it is necessary to improve convenience for businesses engaging in trade in the ports. Second, the ports must take steps to improve the fluidity of personnel as well as their ability to attract talent. Finally, the process of improving the ports' financial systems presents an opportunity to deepen financial reform and improve market openness. Moreover, the government should establish a financial leasing system, so that it can provide sufficient capital support for all businesses in ports and encourage more international companies to establish headquarters in the free trade ports.

The second method is the One Belt, One Road initiative (BRI). The BRI, which was initiated by the Chinese government in 2013, is devoted to improving regional cooperation and connectivity on a transcontinental scale. The initiative aims to strengthen infrastructure, trade, and investment links between China and the other BRI countries. Currently, 64 countries are actively involved in the BRI. These include 10 Association of Southeast Asian Nations countries, 18 countries in Western Asia, 8 in South Asia, 5 in Central Asia, 7 in the Commonwealth of Independent States, and 16 in Central and Eastern Europe. Yu (2018a) found that if China chooses to import more intermediate goods from the European Union and Association of Southeast Asian Nations countries, or countries alongside the BRI instead, the price of the intermediate goods would be more competitive, and the Chinese people can also access cheaper finished goods.

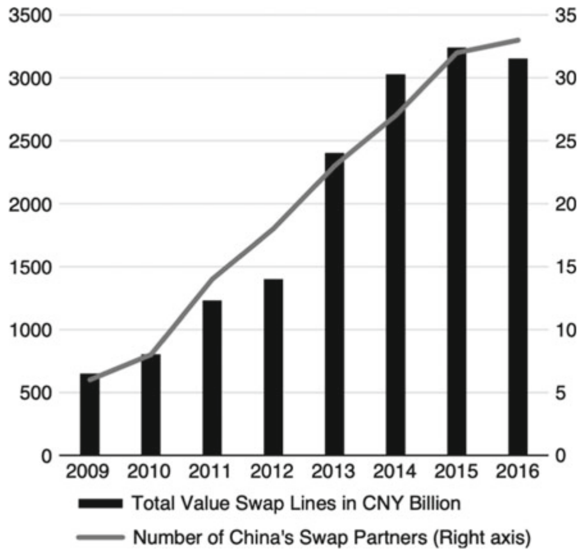
The third method is the internationalisation of the renminbi. Since around 2005, the Government of China has pursued a variety of initiatives designed to encourage wider use of the renminbi. As shown in Fig. 4, these efforts sped up after the global financial crisis in 2008 and have made great progress since 2009. This progress peaked in 2015 and has slowed in some aspects since 2016. The progress of renminbi internationalisation can be categorised into four fields: renminbi trade settlement, renminbi-denominated investment, renminbi bond issuance, and renminbi currency

Fig. 3 Map of the free trade pilot zones and pilot cities. *Source* authors,
Note Data of swaps are from the People's Bank of China (2016). This graph does not include swaps under the Chiang Mai Initiative.

swaps and direct trading (Eichengreen & Kawai, 2014). Zhang et al. (2018) found a significant positive effect of swap agreements on trade. In their benchmark model, the negotiations of the swap agreement would improve 30.4% of bilateral trade values between China and its partners. For BRI countries, the effect is even stronger. This effect is both statistically and economically significant. They believe that renminbi swap agreements support economic integration between China and BRI countries by facilitating bilateral trade.

The fourth method is the construction of the Pearl River Greater Bay Area (GBA). If the BRI and Regional Comprehensive Economic Partnership constructions are treated as the key content of the new pattern of all-around opening up, the Guangdong–Hong Kong–Macau GBA indeed is an important domestic carrier of the BRI. Thus, the construction of the Guangdong–Hong Kong–Macau GBA is the most urgent task of China's opening up. Yu (2018b) suggests that the development of the GBA should focus on the following perspectives. First, it is essential for the GBA to focus on manufacturing industries rather than services industries only. Second, the construction of the GBA should focus on innovation. The third objective is to achieve institutional innovation. Fourth, the GBA should pay more attention to its ecological environment.

Fig. 4 China's bilateral swap values and numbers. *Source* People's Bank of China



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Imported Intermediate Inputs, Firm Productivity and Product Complexity

Miaojie Yu and Jin Li

1 Introduction

The use of imported intermediate inputs is one of the most important topics in empirical trade research, especially in recent years. Initially, trade economists primarily focused on the effect of a firm's exports on firm productivity (Bernard & Jensen, 2004; Park et al., 2010; Yang & Mallick, 2010). However, research interest has gradually shifted to the exploration of the effect of firm imports, which are playing an increasingly important role in raising firm productivity (Amiti & Konings, 2007; Halpern et al., 2011; Kasahara & Rodrigue, 2008). Amiti and Konings (2007) analyse Indonesian firm-level data, including plant-level information on imported inputs, and find that firms gain at least twice as much from input tariff reductions as from output tariff reductions. Halpern et al. (2011) find that during 1993–2002, one-third of the productivity growth in Hungary was attributable to imported inputs.

The present paper uses Chinese firm-level data to confirm the positive effect of imported intermediate goods on firm productivity. The results are primarily attributable to spillover and competition effects from imported goods. However, the present paper finds that the impact of imported intermediate inputs on firm productivity becomes weaker as firms produce more complex products. Differentiated products, which account for four-fifths of total products, to some extent bear less pressure from severe competition but enjoy fewer benefits from foreign imports penetrating the domestic market compared with homogeneous products. However, the growth in productivity of firms that produce heterogeneous goods is slower than that of firms that produce homogeneous goods when product complexity requires more imported intermediate goods. If a homogeneous intermediate input is imported, firms will find

M. Yu (✉) · J. Li
National School of Development, China Center for Economic Research, Peking University, Beijing, China
e-mail: mjyu@ccer.pku.edu.cn

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it easier to adopt its up-to-date technology because homogeneous products are less technology-specific than heterogeneous products.

The present paper contributes to the literature in at least three important ways. First, based on Chinese firm-level data, it confirms the positive effects of both imported inter- mediate inputs and final imports on firm productivity. Compared with some research based on Chinese provincial data or industry-level data, our findings are more micro-grounded and, hence, are more reliable. A few recent papers based on Chinese firm-level data have found strong evidence of the positive effect of imports on firm productivity. However, those papers focus on imports of either intermediate inputs or final goods, but not both. We analyse Chinese firm-level data to examine the effects of imported intermediate inputs and final imports. Although the effects of tariffs on firm productivity have been widely considered in the literature, our paper extends the related analysis by incorporating the effects of both tariffs and nontariff barriers.

Second, the paper enriches our understanding of product heterogeneity, which could help us to understand the phenomenon of "home market bias" in the sense that a larger market will produce more and be a net exporter of differentiated goods. This phenomenon is described in Krugman (1980), although the empirical support is mixed (see e.g. Davis & Weinstein, 1999; Feenstra et al. (2001). Different from previous studies that have directly tested home market effects, the present paper examines the effects of two categories of imported intermediate inputs on firm productivity: homogeneous products and heterogeneous products. Following Rauch (1999), all products are divided into homogeneous products and heterogeneous products. Homogeneous goods are made up of goods whose prices are quoted on organized exchanges and those whose reference prices are quoted only in trade publications. By contrast, heterogeneous goods, for example, shoes (No. 851 in the SITC standard), may include many complex units, such as hiking shoes, sandals, leather shoes, and so on, with no reference price. We find that firms that produce homogeneous goods benefit more from foreign imports. Furthermore, the impact of imported intermediate inputs on firm productivity is weaker as more heterogeneous intermediate products are imported.

Third, to explore the nexus among imported intermediate inputs, firm productivity and product complexity, we follow the standard procedure to investigate the relationship in three steps. First, we use the augmented Olley and Pakes (1996) methodology to construct measures of Chinese firm-level total factor productivity (TFP). Olley and Pakes (1996) provide a semi-parametric approach to address the two estimation biases in the measured TFP that arise when the ordinary least squares (OLS) approach is used: simultaneity bias and selection bias. We adopt this approach with some necessary modifications to fit the case of China, as suggested by Yu (forthcoming). Second, to examine the impact of imported intermediate inputs and final imports on firm productivity, we use fixed-effects estimates for our panel data. Third, we introduce product complexity by merging the data obtained from Rauch (1999) with Chinese firm-level data.

The heterogeneous productivity gains from imports between complex products and simple products are identified by the own coefficients of the import variables and their interactions with product complexity. Because a firm's imported intermediate inputs could foster firm productivity through spillover effects and firms with high-level productivity might also import more intermediate inputs to produce more, our benchmark estimates face a reverse causality problem. To address this, we employ a firm-specific input tariff index as the instrument. Our instrumental variables (IV) estimates show that the impact of imported intermediate inputs on firm productivity is weaker as more heterogeneous inter- mediate products are imported.

This study joins a growing literature on trade and firm productivity, including Amiti and Konings (2007); Topalova and Khandelwal (2011); Ge et al. (2011); Feng et al. (2012) and Yu (forthcoming). Amiti and Konings (2007) use Indonesian manufacturing firm-level data and find that firm productivity increases by 1% (3%) when output tariffs (input tariffs) drop by 10%. Similar to their findings, we also find that firm productivity benefits from both imported intermediate inputs and imports of final goods. Different from their work, we focus on the impact of imports rather than tariffs. As trade protection in many countries today is via nontariff barriers but not import tariffs, our findings have broader implications.

Ge et al. (2011) investigate the channels of productivity gains from trade liberalization and further show improvement in firm performance caused by changes in imports. By way of comparison, we take both imported intermediate inputs and final imports into account and further calculate a firm's productivity gain when more products with different complexity are imported. Yu (forthcoming) finds that the effect of input tariff reductions on productivity improvement is weaker than that of output tariff reductions, as processing imports are already duty free. In this paper, we mainly focus on imports and product complexity. Tariffs are adopted as the IV to address possible endogeneity problems. To this end, our analysis coincides with that of Feng et al. (2012), who also use Chinese tariffs as the IV of imported intermediate inputs. However, their analysis abstracts the role of product complexity.

The remainder of the paper is organized as follows. Section 2 describes the data used in the regressions. Section 3 discusses the estimation results. Section 4 concludes.

2 Data

To calculate the impact of imports on firm productivity taking product complexity into account, we rely on three disaggregated, large panel data sets: firm-level production data, product-level trade data and product complexity data.

Firm production data are derived from a rich panel of data from an annual industrial firm survey from 2002 to 2006, covering all state-owned enterprises (SOEs) and non-SOEs whose annual sales exceed 5 million yuan (equivalent to US$833,000). Following Cai and Liu (2009), we use the following criteria to clean the sample and omit outliers. First, observations with missing key financial variables are excluded.

Second, we drop firms with fewer than eight workers because they fall under a different legal regime, as suggested by Brandt et al. (2012). Third, following Feenstra et al. (forthcoming), we delete observations according to the basic rules of generally accepted accounting principles (GAAP) if any of the following are true: (i) liquid assets are greater than total assets; (ii) total fixed assets are greater than total assets; (iii) the net value of fixed assets is greater than total assets; (iv) the firm's identification number is missing; or (v) an invalid established time exists.

The import data are obtained from China's General Administration of Customs, which records a variety of information for each trading firm's product list, including trading price, quantity and values at the Harmonized System (HS) eight-digit level. More importantly, this rich data set allows us to calculate the value of imported intermediate inputs and firm-level tariffs, which are the main variables in our regressions.

The product complexity data come from Rauch (1999), who follows two approaches, a conservative approach and a liberal approach, to classify traded commodities. The conservative classification is generated by minimizing the number of commodities that are classified as either organized exchange or reference priced commodities (we refer to these as homogeneous products). The liberal classification is obtained by maximizing those numbers.[1] For each approach, the traded goods are classified into three categories: heterogeneous products, homogeneous products traded in organized exchanges, and homogeneous products with guiding prices. As our paper focuses mainly on heterogeneous goods, we combine homogeneous products traded in organized exchanges and homogeneous products with guiding prices and refer to them as homogeneous goods.

Firm-level production data are crucial in measuring TFP, while product-level customs data are non-substitutable in calculating the value of imported intermediate inputs. However, there are some technical challenges in merging the two data sets. Although the data sets share a common variable (i.e. the firm's identification number), the coding system in each data set is completely different.[2] To address this challenge, strictly following Yu and Tian (2012), we use two methods and other common variables to match the two data sets. (See Appendix I for details.) First, we use each firm's Chinese name and year to match the two data sets. That is, if a firm has an exact Chinese name in both data sets in a particular year, it should be the same firm.[3] Second, we use another matching technique to serve as a supplement. Namely, we rely on two other common variables to identify the firms: the zip code and the last seven digits of the firm's phone number. The rationale is that firms should have a unique phone number within a postal district. Although this

[1] See Rauch (1999) for a more detailed description of the definition of the conservative and liberal classifications.

[2] In particular, the firm codes in the product-level trade data are at the ten-digit level, whereas those in the firm-level production data are at the nine-digit level, with no common elements.

[3] The year variable is necessary as an auxiliary identification variable because some firms could change their name in different years and newcomers could possibly take their original name.

Table 1 Summary statistics

Variables	Mean	Standard deviation
Firm productivity	1.30	0.29
Final goods import (in log)	17.58	2.37
Intermediate goods import (in log)	− 3.96	2.86
Product heterogeneity (conservative method)	0.82	0.38
Product heterogeneity (liberal method)	0.80	0.40
State-owned enterprise indicator	0.01	0.11
Foreign indicator	0.72	0.45
Firm labour (in log)	5.50	1.15
Firm input tariffs	2.58	3.97

method seems straight- forward, there are subtle technical and practical difficulties.[4] We merge the product complexity data with the other two data sets. The customs data, the firm-level trade data and the product complexity data are compiled using different international standards. To merge all the data sets together, we benefit from the United Nations concordance, which successfully links product heterogeneity to HS eight-digit products. (See Feenstra et al., (2001) for a detailed discussion).

Table 1 reports the summary statistics for the key variables used in the regressions. We exclude trading companies from our data set and calculate firms' imported intermediate inputs based on firm imports that are reported in the transaction-level trade data set. (See Ahn et al. (2011) for a detailed discussion on the behaviour of trading companies). The rationale is straightforward. The products imported by a manufacturing firm could serve as imported intermediate goods or capital goods, such as machinery for production. Because our main interest is to explore the role of imported intermediate inputs, we first merge the data based on the United Nations Classification by Broad Economic Categories and then drop those goods that are classified as capital goods. Thus, the remaining data in the sample cover only imported intermediate inputs.

By contrast, there is no way for researchers to extract firm imports of final goods from either the firm-level production data set or the product-level trade data set. The firm-level production data set reports firms' exports but not imports. The production-level trade data set only reports each firm's imported intermediate inputs. However, the firm-level data set explicitly reports the four-digit Chinese industrial classification (CIC) level for each firm. Therefore, imports of final goods are calculated based on total industry imports at the four-digit CIC level minus the goods in the same industry that are imported by firms. By measuring firm productivity as the augmented Olley and Pakes (1996) TFP (see Appendix II for a detailed discussion), Figs 1 and 2

[4] For example, the phone numbers in the product-level trade data include both area phone codes and a hyphen, whereas those in the firm-level production data do not.

show that firm productivity is positively correlated with imported intermediate inputs and imports of final goods, respectively, during the post-World Trade Organization (WTO) period (2002–2006), given that China joined the WTO in 2001.

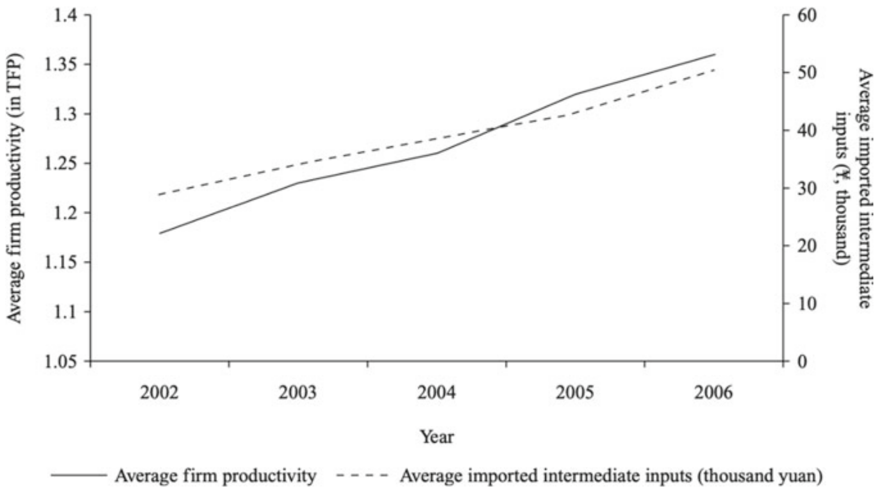

Fig. 1 Firm productivity and imported intermediate inputs. *Source* Customs trade data (2002–2006) and authors' calculations

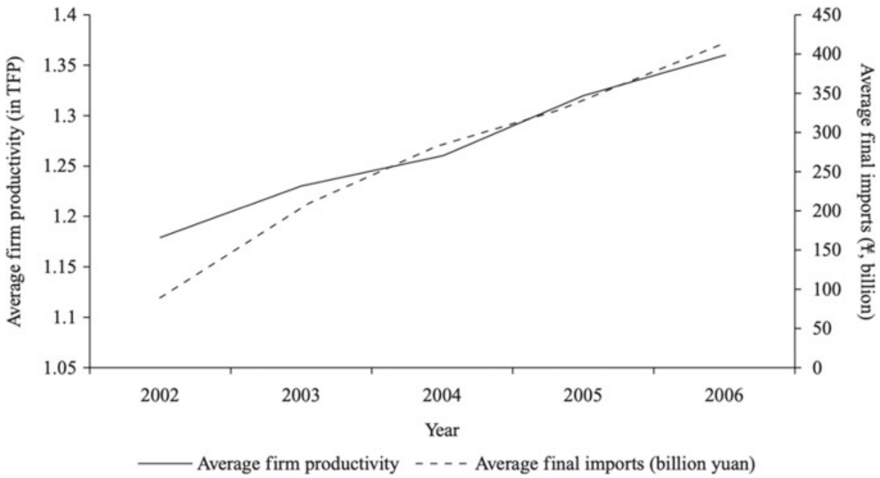

Fig. 2 Firm productivity and imports of final goods. *Source China Statistical Yearbook*, customs trade data (2002–2006) and authors' calculations

3 Measures, Empirics and the Results

3.1 Empirical Specifications

$$
\begin{aligned}
TFP_{ijt}^{OP} &= \alpha_0 + \alpha_1 FIM_{jt} + \alpha_2 IIM_{it} \\
&\quad + \boldsymbol{\theta X_{it}} + \varpi_i + \eta_t + \mu_{it}
\end{aligned}
\tag{1}
$$

To investigate the impacts of imported intermediate inputs and final goods imports on firm prod where the explained variable TFP_{ijt}^{OP} is the logarithm of firm *i*'s measured TFP in industry *j* in year *t*, based on the augmented Olley and Pakes (1996) approach, as in Yu (forthcoming). IIM_{it} denotes the imported intermediate inputs of firm *i* in year *t*. FIM_{jt} denotes the imports of final goods by industry *j* in year *t*. $\mathbf{X}_{it}$ denotes other firm characteristics, such as type of ownership (i.e. SOEs or foreign-invested firms).

State-owned enterprises are traditionally considered to have relatively low economic efficiency and, hence, low productivity (Hsieh & Klenow, 2009). By comparison, foreign- invested firms have higher productivity, partially as a result of international technology spillovers (Keller & Yeaple, 2009) or fewer financial constraints (Manova et al., 2009). We include the two indicators in the empirical specification to measure the roles of SOEs and foreign-invested firms. In particular, if a firm has any investments from other countries (regimes), it is classified as a foreign-invested firm. The majority of the inflow of foreign investment comes from Hong Kong, Macao and Taiwan; therefore, these investments are considered in the construction of the indicators.[5] Similarly, we construct an indicator for SOEs, which is one if a firm has any investment from the government and zero otherwise.[6] Following Eaton et al. (2011). We use the logarithm of total employment to represent the scale of the firm, which serves as an additional control variable, Still, there are some other explanatory variables that we do not control, which are absorbed into the error terms: (i) firm-specific fixed effects, ϖ_i, to control for time-invariant but unobservable factors; (ii) year-specific fixed effects, η_t, to control for firm-invariant factors; and (iii) an idiosyncratic effect, μ_{it}, with normal distribution $\mu_{it} \sim N(0, \sigma^2)$ to control for other unspecified factors.

[5] Specifically, foreign-invested enterprises include the following firms: foreign-invested joint-stork corpo- rations (code: 310), foreign-invested joint venture enterprises (320), fully foreign-invested enterprises (330), foreign-invested limited corporations (340), Hong Kong/Macao/Taiwan joint-stock corporations (210), Hong Kong/Macao/Taiwan joint venture enterprises (220), fully Hong Kong/Macao/Taiwan- invested enterprises (230) and Hong Kong/Macao/Taiwan-invested limited corporations (240).

[6] By the official definition reported in the *China City Statistical Yearbook* (2006), SOEs include firms such as domestic SOEs (code: 110), state-owned joint venture enterprises (141) and state-owned and collective joint venture enterprises (143), but exclude state-owned limited corporations (151).

Several studies use firm-level data to examine the impact of imports in various countries, such as Chile, India and Indonesia. Our baseline regressions are displayed in Table 2. Column (1) presents the results of the regression that includes only the imported inter- mediate inputs as the regressor, without controlling for firm-specific or year-specific fixed effects. It turns out that imported intermediate inputs are positively and statistically significantly correlated with firm productivity, which is consistent with the results of other studies. Moving forward, we add imports of final goods, the firm's type of ownership and firm size (i.e. log of labour) to the regression in column (2). Column (3) takes one step forward to control for the year-specific fixed effects. The coefficient of imported inter- mediate inputs is still positive and significant. We find positive effects of final imports on firm productivity in columns (2) and (3). Finally, after controlling for both the firm-specific fixed effects and the year-specific fixed effects, column (4) confirms our previous findings of significant and positive correlation between imports and firm productivity.

The imported intermediate inputs could foster firm productivity as a result of techno- logical spillovers or quality effects, as suggested by Amiti and Konings (2007). In addition, imports of final goods induce tougher competition for firms within the same industry, so that firms will have to try their best to boost their productivity to survive.

Table 2 Benchmark estimates

Regressand: $lnTFP_{ijt}^{OP}$	OLS (1)	OLS (2)	OLS (3)	FE (4)
Log of imported intermediate inputs	0.013*** (29.81)	0.012*** (25.65)	0.012*** (26.26)	0.012*** (19.23)
Log of final imports	–	0.015*** (28.96)	0.013*** (24.03)	0.013*** (9.98)
Quad indicator	–	– 0.097*** (– 8.36)	– 0.067*** (– 5.92)	– 0.075*** (– 5.05)
Foreign indicator	–	– 0.017*** (– 5.69)	– 0.012*** (– 4.01)	– 0.012*** (– 3.24)
Log of labour	–	0.000 (0.08)	0.000 (0.88)	0.001 (0.95)
Firm-specific fixed effects	No	No	No	Yes
Year-specific fixed effects	No	50	Yes	Yes
Observations	60,209	59,323	59,323	59,323
Probability > F	0	0	0	0
R2	0.02	0.04	0.07	0.06

Notes *** represents significance at the 1% level. Numbers in parentheses are *t*-values. The regression in column (1) describes the basic relationship between imported intermediate inputs and firm productivity. The regressions in columns (2)–(4) use imported intermediate inputs and final imports as described in Eq. (1). FE, fixed effects; OLS, ordinary least squares

3.2 Role of Product Complexity

Thus far, we have found a positive nexus between imports and firm productivity. However, Eq. (1) is a relatively crude specification because imports could be quite different when products with different levels of complexity are imported. For example, on the one hand, if a homogeneous product is introduced to the domestic market, firms will have more incentive to improve their productivity given that the competition in the market is more intense. On the other hand, if a homogeneous intermediate input is imported, firms may find it easier to adopt its up-to-date technology because homogeneous products are less technology-specific than heterogeneous products.

To confirm this, we introduce a product complexity indicator, following Rauch (1999), as explained above. That is, we construct an indicator "N_i" of product complexity, which is zero if a product has a reference price and is thus a homogeneous good, and one otherwise. Taking the complexity indicator into account, we use the following specification for our main estimations:

$$\mathrm{TFP}_{\mathrm{ijt}}^{\mathrm{OP}} = \beta_0 + \beta_1 \mathrm{FIM}_{\mathrm{jt}} + \beta_2 \mathrm{IIM}_{\mathrm{it}} + \beta_3 \mathrm{FIM}_{\mathrm{jt}} \times \mathrm{N_i} + \beta_4 \mathrm{IIM}_{\mathrm{it}} \times \mathrm{N_i} + \delta \mathbf{X_{it}} + \varpi_{\mathrm{i}} + \eta_{\mathrm{t}} + \mu_{\mathrm{it}} \quad (2)$$

In addition to all the regressors listed in Eq. (1), the new regressors in Eq. (2) are the complexity indicator (N_i) and its interactions. The interaction term between imported intermediate inputs (and final imports) and the complexity indicator is included to capture possibly heterogeneous productivity gains from imports caused by different product complexity. Following previous studies, such as Yu et al. (2013), we use the conservative method as a default measure of the complexity indicator.

Column (1) in Table 3 includes the interaction terms for product complexity and imported intermediate inputs and final imports. The coefficients of imported intermediate inputs and final imports are still positive and significant, whereas their interaction terms with the complexity indicator are negative and significant. This suggests that imports have greater impact on the productivity of firms that produce homogeneous goods. In column (2), we control for the firm's type of ownership, firm size and year dummies. The results remain almost the same as those in column (1), except that the coefficient of the interaction term between imported intermediate inputs and the complexity indicator is insignificant. It could be that this result is caused by the measure of the complexity indicator.

To confirm this, we use the liberal method as an alternative measure of the complexity indicator. Results when the liberal approach is used to define the complexity indicator are displayed in column (3), but the results are similar to as those in column (2). Controlling for firm-specific and year-specific fixed effects with either the liberal measure in column (4) or the conservative measure in column (5) does not change the insignificance of the interaction term of imported intermediate inputs and the complexity indicator. We suspect that this is because of the lack of control for the endogeneity of imported inter- mediate inputs. We now turn to address this issue.

Table 3 Estimates with different measures of product complexity

Regressand: lnTFP	OLS (1) conservative	OLS (2) conservative	OLS (3) liberal	FE (4) conservative	FE (5) liberal
Log of imported intermediate inputs	0.013*** (12.99)	0.013*** (12.96)	0.013*** (12.17)	0.006*** (3.16)	0.004*** (2.18)
Log of final imports	0.018*** (32.40)	0.015*** (26.95)	0.015*** (26.93)	0.007*** (3.73)	0.006*** (3.49)
Log of imported intermediate inputs × Complexity indicator	− 0.002*** (− 2.02)	− 0.001 (− 1.52)	− 0.001 (− 1.32)	− 0.001 (− 0.61)	0.001 (0.64)
Log of final imports × Complexity indicator	− 0.003*** (− 10.83)	− 0.003*** (− 10.81)	− 0.003*** (− 10.72)	− 0.001*** (− 2.21)	− 0.001 (− 1.20)
State-owned enterprise indicator	–	− 0.068*** (− 6.01)	− 0.068*** (− 6.00)	0.02 (0.85)	0.02 (0.82)
Foreign indicator	–	− 0.009*** (− 2.99)	− 0.009*** (− 2.96)	0.016 (1.25)	0.016 (1.24)
Log of labour	–	0.002 (1.59)	0.002 (1.62)	0.000 (0.08)	0.000 (0.07)
Firm-specific fixed effects	No	No	No	Yes	Yes
Year-specific fixed effects	No	Yes	Yes	Yes	Yes
Observations	60.209	59,323	54,323	59,323	59,323
R2	0.03	0.07	0.07	0.1	0.11

Notes *** and ** represent significance at the 1 and 5% level, respectively. Numbers in parentheses are *t*-values. The regressions in columns (1)–(5) use product heterogeneity data, which can be derived using the conservative method or the liberal method as described in Eq. (2). Columns (1)–(2) and (4) use the conservative method whereas columns (3) and (5) use the liberal method, as discussed in the text. FE, fixed effects; OLS, ordinary least squares

3.3 Endogeneity Issues

The specifications in Tables 2 and 3 face possible endogeneity problems. Previous studies, such as Krugman (1980); Melitz (2003); Alcala and Ciccone (2004) and Kasahara and Lapham (2013), have recognized that the firm's imports and exports largely depend on the firm's productivity. On the one hand, imported intermediate inputs will increase firm productivity because of spillover effects; on the other hand, firms with high productivity tend to import more intermediate inputs to produce more. We thus use an IV to address the potential endogeneity issue.

China was committed to set its tariffs at the designated levels set by the WTO after its accession in 2001. Hence, tariffs can be treated as an exogenous IV. When tariffs are higher, firms import fewer intermediate inputs, suggesting that the two variables are highly correlated. Thus, the input tariff is a good IV for imported intermediate inputs.

Because the imported intermediate inputs are measured at the firm level, we use firm- specific input tariffs to avoid possible aggregation bias. In China, firms' imports are divided into ordinary imports and processing imports. Processing trade usually means processing with imported materials and processing with supplied materials. Since processing imports are duty free, given that a firm could engage in both processing imports (P) and non-processing imports (O), following Yu et al. (2013), we construct a firm-specific input tariff index (FIT_{it}) as follows:

$$FIT_{it} = \sum_{k \in O} \left(m^k_{i,initial\_year} / \sum_{k \in M} m^k_{i,initial\_year} \right) \tau^k_t ,$$

where $m^k_{i,initial\_year}$ is firm i's imports of product k in the first year the firm appears in the sample. Note that $O \cup P = M$, where M is the set of the firm's total imports.

Table 4 lists the results using IV to mitigate the endogeneity problem. Columns (1)–(3) use the conservative complexity measure, whereas column (4) adopts the liberal complexity measure as a robustness check. Columns (1)–(4) in Table 4 present two-stage least squares (2SLS) fixed-effects estimates for the input tariff and its interaction with the product complexity indicator as the instruments. As shown in column (1), after controlling for reverse causality, imported intermediate inputs boost firm productivity, although the coefficient is statistically insignificant. The coefficient of imported intermediate inputs turns out to be significant after adding more control variables in columns (2)–(4). Once again, with more imported intermediate inputs, firm productivity is higher. More importantly, the impact becomes weaker as firms produce more complex products.

The economic rationale is as follows. A firm could realize productivity gains from importing because imported intermediate inputs involve better technology, which, in turn, fosters firm productivity, as suggested by Amiti and Konings (2007). Compared with heterogeneous products, the advanced technology in homogeneous goods is less product- specific and, hence, easier for firms to absorb. Therefore, we see that there is greater improvement in the productivity of firms with homogeneous products than in firms with heterogeneous products.

To check whether final imports have similar effects, column (2) in Table 4 includes imports of final goods and their interactions with the complexity indicator. The results are similar to those for imported intermediate inputs. Column (3) includes the firm's ownership type and firm size in the estimates and yields similar results for the key coefficients as in column (2). Finally, when a similar regression is run with the liberal measure of complexity to capture the role of product complexity (see column 4), close results are found.

Table 4 Instrumental variable estimates

Regressand: $lnTFP_{ijt}^{OP}$	(1) Conservative	(2) Conservative	(3) Conservative	(4) Liberal
Log of imported intermediate inputs	0.013 (1.17)	0.072*** (2.43)	0.077*** (2.45)	0.051*** (2.48)
Log of final imports	–	0.019*** (– 3.73)	0.020*** (3.74)	0.015*** (4.16)
Log of imported intermediate inputs × Complexity indicator	– 0.010*** (– 1.98)	– 0.075*** (– 2.73)	– 0.080*** (– 2.75)	– 0.050*** (– 2.96)
Log of final imports × Complexity indicator	–	– 0.016*** (– 2.92)	– 0.017*** (– 2.93)	– 0.010*** (– 3.24)
State-owned enterprise indicator indicator	–	–	0.041 (1.52)	0.034 (1.40)
Foreign indicator	–	–	0.021 (1.44)	0.018 (1.28)
Log of labour	–	–	– 0.001 (– 0.20)	– 0.002 (– 0.35)
Kleibergen-Paap rk Lagrange multiplier χ^2 statistic	109.6	21.7	20.2	42.4
Kleibergen-Paap rk lagrange multiplier Whald F-statistic	50.6	10	9	18.2
Firm-specific fixed effects	Yes	Yes	Yes	Yes
Year-specific fixed effects	Yes	Yes	Yes	Yes
Observations	46,083	46,083	44,976	44,976
R2	0.1008	0.0534	0.0465	0.0757
First-stage regressions				
IV1: Firm input tariffs	– 0.024*** (– 2.96) [68.41]	– 0.024*** (– 2.84) [66.75]	– 0.021*** (– 2.53) [62.84]	– 0.022*** (– 2.74) [62.25]
IV2: Firm input tariffs × Product complexity	– 0.219*** (– 21.07) [239.03]	– 0.081*** (– 10.00) [74.85]	– 0.081*** (– 10.02) [71.63]	– 0.102*** (– 12.09) [91.15]

Notes *** and ** represent significance at the 1 and 5% level, respectively. Numbers in parentheses are *t*-values, whereas those in brackets are F-statistics. In the first-stage regressions, IV1 reports the coefficient of firm-specific input tariffs, using imported intermediate inputs as the regressand. IV2 reports the coefficient of the interaction between firm-specific input tariffs and the product complexity indicator, using the interaction between imported intermediate inputs and the product complexity indicator as the regressand

Several tests are performed to verify the quality of the instruments. First, we use the Kleibergen–Paap Lagrange multiplier χ^2-statistic to check whether the excluded instruments are correlated with the endogenous regressors. Second, the Kleibergen and Paap (2006) F-statistics provide strong evidence for rejecting the null hypothesis that the first stage is weakly identified at a highly significant level. Finally, the first-stage estimates offer strong evidence to justify such instruments. In particular, all the t-values of the instruments are significant.

Our final task is to provide some economic intuition for our findings. From Table 4, we see that more imported intermediate inputs lead to higher firm productivity, which is consistent with previous studies. More importantly, the impact of imports on firm productivity is weaker as firms produce more complex products. This result is intuitive. If firms produce complex final products, they face less severe competition in the final goods market because the final goods are more differentiated. Therefore, the firms have less incentive to improve their productivity compared with firms producing homogeneous products. Mean-while, the spillover effects of imported intermediate inputs might help firms increase their productivity, which would encourage firms to produce more or higher-quality products. Therefore, if firms import more intermediate inputs, producers of less complex commodities would tend to produce more or higher-quality products, which could help them to realize greater productivity gains.

4 Concluding Remarks

This paper explores the nexus among imports, firm productivity and product complexity. Using a Chinese firm-level production data set and a transaction-level trade data set, we find that imports boost firm productivity. First, if there are more imported intermediate inputs, the firm's productivity gain will be higher. This is possibly because of technology spillovers and learning from imports. Second, manufacturing firms would enjoy productivity gains from the imports of final goods in their own industry through competition effects.

More importantly, we find that the impact of imported intermediate inputs on firm productivity becomes weaker as firms produce more complex products. By separating products into homogeneous products and heterogeneous products, our empirical analysis shows that firms with homogeneous products realize more productivity gains, possibly because the competition and learning effects for such firms would be greater.

Our findings have the following policy implications. If imports boost firm productivity, it is a good development strategy for the government of China (and perhaps some other developing countries) to import more from the rest of the world. In this way, countries can approach a balanced trade position and, more importantly, increase their firms' productivity and, hence, national welfare.

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Appendix 1: Matched Statistics-Number of Firms

	Trade data		Production data		Matched data			
Year# of	transactions	Firms	Raw firms	Filtered firms	With raw firms	With filtered firms	With raw firms	With filtered firm
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2000	10,586,696	80,232	162,883	83,628	18,580	12,842	21,425	15,748
2001	12,667,685	87,404	169,031	100,100	21,583	15,645	24,959	19,091
2002	14,032,675	95,579	181,557	110,530	24,696	18,140	28,759	22,291
2003	18,069,404	113,147	196,222	129,508	28,898	21,837	33,901	26,930
2004	21,402,355	134,895	277,004	199,927	44,338	35,007	49,891	40,711
2005	24,889,639	136,604	271,835	198,302	44,387	34,958	49,891	40,387
2006	26,685,377	197,806	301,960	224,854	53,748	42,833	49,680	47,591
All years	128,333,831	286,819	615,951	438,165	83,679	69,623	91,299	76,823

Notes Column (1) reports the number of observations of Harmonized System eight-digit monthly transaction- level trade data from China's General Administration of Customs by year. Column (2) reports the number of firms covered in the transaction-level trade data by year. Column (3) reports the number of firms covered in the firm-level production data set compiled by China's National Bureau of Statistics without any filter or cleaning. By contrast, column (4) presents the number of firms covered in the firm-level production data set with careful filtering according to the requirements of GAAP. Accordingly, column (5) reports the number of matched firms using exactly identical company names in both the trade data set and the raw production data set. By contrast, column (6) reports the number of matched firms using exactly identical company names in both the trade data set and the filtered production data set. Finally, column (7) reports the number of matched firms using exactly identical company names and exactly identical zip codes and phone numbers in both the trade data set and the raw production data set. By contrast, column (8) reports the number of matched firms using exactly identical company names and exactly identical zip codes and phone numbers in both the trade data set and the filtered production data set.

Appendix 2: Estimates of Olley–Pakes TFP by Processing and Ordinary Firms Separately

Chinese	Ordinary firms			Processing firms		
Industry	Labour	Materials	Capital	Labour	Materials	Capital
13	0.051	0.875	0.247	0.116	0.884	0.066
14	0.048	0.928	0.027	0.037	0.925	0.074
15	0.298	0.500	0.193	0.243	0.505	0.088
17	0.059	0.884	0.017	0.089	0.834	0.041
18	0.076	0.858	0.054	0.177	0.669	0.142
19	0.044	0.925	0.040	0.118	0.808	0.000
20	0.023	0.895	0.126	0.044	0.913	0.003
21	0.042	0.917	0.055	0.101	0.873	0.103
22	0.008	0.907	0.111	0.027	0.896	0.063
23	0.039	0.821	0.023	0.105	0.836	0.025
24	0.123	0.764	0.068	0.104	0.863	0.036
26	0.049	0.800	0.107	0.007	0.927	0.024
27	0.040	0.865	0.059	0.038	0.860	0.038
28	0.011	0.795	0.045	0.016	0.837	0.041
29	0.177	0.545	0.090	0.073	0.938	0.032
30	0.172	0.624	0.158	0.125	0.696	0.114
31	0.044	0.853	0.059	0.050	0.870	0.035
32	0.028	0.985	0.018	0.038	0.961	0.010
32	0.028	0.985	0.018	0.038	0.961	0.010
33	0.081	0.820	0.051	0.055	0.850	0.076
34	0.046	0.870	0.040	0.044	0.883	0.026
35	0.017	0.875	0.066	0.032	0.917	0.026
36	0.061	0.832	0.043	0.038	0.869	0.111
37	0.043	0.891	0.044	0.054	0.924	0.029
39	0.101	0.834	0.018	0.102	0.826	0.000
40	0.067	0.836	0.078	0.086	0.878	0.086
41	0.000	0.927	0.082	0.139	0.567	0.168
42	0.044	0.918	0.004	0.142	0.818	0.094

Notes This table reports the estimated log of Olley–Pakes total factor productivity (TFP) by separating ordinary and processing firms. The Chinese industries and associated codes are classified as follows: Processing of foods (13), Manufacture of foods (14), Beverages (15), Textiles (17), Apparel (18), Leather (19), Timber (20), Furniture (21), Paper (22), Printing (23), Articles for culture and sports (24), Petroleum (25), Raw chemicals (26), Medicines (27), Chemical fibers (28), Rubber (29), Plastics (30), Non-metallic minerals (31), Smelting of ferrous metals (32), Smelting of non-ferrous metals (33), Metal (34), General machinery (35), Special machinery (36), Transport equipment (37), Electrical machinery (39), Communication equipment (40), Measuring instruments (41) and

Manufacture of artwork (42). We do not report standard errors for each estimated coefficient to save space, although standard errors are available upon request

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Trade Liberalisation, Product Complexity and Productivity Improvement: Evidence from Chinese Firms

Miaojie Yu, Guangliang Ye, and Baozhi Qu

1 Introduction

This paper investigates the effect of trade liberalisation on Chinese firms' productivity. In the past three decades, China has experienced dramatic trade liberalisation as well as productivity gains. The average unweighted tariffs decreased from around 55% in the early 1980s to about 13% in 2002. At the same time, China's average annual increase in total factor productivity (TFP) in the first two decades since economic reform in 1978 was around 4%, although this pace seems to have slowed down after that (Zheng et al., 2009). It is interesting to see whether or not China's trade liberalisation has boosted its productivity. Although economists have paid some attention to this issue, the research is far from conclusive and deserves further exploration.

First, in much of the existing work on TFP, TFP is usually measured as the Solow residual, defined as the difference between the observed output and its fitted value calculated via ordinary least squares (OLS) regressions. However, this method suffers from a number of econometric problems, including simultaneity bias and selection bias. The first bias comes from the fact that a profit-maximising firm would respond to productivity shocks by adjusting its output, which, in turn, requires reallocating its inputs. Since such a productivity shock is observed by firms and not by econometricians, this creates an endogeneity issue. Moreover, firms covered in the samples are

M. Yu (✉)
National School of Development, China Center for Economic Research, Peking University, Beijing, China
e-mail: mjyu@ccer.pku.edu.cn

G. Ye
School of Economics, Hanqing Institute of Economics and Finance, Renmin University of China, Beijing, China

B. Qu
China Merchants Group, Hong Kong, China

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usually those that have relatively high productivity and survived during the period of investigation. Those firms that have exited the market due to low productivity were not observed and thus excluded from the samples. Ignoring the firms' entry and exit from the market means that the samples are not randomly selected, and hence, the estimation results may suffer from selection bias.

Second, previous studies ignored the heterogeneity of goods in their estimations. Complex products are differentiated and have many characteristics, including size, design, material and other specifications (Berkowitz et al., 2006). In contrast, simple goods are more homogeneous, and they are either traded on organised exchanges or are reference-priced. When facing trade liberalisation, firms that produce complex goods may react differently with those that produce simple goods. However, there has been no empirical evidence on whether trade liberalisation affects the productivity of producers of complex goods and simple goods differently.

Third, much of the literature has used output tariffs as an indicator of trade liberalisation. Recently, Amiti and Konings (2007) took a step forward to take input tariffs into account. However, a tariff is just one of the many instruments in trade policies, which has already been reduced to a very low level after the Uruguay Round of the WTO in 1994. Other trade policy instruments, including various non-tariff barriers (NTBs), also play important roles in protecting domestic import-competing industries. Restricting the scope to tariffs only is insufficient in understanding the impact of trade liberalisation on productivity.

Last but not least, the existing literature has faced an empirical challenge in using China's data. Holz (2004) emphasised the bias of using China's aggregated data since there is a mismatch between disaggregated and aggregated statistical data. This is consistent with Krugman's (1994) complaint that it is a challenging job to explain China's economic growth due to its low-quality data. Young (2003) argued that China's TFP growth rate was quite modest and perhaps negative in the post-Mao era. However, his work is based on aggregated industrial data, which would be subject to some bias as well.

In this paper, to mitigate the above-mentioned estimation issues, the effect of China's trade liberalisation on its productivity was estimated by precisely measuring TFP, by taking into account the difference in complex goods and simple goods, by choosing an appropriate indicator of trade liberalisation and by using the most disaggregated firm-level data.

First, to address the two empirical challenges (i.e. simultaneity bias and selection bias) caused by OLS, we adopt the Olley–Pakes (1996) approach. This approach was also revised by imbedding a survival probability model to control for the problem of selection bias. Second, we estimate the effect of trade liberalisation on firm productivity for complex and simple goods separately using a classification system in line with Rauch (1999). Third, as stated above, trade liberalisation includes the removal of various NTBs in addition to tariff cuts. However, data on NTBs are very difficult to obtain, especially for developing countries like China. The import penetration ratio, which is defined as industrial imports over its outputs, is the economic consequence of both tariffs and NTBs. Compared to tariffs, the import penetration ratio is a better instrument for measuring trade liberalisation (Levinsohn, 1993). In this paper, the import penetration ratio is used to measure trade liberalisation. Finally, the sample in this paper is a rich firm-level panel, covering more than 150,000 manufacturing firms per year from 1998 to 2002. For each firm, the coverage is more than 100 financial variables listed in the main accounting sheets of all state-owned enterprises (SOEs) and those non-SOEs firms, whose sales are more than five million yuan RMB per year.

The estimation results suggest that trade liberalisation significantly increases productivity for firms that produce complex goods. In contrast, we find that trade liberalisation has the opposite effect on the productivity of producers of simple goods. These findings are robust after controlling for potential endogeneity. We further find that the effect of trade liberalisation on firm productivity to exporting firms is smaller than non-exporting firms.

This paper joins the growing literature on the nexus between trade liberalisation and productivity. To measure productivity, papers such as Trefler (2004) emphasised labour productivity, although most studies have concentrated on TFP. In the early stage, researchers usually rely on industrial-level data to measure TFP. These include, among others, Tybout et al. (1991), Levinsohn (1993), Harrison (1994) and Head and Ries (1999). Most recent studies, such as Pavcnik (2002) and Amiti and Konings (2007), consider firm productivity by using plant data. However, most of these above-mentioned works only use tariffs to measure trade liberalisation. Only a few exceptions, like Harrison (1994), include the import penetration ratio as a robustness check.

Our study also contributes to the recent development in the literature that emphasises on the difference in trade patterns of complex goods and simple goods (Berkowitz & Moenius, 2011; Berkowitz et al., 2006; Ma et al., 2011). We find empirical evidence showing that the effect of China's trade liberalisation on firm productivity depends on the product complexity. We argue that since complex goods are highly differentiated products, the increased degree of trade liberalisation creates learning opportunities and encourages firms to engage in more innovative activities to develop more differentiated products. However, for firms that produce simple goods, a high level of import penetration means that these firms face severe competition from abroad and their operating performance may decline. As a result, these firms have less resources to invest in technology improvement.

The remainder of the paper is organised as follows: Sect. 2 reviews China's trade liberalisation in the last three decades. Section 3 introduces the estimation methodology. Section 4 describes data. Section 5 discusses estimation results and robustness checks, and Sect. 6 concludes the paper.

2 China's Trade Liberalisation

In the past three decades, China has experienced dramatic trade liberalisation. As a result, China changed from an almost fully isolated economy to the second largest open economy today. China's openness ratio (i.e. the sum of exports and imports relative to GDP) increased from around 10% in the early 1970s to 64% in 2007. The 'open-door' policy has become one of the two most fundamental doctrines of the Chinese government after 1978.[1] During the last three decades, China has proceeded with its trade liberalisation by setting up export-processing zones (EPZs) to absorb foreign direct investments (FDIs), by acceding to the WTO and by significantly cutting tariffs.

Before 1978, China's foreign trade was completely monopolised by 12 national foreign trade companies (FTCs). They imported products at world prices and sold them domestically at projected prices. As a result, China was insulated from the world economy (Naughton, 2006). Like many other East Asian countries, the Chinese government set up EPZs in 1978 to launch trade liberalisation. The first wave of the EPZs formation saw the setting up of four special economic zones (SEZs) in the early 1980s, which allowed export-processing duty-free imports. The second wave mainly opened up two eastern coastal provinces (i.e. Guangdong and Fujian) by allowing foreign firms to sign 'export-processing' contracts with domestic firms. In the early 1990s, China experienced its third wave of dramatic proliferation of SEZs by generalising the open-door policy to many other eastern coastal provinces. China then set up 18 economic and technical development zones (ETDZs), in which foreign investors are encouraged to set up joint ventures with rural collectives and various subsidiaries. By the end of 2003, China had already more than 100 investment zones that enjoy various special foreign trade policies.

Before the economic reform, tariffs did not play an important role since FTCs had already served as an 'air-lock' to insulate China from the world. In the 1980s, China began to set up a whole system of tariff rates. In 1992, China's unweighted average tariffs were 42.9%, which was similar to the level of other developing countries. Shortly after the Uruguay Round of the WTO, China experienced huge tariff reductions due, in large part, to the WTO accession application. China cut its tariffs from 35% in 1994 to around 17% in 1997. After that, from 1998 to 2002, China's average tariffs did not decrease much. The largest adjustment was in 2001, in which the average tariff rates decreased from 16.4 to 15.3%. Besides tariffs, China also used various NTBs to protect its import-competing industries.

According to UNCTAD's classification, the NTBs include many types of measures, such as price control measures, quantity control measures, customs charges and taxes, financial measures, technical measures, monopolistic measures and miscellaneous measures. According to Fujii and Ando's (2000) calculation, China maintained a large number of NTBs in various products. For example, the core non-tariff measures was 51.9% for wood products, whereas it was 55.1% for chemicals in 1996.

Moreover, to fully integrate into the world trade system, China applied to rejoin the GATT in 1986. It took China 15 years to accede to the WTO in 2001, as its 143rd member. Although such a long march was not expected, China's trade policies were changed many times to fit this largest international trading organisation. China's inward FDI increases dramatically after Deng Xiaoping's southern China tour in

[1] The other fundamental doctrine is the 'deepen economic reform' policy.

1992. In 2007, China's FDI reached $74.7 billion, which was 17 times higher than that in 1991. According to *The Economist*,[2] it is predicted that China's inward FDI will become the third largest, followed by the US and the UK, in 2011.[3]

Following trade liberalisation, China also maintains a huge volume of processing exports (i.e. China imports the parts or raw materials from abroad and exports the finished products to other countries). According to *China's Statistical Yearbook*, the value of China's processing exports is much higher than that of its ordinary exports since the 1990s. Although the level of processing trade has been decreasing over the recent years, in 2006, China's processing export still accounted for around 52% out of its total exports.

3 The Methodology

3.1 Measuring Total Factor Productivity

The literature on TFP usually suggests a Cobb–Douglas production function to introduce technology improvement.[4] Following Amiti and Konings (2007), we consider a form as follows:

$$Y_{it} = \pi_{jt}\left(\tau_{jt}\right) M_{it}^{\beta_m} K_{it}^{\beta_k} L_{it}^{\beta_l} \tag{1}$$

where Y_{it}, M_{it}, K_{it}, L_{it} are firm i's output, materials, capital and labour at year t, respectively. Firm i's productivity, p_{it}; is affected by trade policy, s_{jt}, in its industry level j in year t. To measure firm's TFP, one needs to estimate Eq. (1) by taking a log-function first:

$$\ln Y_{it} = \beta_0 + \beta_m \ln M_{it} + \beta_k \ln K_{it} + \beta_l \ln L_{it} + \varepsilon_{it} \tag{2}$$

Traditionally, the TFP is measured by the estimated Solow residual between the true data on output and its fitted value, $\ln \hat{Y}_{it}$. That is:

$$TFP_{it} = \ln Y_{it} - \ln \hat{Y}_{it} \tag{3}$$

However, this approach suffers from two problems: simultaneity bias and selection bias. As first suggested by Marschak and Andrews (1944), at least some parts of TFP changes could be observed by the firm early enough so that the firm could change its input decision to maximise profit. From another perspective, the firm's TFP could

[2] Source: The *Economist* (5 September 2007), via http://www.economist.com.

[3] However, since China also has a remarkable growth rate of its economy scale, the ratio of FDI over GDP is only 2.1%, which is lower than many OECD countries (World Bank, 2007).

[4] An alternative specification is to use a trans-log production function, which also leads to very similar estimation results.

have reverse endogeneity in its input factors. The lack of such a consideration would make the firm's maximising choice biased. In addition, the firms' dynamic behaviour also introduces selection bias. In a panel data set, the firms observed are those that have already survived. On the other hand, firms with low productivity that collapsed and exited from the market are not included in the data set. This means that the samples covered in the regression actually are not randomly selected, which in turn causes estimation bias.

Econometricians tried hard to address these empirical challenges, but were not successful until the pioneering work by Olley and Pakes (1996). In the beginning, researchers used two-way (i.e. firm-specific and year-specific) fixed effects to mitigate simultaneity bias. Although the fixed-effect approach controls for some unobserved productivity shocks, it does not offer much help in dealing with reverse endogeneity. So this approach still seems unsatisfactory. Similarly, to mitigate selection bias, one may estimate a balanced panel by dropping those observations that disappeared during the period of investigation. The problem is that a substantial part of information contained in the data set is wasted, and the firm's dynamic behaviour is completely unknown.

The Olley–Pakes (1996) methodology makes a significant contribution in addressing these two empirical challenges. By assuming that the expectation of future realisation of the unobserved productivity shock, t_{it}, relies on its contemporaneous value, firm i's investment is modelled as an increasing function of both unobserved productivity and log-capital, $k_{it} \equiv \ln k_{it}$. Following previous work (Amiti & Konings, 2007; Van Biesebroeck, 2005), the Olley–Pakes approach is revised (Eq. 4 below) by adding the firm's export decision as an extra argument of the investment function, since most of the firms' export decisions are determined in the previous period (Tybout, 2003).

$$I_{it} = \tilde{I}(\ln K_{it}, \upsilon_{it}, EF_{it}) \tag{4}$$

where EF_{it} is a dummy to measure whether firm i exports in year t. Therefore, the inverse function of Eq. (4) is $\upsilon_{it} = I^{-1}(\ln K_{it}, I_{it}, EF_{it})$.[5] The unobserved productivity also depends on log-capital and the firm's export decision. Accordingly, the estimation specification (Eq. 2) can now be written as:

$$\ln Y_{it} = \beta_0 + \beta_m \ln M_{it} + \beta_l \ln L_{it} + g(\ln K_{it}, I_{it}, EF_{it}) + \varepsilon_{it} \tag{5}$$

where $g(\ln K_{it}, I_{it}, EF_{it})$ is defined as $\beta_k \ln K_{it}, + I^{-1}(\ln K_{it}, I_{it}, EF_{it})$. Following Olley–Pakes (1996) and Amiti–Konings (2007), fourth-order polynomials are used in log-capital, log-investment and the firm's export dummy to approximate g(·).[6] In addition, since our firm data set is from 1998 to 2002, we include a WTO dummy

[5] Olley and Pakes (1996) show that the investment demand function is monotonically increasing in the productivity shock t_{it}, by making some mild assumptions about the firm's production technology.

[6] Using a higher-order polynomials to approximate $g(\cdot)$ does not change the estimation results.

(i.e. one for year after 2001 and zero for before) to characterise the function g(·) as follows:

$$g(K_{it}, I_{it}, EF_{it}, WTO_t) = (1 + \theta_{WTO} WTO_t + \theta_{EF} EF_{it}) \sum_{h=0}^{4} \sum_{q=0}^{4} \delta_{hq} k_{it}^h I_{it}^q \quad (6)$$

After estimating the coefficients $\hat{\beta}_m$ and, $\hat{\beta}_l$ we calculate the residual R_{it}, which is defined as $\mathrm{R_{it}} \equiv \ln \mathrm{Y_{it}} - \hat{\beta}_m \ln \mathrm{M_{it}} - \hat{\beta}_l \ln \mathrm{L_{it}}$.

The next step is to obtain an unbiased estimated coefficient of $\hat{\beta}_k$. To correct the selection bias as mentioned above, Amiti–Konings (2007) suggested estimating a probability of a survival indicator on a high-order polynomial in log-capital and log-investment. Precisely, one can estimate the following specification:

$$R_{it} = \beta_k \ln K_{it} + \tilde{I}^{-1}\left(g_{i,t-1} - \beta_k \ln K_{i,t-1}, \hat{p}r_{i,t-1}\right) + \varepsilon_{it} \quad (7)$$

where $\hat{p}r_i$ denotes the fitted value for the probability of the firm's exit in the next year. Since the specific 'true' functional form of the inverse function $\tilde{I}^{-1}$ (·) is unknown, it is appropriate to use fourth-order polynomials in $g_{i,t-1}$ and $\ln K_{i,t-1} i$ to approximate that. In addition, Eq. (7) also requires the estimated coefficients of the log-capital in the first and second term to be identical. Therefore, non-linear least squares seem to be the most desirable econometric technique (Arnold, 2005; Pavcnik, 2002). Finally, the Olley–Pakes (OP) type of TFP for each industry j is obtained once the estimated coefficient b_k is obtained:

$$TFP_{ijt}^{OP} = \ln \mathrm{Y_{it}} - \hat{\beta}_m \ln \mathrm{M_{it}} - \hat{\beta}_l \ln \mathrm{L_{it}} - \hat{\beta}_k \ln \mathrm{K_{it}} \quad (8)$$

3.2 Econometric Model

We estimate the equation as follows:

$$\begin{aligned} \ln \mathrm{TFP_{ijt}^{OP}} &= \alpha_0 + \alpha_1 \ln \mathrm{imp_{jt}} + \alpha_2 \mathrm{EF_{it}} + \alpha_3\left(\ln \mathrm{imp_{jt}} \times \mathrm{EF_i}\right) \\ &\quad + \alpha_4 \mathrm{exit_{it}} + \theta X_{\mathrm{it}} + \varpi_{\mathrm{i}} + \eta_{\mathrm{t}} + \mu_{\mathrm{iit}} \end{aligned} \quad (9)$$

where ln $TFP_{ijt}{}^{OP}$ is the logarithm of firm i's OP-type TFP in industry j in year t, whereas ln imp_{jt} denotes the logarithm of import penetration ratio for industry j in year t. EF_{it} is a dummy for exporting firm i in year t, whereas $exit_{it}$ denotes a dummy for firm i's exit in year t.[7] X_{it} denotes other control variables for firm i in year t, such as FDI dummy and SOE dummy, and if so, whether it is controlled by the central

[7] The reason that we do not include a dummy for importing firm here is that our data set does not include information on importing firms.

government. The error term is decomposed into three components: (i) firm-specific fixed effects ϖ_i to control for time-invariant factors; (ii) year-specific fixed effects η_t to control for firm-invariant factors like Chinese *yuan* real appreciation; and (iii) an idiosyncratic effect μ_{ijt} with normal distribution $\mu_{ijt} N\left(0, \sigma_{ij}^2\right)$ to control for other unspecified factors.[8]

From Eq. (9), the import penetration ratio in industry *j* has two following effects on productivity of firm *i*, within industry *j*:

$$\partial \ln \mathrm{TFP}_{\mathrm{ijt}}^{\mathrm{OP}} / \partial \ln \mathrm{imp}_{\mathrm{jt}} = \alpha_1 + \alpha_3 \mathrm{EF}_{\mathrm{it}} \tag{10}$$

where parameter α_1 measures the impact of trade liberalisation, which is measured by industry *j*'s import penetration, on non-exporting firm *i* in that industry. In contrast, the effect of trade on an exporting firm's productivity is $a_1\ a_3$. Previous works, such as Levinsohn (1993) and Harrison (1994), emphasised that the high import penetration ratio, an indicator of trade liberalisation, made domestic firms face more intense competition from foreign firms. Therefore, it is reasonable to hypothesise that both α_1 and $\alpha_1 + \alpha_3$ are positive since tougher import competition would force both non-exporting and exporting firms to exert every effort to improve their efficiency for survival.

Moreover, the productivity of exporting firms is expected to increase less than those of non-exporting firms. Put another way, the coefficient α_3 is expected to be negative. This is possibly because more than half of exporting firms in China also import raw materials and parts from overseas, as was discussed in the previous section.[9] With trade liberalisation, processing exporting firms are now able to acquire raw materials and parts from foreign producers at relatively lower costs. They would still enjoy a large price–cost markup by their access to low-priced imports. Therefore, the processing exporting firms have less incentive to adopt up-to-date technology to improve their efficiency, given the fact that they do not face strong competition.

3.3 Classification of Complex and Simple Goods

We classify goods into complex and simple goods in line with Rauch (1999), and this classification method has also been used by previous research (Berkowitz et al., 2006; Ma et al., 2011). Our data set reports firm's industry according to the Harmonised System (HS) 10-digit industry codes. Based on a concordance table provided by the

[8] In this paper, we only include firm-level fixed effects and year-specific fixed effects. The province-level fixed effect is not included here since data on industry-level import penetrations and firm-level TFP do not uniquely match.

[9] Of course, some firms also import parts and raw materials from abroad but only sell their products in the domestic market. Such importing firms still face tough import competition for their final outputs in China and hence only enjoy reasonable markup from lower cost on raw materials. Put another way, such non-exporting firms still bear relatively large price pressure, compared to exporting firms.

Statistical Office of the European Communities, we are able to link the HS code identified in the enterprise survey to the four-digit SITC code in the classification table provided by Rauch (1999). Rauch (1999) has two classification methods: liberal and conservative. We adopt the conservative method. Rauch (1999) classifies four-digit SITC industries into three categories: (i) goods that are traded on organised exchanges; (ii) goods that are reference-priced; and (iii) goods that are not traded on organised exchanges and do not have reference prices. We regard category (i) and (ii) as simple goods and category (iii) as complex goods.

4 Data

The sample used in this paper comes from two large data sets. The first is a rich firm-level panel that covers more than 150,000 manufacturing firms per year for the years 1998–2002.[10] Such data were collected from China's National Bureau of Statistics (2007) as an annual survey for manufacturing enterprises. It covers more than 100 financial variables listed in the main accounting sheets of all SOEs, and those non-SOEs firms, whose sales are more than five million yuan per year.[11]

Table 1 provides some basic statistical information about the Chinese plant data. Although this data set contains rich information, a few samples in the data set are noisy and misleading due, in large part, to the misreporting by some firms (Holz, 2004). For example, data information for some family-based firms, which usually did not set up a formal accounting system, is based on a unit of 1000, whereas the official requirement is a unit of 10,000. Following Jefferson et al. (2008), the observations were dropped if (i) the number of employees hired for a firm is less than eight people[12] and (ii) the ratio of value-added relative to the sales is less than zero or higher than one. As seen in Table 1, FDI-type firms[13] account for more than two-thirds of all plants in each year. In contrast, SOE-type firms account for around one-third.

The previous TFP literature suggests that output should also be measured in physical terms. Recent papers, such as Felipe et al. (2004), have emphasised the estimation bias of using monetary terms to measure output when estimating the production function. In that way, what one actually did is to estimate an accounting identity. To get a precise measure of TFP, one should work on physical data or, at least, deal with deflated terms of output. However, like the problems that many previous studies

[10] Following Levinsohn and Petrin (2003), plants were treated as firms. In the present paper, I do not capture scope economics due to their multi-plant nature. This remains a topic for future research.

[11] Indeed, aggregated data of the industrial sector in the annual *China's Statistical Yearbook* by the Natural Bureau of Statistics is compiled from such a data set.

[12] Levinsohn and Petrin (2003) suggest covering all Chilean plants with at least 10 workers instead.

[13] Here a firm is classified as a FDI-type, one if it, by nature, belongs to one of the followings: (i) equity joint venture; (ii) wholly foreign-owned venture; (iii) contractual joint venture; or (iv) foreign-owned limited liability corporation.

Table 1 Basic Chinese plants data

Year	1998	1999	2000	2001	2002
Raw observation	154,882	154,882	162,883	169,031	140,741
Filtered observation	146,490	149,557	156,400	164,037	137,060
FDI firms	10,718	10,718	11,956	13,116	10,063
SOE firms	49,098	49,098	51,363	35,327	27,304

Table 2 Summary statistics (1998–2002)

Variables	Mean	Standard deviation	Minimum	Maximum
Year	2000	1.14	1999	2002
Log-import penetration ratio	1.576	2.27	− 8.41	11.62
Dummy of SOE	0.25	0.433	0	1
Dummy of central-control SOE	0.014	0.117	0	1
Dummy of foreign-invested enterprises	0.074	0.261	0	1
Log of labour productivity	2.21	3.08	− 11.69	13.15
Log of total factor productivity (Olley–Pakes)	1.84	1.29	− 8.51	8.14

Notes (i) Observations of output, materials and value-added are dropped from the data set if negative. (ii) We obtain different real investment by allowing different depreciation rates (depre.), respectively

have encountered, the data on physical output are unavailable. We therefore deflate each firm's output following Amiti and Konings (2007). The statistical information is reported in Table 2.

Column (2) of Table 3 reports the estimated firm's survival probability in the next year by industry.[14] They varied from 0.97 to 0.99 with the mean of 0.978, which suggests that the firm exits are not so severe during this period. The rest of Table 3 presents the difference in the estimated coefficients for labour, materials and capital by using both the OP methodology and the usual OLS approach. A total of 39 manufacturing industries were covered and coded from 6 to 46 according to China's industrial classifications (GB = T4754-2002). Compared to OLS estimates, as seen from the bottom line of Table 3, the inputs' coefficients for all manufacturing industries estimated by the OP approach seem much lower. This suggests that, without controlling for simultaneity bias and selection bias, the estimated industrial TFP using the OLS approach has a downward bias, which could partially explain why some previous researchers did not find large productivity growth in China (Young, 2003).

[14] Noted that here 'firm's exit' means a firm either died and exited from the market or simply had an annual sale, which is lower than the 'large scale' (i.e. 5 million sales per year) and dropped from the data set. Due to the restriction of the data set, we are not able to distinguish the difference between the two.

Table 3 Total factor productivity of Chinese plants

Industry (code)	Estimated probability	Labour		Materials		Capital	
		OLS	OP	OLS	OP	OLS	OP
Mining and washing of coal (6)	0.983	0.092	0.062	0.431	0.468	0.382	0.237
Extraction of petroleum and natural gas (7)	0.989	0.099	0.048	0.239	0.21	0.646	0.592
Mining and processing of ferrous metal ores (8)	0.984	0.125	0.087	0.466	0.442	0.299	0.184
Mining and processing of non-ferrous metal (9)	0.971	0.112	0.126	0.474	0.484	0.303	0.154
Mining and processing of non-metal ores (10)	0.982	0.131	0.106	0.473	0.494	0.213	0.109
Processing of food (13)	0.972	0.17	0.147	0.508	0.521	0.304	0.202
Manufacture of foods (14)	0.974	0.155	0.141	0.569	0.535	0.359	0.283
Manufacture of beverages (15)	0.975	0.15	0.124	0.463	0.476	0.41	0.264
Manufacture of tobacco (16)	0.97	0.076	0.078	0.214	0.224	0.777	0.51
Manufacture of textile (17)	0.983	0.137	0.12	0.341	0.345	0.296	0.228
Manufacture of apparel, footwear	0.988	0.132	0.104	0.294	0.287	0.296	0.276
Manufacture of leather, fur and feather	0.982	0.139	0.107	0.371	0.385	0.265	0.212
Processing of timber, manufacture of wood, bamboo, rattan, palm and straw products (20)	0.983	0.148	0.109	0.457	0.453	0.238	0.141
Manufacture of furniture (21)	0.988	0.142	0.102	0.427	0.434	0.294	0.222
Manufacture of paper and paper products (22)	0.981	0.114	0.086	0.366	0.378	0.346	0.226
Printing, reproduction of recording media (23)	0.983	0.128	0.098	0.502	0.514	0.381	0.265

(continued)

Table 3 (continued)

Industry (code)	Estimated probability	Labour		Materials		Capital	
		OLS	OP	OLS	OP	OLS	OP
Manufacture of articles for culture, education and sport activities (24)	0.99	0.141	0.111	0.291	0.286	0.343	0.348
Processing of petroleum, coking and fuel (25)	0.979	0.109	0.084	3	0.295	0.469	0.35
Manufacture of raw chemical materials (26)	0.98	0.14	0.114	0.366	0.378	0.352	0.253
Manufacture of medicines	0.986	0.119	0.09	0.359	0.342	0.404	0.285
Manufacture of chemical fibers	0.975	0.155	0.099	0.301	0.279	0.371	0.309
Manufacture of rubber (29)	0.98	0.135	0.115	0.315	0.336	0.367	0.267
Manufacture of plastics (30)	0.985	0.12	0.106	0.36	0.352	0.35	0.268
Manufacture of non-metallic mineral goods (31)	0.981	0.111	0.095	0.389	0.395	0.334	0.207
Smelting and pressing of ferrous metals (32)	0.975	0.148	0.108	19	0.383	0.339	0.249
Smelting and pressing of non-ferrous metals (33)	0.981	0.133	0.099	0.369	0.332	0.319	0.246
Manufacture of metal products (34)	0.986	0.14	0.117	0.358	0.354	0.316	0.252
Manufacture of general-purpose machinery (35)	0.985	0.159	0.109	0.423	0.401	0.203	0.19
Manufacture of special purpose machinery (36)	0.982	0.174	0.116	0.502	0.472	0.271	0.226
Manufacture of transport equipment (37)	0.985	0.133	0.102	0.414	0.415	0.377	0.309
Electrical machinery and equipment (39)	0.989	0.211	0.126	0.715	0.761	0.045	0.152

(continued)

Table 3 (continued)

Industry (code)	Estimated probability	Labour		Materials		Capital	
		OLS	OP	OLS	OP	OLS	OP
Manufacture of communication equipment, computers and other electronic equipment (40)	0.99	0.118	0.094	0.341	0.345	0.35	0.328
Manufacture of measuring instruments and machinery for cultural activity and office (41)	0.986	0.175	0.1	0.37	0.338	0.329	0.361
Manufacture of artwork (42)	0.987	0.202	0.111	0.708	0.466	0.185	0.208
Recycling and disposal of waste (43)	0.987	0.201	0.187	0.335	0.354	0.272	0.268
Electric power and heat power (44)	0.994	0.19	0.082	0.384	0.316	0.403	0.379
Production and supply of gas (45)	0.99	0.079	0.039	0.366	0.33	0.432	0.382
Production and supply of water (46)	0.998	0.069	0.049	0.324	0.299	0.523	0.221
All industries	0.978	0.15	0.097	0.439	0.406	0.307	0.214

Note (i) We do not report standard errors for each coefficient to save space, which are available upon request

As introduced above, we use import penetration ratio as an index to measure trade liberalisation since it captures the effects from both tariffs and NTBs.[15] Our import data are at the HS 10-digit level, which are from the General Administration of China's Customs. Although highly aggregated HS 2-digit import data are publicly available in various publications, such as *China Statistical Yearbook*, their disaggregated data are not. In this paper, we access HS 10-digit import data up to 2002.[16] To calculate industry j's import penetration ratio, the HS 10-digit imports (IM_h) up to HS 4-digit industrial level, $\sum_h IM_h^j$, were first aggregated. The firm's output, y_i, was simultaneously aggregated up to China's 2-digit sector classifications, $\sum_i y_i^j$. Finally, we obtained the industry j's import penetration ratio imp^j as $\sum_h IM_h^j / \sum_i y_i^j$

[15] Ideally, it would be a plus to use both tariffs and NTBs as alternative measures of trade liberalisation. Unfortunately, we are currently not able to access the data sets, although China's disaggregated tariff data in 2001 are accessible.

[16] An alternative source for such disaggregated data is the Center for International Data maintained by Robert Feenstra at the University of California-Davis.

according to the concordance between HS 4-digit level and China's sector classifications two-digit level. For the readers' convenience, we report the industrial concordance in Table 4, in which only HS 2-digit level of the customs code is reported to save space.

Figure 1 shows the average magnitudes of both the import penetration ratio and the industrial-augmented OP-type TFP over 1998–2002. Although there are firm data for all industries, products for some industries are non-tradable, and hence, there are no matching data on imports. If the industrial data on either TFP or import penetration ratio are unavailable, such an industry is dropped from the sample since there is no way to investigate the effect of its trade liberalisation on its productivity. As a result, eight industries are dropped, and only 32 industries were covered in the data set.[17] Although most industries have both positive TFP and log of import penetration ratios, a few exceptions occur: industries like coal, foods, leather, petroleum and smelting and pressing of furious metals have negative log of import penetration ratios, which suggest that imports from these industries are less than sales. On the other hand, the manufacture of smelting and pressing of furious metals also suffers from a negative TFP. Yet, overall, Fig. 1 suggests that an industrial import penetration ratio is positively associated with its TFP.

Table 4 Concordance of products

Industry (code)	HS code (2-digit)
Mining and washing of coal (6)	27
Extraction of petroleum and natural gas (7)	27
Mining and processing of ferrous metal ores (8)	26
Mining and processing of non-ferrous metal (9)	25, 26
Mining and processing of non-metal ores (10)	25, 71
Processing of food (13)	02, 03, 04, 07, 11, 15, 17, 20, 23
Manufacture of foods (14)	04, 17, 19, 21, 22, 23, 25, 76
Manufacture of beverages (15)	09, 20, 22
Manufacture of tobacco (16)	24
Manufacture of textile (17)	50, 51, 52, 53, 54, 56, 60
Manufacture of apparel, footwear	41, 42, 43, 64, 67
Manufacture of leather, fur and feather	44, 45, 46
Processing of timber, manufacture of wood, bamboo, rattan, palm and straw products (20)	

(continued)

[17] The eight industries dropped include extraction of petroleum and natural gas, mining and processing of ferrous metal ores, mining of other ores, recycling and disposal of waste, electrical power and heat power, production and supply of electric power and heat power, production and supply of gas, and production and supply of water.

Table 4 (continued)

Industry (code)	HS code (2-digit)
Manufacture of furniture (21)	94
Manufacture of paper and paper products (22)	48
Printing, reproduction of recording media (23)	49
Manufacture of articles for culture, education and sport activities (24)	32, 92, 95, 96
Processing of petroleum, coking and fuel (25)	27
Manufacture of raw chemical materials (26)	28, 29, 31, 32, 33, 34, 38, 39, 40, 54, 55
Manufacture of medicines	30
Manufacture of chemical fibers	47, 54, 55
Manufacture of rubber (29)	40, 64
Manufacture of plastics (30)	30, 39, 64
Manufacture of non-metallic mineral goods (31)	13, 25, 68, 69, 70
Smelting and pressing of ferrous metals (32)	72
Smelting and pressing of non-ferrous metals (33)	28, 74, 75, 76, 78, 80, 81
Manufacture of metal products (34)	72, 76, 82, 83, 86
Manufacture of general-purpose machinery (35)	84
Manufacture of special purpose machinery (36)	84
Manufacture of transport equipment (37)	86, 87, 88, 89
Electrical machinery and equipment (39)	85, 94
Manufacture of communication equipment, computers and other electronic equipment (40)	85
Manufacture of measuring instruments and machinery for cultural activity and office (41)	90, 91
Manufacture of artwork (42)	96, 97
Recycling and disposal of waste (43)	
Electric power and heat power (44)	
Production and supply of gas (45)	27
Production and supply of water (46)	

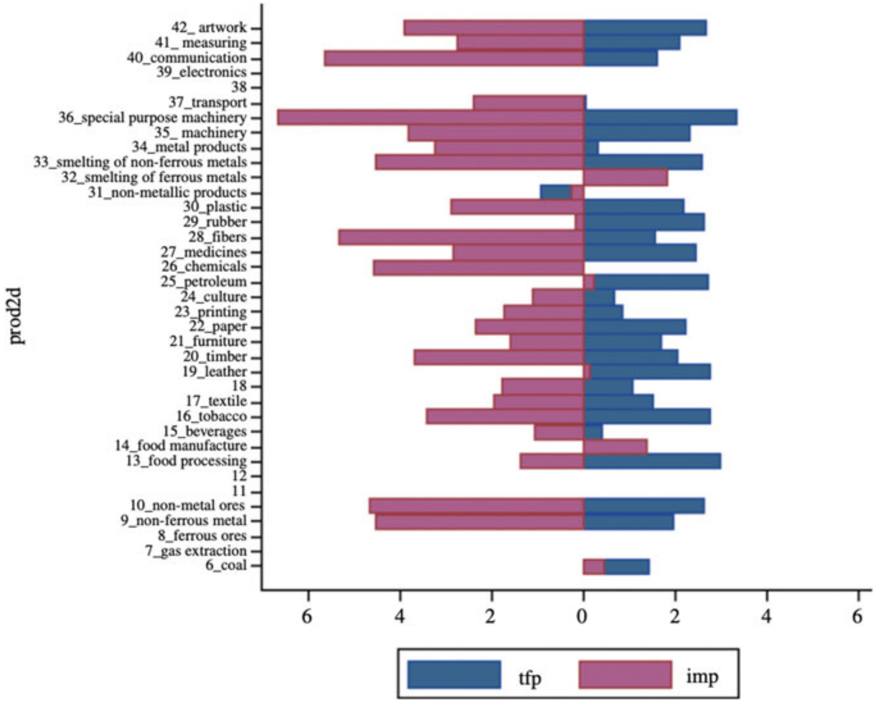

Fig. 1 Total factor productivity (TFP) and import penetration ratio by industry. *Notes* (i) This figure plots the average number of log-import penetration ratio and TFP by industry over 1998–2002. (ii) An industry with blank bar means that import penetration ratio or (and) TFP is (are) unavailable for such an industry in the data set. (iii) As seen from the figure, for some industries such as the manufacture of foods (14) and smelting and pressing of ferrous metals (32), their magnitudes of TFP are much smaller than those of log-import impetration ratio

5 Empirical Results

5.1 Main Estimation Results

Table 5 reports the estimation results for Eq. (9).[18] To consider the effect of the import penetration ratios on TFP, we first run a regression on TFP of import penetration ratio, a dummy for export firms, and their interaction term as a benchmark. The estimated coefficient of a_1 in Eq. (9) is 0.006, which is significant at the conventional statistical level. This suggests that strong trade liberalisation tends to result in high productivity gains. As discussed above, some firms could collapse and drop out next period due to bad operations or other reasons. Ignoring such behaviour would cause a selection

[18] In our estimation, we allow for different coefficients for *WTO* and *EF* dummy in Eq. (6), that is, the effect from accession to WTO is different with that of a firm being in the export market. We thank one anonymous referee for pointing this out.

bias problem. Therefore, the firms' dynamic behaviours were taken into account for the estimations in Columns (2) and (3) by adding a variable to measure a firm's exit from the market in the next period. As shown in Table 5, firms that dropped out from the market have low productivity compared to those that did not.

After controlling for firm exits, Column (2) shows that the effect of trade liberalisation on firm TFP is still positive and significant. In addition, the effect of trade liberalisation on a firm's productivity in exporting firms is smaller than in non-exporting firms, since the interaction term, $\ln imp_{jt} \times EF_{it}$; is significantly negative. Given that the mean of the variable of exporting firms is 0.49, the net elasticity of firm's TFP with respect to trade liberalisation for exporting firm is still positive (0.006 0.005 0.49 = 0.004). These results suggest that compared to non-exporting firms, exporting firms seem to enjoy few benefits from trade liberalisation than do non-exporting firms. One possible reason is that most of the exporting firms also import products from abroad. Instead of introducing tougher competition, trade liberalisation allows exporting firms to access raw materials at lower costs. Such exporting firms can still enjoy some profit margin without increasing their productivity. Put another way, trade liberalisation, to some extent, hampers their incentive to adopt up-to-date technology.

Table 5 Benchmark estimation results

Dependent variable $\ln TFP_{ijt}^{OP}$	(1)	(2)	(3)
Import penetration ($\ln imp_{jt}$)	0.006** (2.23)	0.006** (2.19)	0.006** (2.11)
Exporting firm (EF_{it})	0.045** (6.30)	0.045** (5.98)	0.044** (5.88)
$\ln imp_{jt} \times EF_{it}$	– 0.005** (– 2.47)	– 0.005** (– 2.46)	– 0.005** (– 2.46)
Firm exit in next year		– 0.209** (– 2.83)	– 0.209** (– 2.83)
SOE_{it}		– 0.028 (– 1.52)	– 0.038 (– 1.43)
$SOE \times central - control_{it}$			– 0.099** (– 4.09)
FDI_{it}		– 0.007 (– 0.62)	– 0.008 (– 0.60)
$SOE_{it} \times \ln imp_{jt}$			0.005 (0.66)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
R-squared	0.860	0.860	0.860

Notes (i) Following Amiti–Konings (2007), the depreciation rate is taken as 15% to measure investment by using the perpetual inventory method. (ii) Dependent variables are logarithm of total factor productivity (TFP_{OP}). (iii) Robust *t*-values corrected for clustering at the firm level in parentheses. (iv) There are 175,764 observations for each estimate

** Means significant at the 15% level

An alternative explanation is that since exporting firms achieved TFP improvement at very early stage when they started to export and to face foreign competition, the exporting firms have relatively high TFP and there is not much room for the trade liberalisation to make further productivity improvement. On the other hand, non-exporting firms, ones with low TFP, have much room to improve their efficiency. They learn and benefit more from trade liberalisation. This would result in more significant effect for non-exporting firms.

In the absence of trade liberalisation, other channels, such as preferential taxation reduction, might affect an exporting firm's productivity. The parameter α_2 in Eq. (9) investigates the effects on the exporting firm's productivity from such channels.[19] It turns out that $\widehat{\alpha_2}$ is significantly positive, which suggests that exporting firms are associated with higher productivity even in the absence of strong import penetration.

Previous work also suggests that SOEs have relative low productivity compared to non-SOEs due to their low efficiency and impotent incentive systems (Jefferson et al., 2000; Wu, 2005). Therefore, a dummy of SOEs as a controllable variable in Column (2) is included. It turns out that the coefficient is negative but not significant. By definition, the SOEs are controlled by the government. However, the central government and the local government have different economic interests. For the purpose of self-promotion, the main objective of local government officials is to maximise gross local output (Wu, 2005). To do so, they are more likely to give incentives to SOEs, which, in turn, would lead to greater productivity and profits. As predicted, the interaction term between SOEs and the central-controlled dummy of Column (3) is shown to be significantly negative. In addition, SOEs may have more connection with the government than non-SOE firms and thus have more channels to bypass trade restrictions before trade liberalisation. Hence, the differential effect of trade liberalisation may be different for these various types of firms. A similar argument is stated in Chan et al. (2012) for financial liberalisation. To examine this potential effect, an interaction term of import penetration ratio and SOE is added to the regression (Column 3 of Table 5). There is no significant effect identified, and adding this term does not change the benchmark results.[20]

Finally, foreign-owned enterprises are expected to have high productivity due to their quick learning, better technology adoption or higher quality inputs (Amiti & Konings, 2007). The FDI is included in Columns (2) and (3). However, the coefficient estimates are insignificant.

[19] Mathematically, the parameter a_2 equals the partial derivative of log TFP with respect to the *EF* variable: $\partial \ln TFPijt = \partial EF_{it}$.

[20] We include the interaction term of import penetration ratio and SOE in other regressions (as reported in Tables 6, 7, 8, 9, 10 and 11). The coefficient on this term is generally insignificant, and the main estimation results are robust. We thank one anonymous referee for making this suggestion.

5.2 Complex Goods Versus Simple Goods

In this section, we re-estimate Eq. (9) for complex and simple goods separately. The results are reported in Tables 6 and 7, respectively. Similar to the regression results reported in Table 5, in the regressions with complex goods (Table 6), the coefficients of the import penetration are all positive and statistically significant (at the 5% level). The coefficient estimates of other variables are also quite similar to those of the full sample regressions reported in Table 5.

Turning to simple goods estimation, the coefficient of import penetration turns negative and is statistically significant, while the coefficients of the other variables are insignificant (Table 7). This is probably because a higher degree of import penetration has two opposite effects on firm productivity. First, a high level of import penetration means that these firms face great competition from abroad and their operating performance may decline. As a result, these firms have less resources to invest in technology improvement. Second, more trade may bring in newer and more differentiated products with more advanced technology. This may create learning

Table 6 Benchmark estimation results (complex goods)

Dependent variable ln TFP_{ijt}^{OP}	(1)	(2)	(3)
Import penetration (ln imp_{jt})	0.007** (2.36)	0.007** (2.33)	0.006** (2.20)
Exporting firm (EF_{it})	0.045** (6.15)	0.045** (6.10)	0.044** (6.00)
ln $imp_{jt} \times EF_{it}$	– 0.006** (– 2.66)	– 0.006** (– 2.65)	– 0.005** (– 2.66)
Firm exit in next year		– 0.210** (– 2.81)	– 0.210** (– 2.81)
SOE_{it}		– 0.026 (– 1.39)	– 0.039 (– 1.47)
$SOE \times central - control_{it}$			– 0.100** (– 4.13)
FDI_{it}		– 0.008 (– 0.62)	– 0.008 (– 0.60)
$SOE_{it} \times \ln imp_{jt}$			0.0066 (0.85)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
R-squared	0.860	0.860	0.860

Notes (i) Following Amiti–Konings (2007), the depreciation rate is taken as 15% to measure investment by using the perpetual inventory method. (ii) Dependent variables are logarithm of total factor productivity (TFP_{OP}). (iii) Robust *t*-values corrected for clustering at the firm level in parentheses. (iv) There are 175,141 observations for each estimate

** Means significant at the 5% level

Table 7 Benchmark estimation results (simple goods)

Dependent variable $\ln TFP_{ijt}^{OP}$	(1)	(2)	(3)
Import penetration ($\ln imp_{jt}$)	− 12.400** (− 4.30)	− 12.272** (− 4.22)	− 11.872** (− 4.00)
Exporting firm (EF_{it})	4.502 (0.65)	5.806 (0.82)	6.293 (0.86)
$\ln imp_{jt} \times EF_{it}$	− 0.824 (− 0.64)	− 1.076 (− 0.81)	− 1.167 (− 0.86)
Firm exit in next year		− 0.429 (− 0.90)	− 0.403 (− 0.81)
SOE_{it}		− 0.535 (− 1.18)	2.81 (0.73)
FDI_{it}		− 0.051 (− 0.41)	− 0.099 (− 0.76)
Time	1.670** (5.99)	1.665** (5.92)	1.649** (5.71)
$SOE_{it} \times \ln imp_{jt}$			− 0.64 (− 0.88)
Firm fixed effects	Yes	Yes	Yes
R-squared	0.780	0.784	0.786

Notes (i) Following Amiti–Konings (2007), the depreciation rate is taken as 15% to measure investment by using the perpetual inventory method. (ii) Dependent variables are logarithm of total factor productivity (TFP_{OP}). (iii) Robust t-values corrected for clustering at the firm level in parentheses. (iv) (SOE × central-control)$_{it}$ is dropped because there are no centrally controlled SOEs in this sample. (v) The time fixed effects are replaced with time variable due to multi-collinearity. (vi) There are 623 observations for each estimate
** Means significant at the 5% level

opportunities for domestic firms and induce them to enhance their productivity to meet the foreign competition. Since complex goods are highly differentiated products, the increased degree of trade liberalisation encourages firms to engage in more innovative activities to develop more differentiated products. The higher degree of product differentiation also shields the domestic firms from the first (negative) effect of important penetration to some degree. However, for firms that produce simple goods, the first effect on productivity is stronger and it is relatively difficult to develop differentiated products due to the high degree of product homogeneity. Therefore, the effect of import penetration on firm productivity (the coefficient of ln imp_{jt}) is different in the sample of complex goods with that of the simple goods.

Since our empirical findings suggest that the improvement in firm productivity induced by trade liberalisation is primarily driven by firms that produce complex goods, in the further econometric work that follows, we only include firms that produce complex goods in the sample, which is actually the majority of the full sample.

5.3 Choices of Depreciation Rates

An essential component in the calculation of the Olley–Pakes's TFP variable is to obtain data on investment, which is usually calculated by adopting the perpetual inventory method as follows:

$$I_{it} = K_{it} - (1 - \delta)K_{i,t-1} \tag{11}$$

where I_{it}; K_{it} denotes investment and fixed capital in year t for firm i, respectively.[21] The parameter d denotes a common depreciation rate across firms and years given that China did not change its depreciation rate over 1998–2002.[22]

The only problem left to calculate investment is the appropriate value for the depreciation rate. As recommended by Perkins (1988) and Wang and Yao (2003), a 5% depreciation rate is a good choice, since this number is adopted to calculate SOEs' depreciation in *China's Statistical Yearbook*. However, some other researchers have different views on this number. Liang (2006) suspected that the number should be 4% instead. Amiti and Konings (2007) adopted 15% for Indonesia, another large developing country. China, indeed, may adopt a number up to 16% as its depreciation rate in some years in the 1990s (Wang & Yao, 2003). Therefore, the depreciation rate is allowed to show its flexibility to form the firm's investment level. Following Amiti and Konings (2007), 15% is adopted as a default number, but performed the robustness check by using 10, 5 and 4% as alternative depreciation rates. As seen in Table 8, the estimation results are robust to using different depreciation rates.

5.4 Specifications of Periodic Differences

To reduce estimation bias caused by unobserved firm heterogeneity, estimations in Tables 5, 6, 7 and 8 control for the firm-specific and year-specific fixed effects by adopting the firm annual level data. However, some unobserved factors would change according to firms and the relevant year. One possible example is that taxation reduction policies in SEZs vary by year, affecting the productivity of firms based in these zones. The regular two-way fixed effects seem not be able to fully control for this omitted-variable problem.

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[21] Another way to form investment data is to use information on net physical capital by adopting the formula $I_{it} = K_{it} - NK_{it}$ where NK_{it-1} is firm i's net fixed assets in year $t - 1$. Since only data on net physical capital for years 2000–02 were accessed, the main estimations on raw physical capital data use such expression (depreciation).

[22] Another assumption of Olley–Pakes approach is that a productivity shock should be increasing monotonically with investment conditional predetermined capital. The investment proxy is only valid for firms reporting non-zero investment. To avoid this possible challenge, the Levinsohn–Petrin (2003) approach is a useful alternative to calculate TFP. However, the Levinsohn–Petrin type TFP is found to be similar to the OP type TFP in my data set, which are not reported here to save space, although available upon request.

Table 8 Alternative investment measures

Dependent variable $\ln TFP_{ijt}^{OP}$	(1) Depreciation rate (15%)	(2) Depreciation rate (10%)	(3) Depreciation rate (5%)	(4) Depreciation rate (4%)
Import penetration ($\ln imp_{jt}$)	0.006** (2.21)	0.007** (2.19)	0.007** (2.19)	0.005** (1.94)
Exporting firm (EF_{it})	0.043** (5.86)	0.046** (6.21)	0.046** (6.21)	0.049** (7.22)
$\ln imp_{jt} \times EF_{it}$	– 0.005** (– 2.45)	– 0.005** (– 2.23)	– 0.005** (– 2.23)	– 0.004** (– 2.07)
Firm exit in next year	– 0.209 (– 2.83)	– 0.226** (– 2.93)	– 0.226** (– 2.93)	– 0.169** (– 2.50)
SOE_{it}	– 0.026 (– 1.38)	– 0.038 (– 1.45)	– 0.038 (– 1.45)	– 0.049* (– 1.77)
$SOE \times central - control_{it}$	– 0.099** (– 4.07)	– 0.089** (– 3.59)	– 0.089** (– 3.59)	– 0.088** (– 3.49)
FDI_{it}	– 0.008 (– 0.60)	– 0.019 (– 1.16)	– 0.019 (– 1.17)	– 0.014 (– 1.13)
$SOE_{it} \times \ln imp_{jt}$		0.008 (0.98)	0.008 (0.98)	0.083 (0.95)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	175,764	175,046	175,047	175,764
R-squared	0.860	0.857	0.858	0.864

Notes (i) Depreciation rate *n* per cent means taking a *n* per cent depreciation rate to measure investment by using perpetual inventory method (*n* takes 15, 10, 4 and 5, respectively). (ii) Robust *t*-values corrected for clustering at the firm level in parentheses
*(**) Means significant at the 10(5) per cent level

To address this empirical challenge, alternative econometric specifications with data on periodic differences were considered and are reported in Table 9. Since the samples cover 1999–2002, several specifications from one to three periodic difference(s) were considered.[23] The periodic differences in import penetration ratio and the exporting firm's dummy have expected positive signs, which are consistent with the findings in Tables 5, 6, 7 and 8. However, the coefficients of the interaction term of the import penetration ratio and the dummy for exporting firms become insignificant and those of the SOE dummies are significantly positive in one (two) periodic difference(s) estimates, which seems inconsistent with the estimates of the three periodic differences, as well as the previous findings in Table 5. Since most measurement errors and possible serial correlations are controlled by the fixed-effect

[23] Although the data covers the years 1998–2002, to calculate the investment, one needs to use one-year lag data. Accordingly, only the data for the years 1999–2002 are covered in the estimations.

Table 9 Alternative econometric specifications

Dependent variable $\ln TFP_{ijt}^{OP}$	1-period difference		2-period difference		3-period difference	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln imp_{jt}$	0.004 (1.39)	0.004 (1.57)	0.001 (1.35)	0.001 (0.51)	0.007** (2.17)	0.007** (2.20)
ΔEF_{it}	0.039** (7.64)	0.039** (7.86)	0.022** (4.66)	0.024** (4.89)	0.009 (1.37)	0.011* (1.66)
$\Delta \ln imp_{jt} \times EF_{it}$	0.001 0.14	0.001 (0.27)	0.001 (0.12)	0.001 (0.25)	− 0.001 (− 0.17)	− 0.000 (− 0.05)
Firm exit in next year	− 0.151** (− 3.12)	− 0.153** (− 3.16)	− 0.274** (− 2.91)	− 0.312** (− 3.33)	− 0.305** (− 3.82)	− 0.299** (− 3.74)
ΔSOE_{it}	0.135** (3.44)	0.135** (3.46)	0.123** (2.87)	0.100** (2.32)	− 0.181** (− 2.04)	− 0.187** (− 2.12)
$\Delta SOE \times central - control_{it}$	0.085** (4.05)	0.082** (3.95)	0.150** (3.97)	0.123** (3.30)	− 0.149* (− 1.66)	− 0.156* (− 1.75)
ΔFDI_{it}	− 0.006 (− 0.49)	− 0.005 (− 0.43)	− 0.003 (− 0.34)	− 0.002 (− 0.25)	− 0.023 (− 1.70)	− 0.023** (− 1.68)
$\Delta SOE_{it} \times \ln imp_{jt}$	0.03 (1.17)	− 0.028 (1.1)	− 0.036* (− 1.92)	− 0.038** (− 2.02)	− 0.018 (− 1.06)	− 0.017 (− 1.01)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No	Yes	No
Province xx year fixed effects	No	Yes	No	Yes	No	Yes
Observations	87,336	87,336	44,116	44,116	17,007	17,007
R-squared	0.700	0.705	0.604	0.613	0.006	0.009

Notes $\Delta \ln \mathrm{imp}_{jt}$ denotes n-period difference for import penetration (n = 1–3). Similarly, $\Delta \mathrm{EF}_{it}$, ($\Delta \ln \mathrm{imp}_{jt} \times \mathrm{EF}_{it}$, $\Delta \mathrm{SOE}_{it}$, $\Delta \mathrm{SOE} \times$ central − control$_{it}$, $\Delta \mathrm{SOE}_{it} \times \ln \mathrm{imp}_{jt}$, $\Delta \mathrm{FDI}_{it}$) denotes n-period difference for dummy of exporting firm (interaction term of import penetration and exporting firm's dummy, dummy of state-owned enterprises (SOE), whether the SOE is directly controlled by the central government and foreign direct investment, respectively). (ii) Robust t-values corrected for clustering at the firm level in parentheses

econometric method, there is suspicion that such inconsistency mainly comes from reverse causality, which will be addressed shortly.

5.5 *Endogeneity*

Trade liberalisation is not exogenously given, but affected by firm productivity. With better performance, some firms have stronger incentive to expand their economic scale, which, in turn, requires more inputs from the international market. The strong demand from firms leads to a greater import penetration ratio for each industry.

One needs to control for the endogeneity of trade liberalisation in order to obtain accurate estimated effects of trade liberalisation on TFP. The instrumental variable (IV) estimation is a powerful econometric method that can address this problem (Wooldridge, 2002).

In the paper, provincial government savings is chosen as the instrument for import penetration. The economic rationale is as follows. As many economists like Krugman (1998) emphasised, trade deficit means, in essence, government deficit. To reduce the sizable government deficit, the government usually appreciates its currency to generate more trade deficit. With a greater trade deficit, the government can finance government deficits from foreigners. Put another way, more government savings tends to lower trade deficits. Given that other factors remain constant, an incremental amount of government savings is correlated with lower import penetration.

Several tests were performed to verify the quality of the instrument. First, Anderson's canonical correlation likelihood-ratio test is conducted to check whether or not the excluded instrument (i.e. government savings) is correlated with the endogenous regressors (i.e. import penetration ratio). The null hypothesis that the model is under-identified is rejected at the 1% level. Second, we also take another step to see whether or not government savings is weakly correlated with import penetration. If so, then the estimates will perform poorly in this IV estimate. Luckily enough, the Cragg and Donald F-statistics provide strong evidence to reject the null hypothesis that the first stage is weakly identified at a highly significant level. Third, the Anderson and Rubin v^2 statistics reject the null hypothesis that the coefficient of the endogenous regressor is equal to zero. In short, such statistical tests give sufficient evidence that the instrument is well performed, and therefore, the specification is well justified. Estimates in Table 10 show that, after controlling for endogeneity, trade liberalisation still has a positive effect on a firm's productivity. In all estimations, the coefficients $\hat{\alpha}_1^{IV}$ are quite stable and much higher than its counterparts $\hat{\alpha}_1$ without controlling for the endogeneity shown in Table 5. The interaction term of the import penetration ratio and the exporting firm dummy, $\hat{\alpha}_3^{IV}$ is still significantly negative, which is consistent with previous findings. This implies that the implicit negative reverse causality undercuts the effect of trade liberalisation on firm productivity.

5.6 Alternative Measure of Firm Productivity

As discussed above, the augmented Olley–Pakes approach to calculate the TFP is able to deal with both the simultaneity bias and selection bias. The approach is based on an assumption that capital is more aggressively responsive to the unobserved productivity shock compared with labour. Put another way, labour input here is assumed to be exogenous to the productivity shock. However, China is a labour-abundant country, and hence, labour costs are relatively low. When facing a productivity shock, China's firms are more likely to adjust their labour input to reoptimise their production behaviour. This is consistent with the idea suggested by papers

Table 10 Estimates with controlling for endogeneity

Dependent variable $\ln TFP_{ijt}^{OP}$	(1)	(2)	(3)	(4)
$\ln imp_{jt}$	0.433** (4.07)	0.231** (2.97)	0.199** (2.77)	0.226** (2.89)
EF_{it}	0.714** (4.48)	0.399** (3.43)	0.355** (3.29)	0.371** (3.42)
$\ln imp_{jt} \times EF_{it}$	− 0.268** (− 4.11)	− 0.142** (− 2.98)	− 0.123** (− 2.78)	− 0.130 ** (− 2.93)
Firm exit in next year	− 0.140** (− 3.15)	− 0.158** (− 4.69)	− 0.166** (− 5.15)	− 0.166** (− 5.14)
SOE_{it}		− 0.445** (− 45.20)	− 0.450** (− 46.08)	− 0.201** (− 2.22)
$SOE \times central - control_{it}$			0.098** (5.18)	0.108** (5.15)
FDI_{it}	0.132** (7.59)	0.061** (4.86)		0.062** (4.80)
$SOE_{it} \times \ln imp_{jt}$				− 0.101** (− 2.56)
Firm-specific fixed effects	Yes	Yes	Yes	Yes
Year-specific fixed effects	Yes	Yes	Yes	Yes
F-statistic	2637.36	4410.60	4738.37	3620.93
Anderson likelihood-ratio χ^2 statistic	30.27	32.7	35.62	33.67
Cragg–Donald χ^2 statistic	30.28	32.72	35.64	33.69
Anderson–Rubin χ^2 statistic	36.49	12.01	9.7	11.12
Probability > F or probability > χ^2	0	0	0	0
R-squared	0.384	0.2	0.255	0.219

Notes (i) The logarithm of import penetration ratio ($\ln imp_{jt}$) is taken as an endogenous variable whose instrument is government saving at province j in year t. (ii) There are 137,312 observations in each estimation. (iii) Robust t-values corrected for clustering at the firm level in parentheses. (iv) All the test statistics are significant at 1% level. (v) The Hansen over-identification test is included but not reported here since the estimation is exactly identified

such as Blomström and Kokko (1996) that labour would embody more productivity improvements than capital.

Table 11 reports the estimated effects of trade liberalisation on labour productivity. The key coefficients $\hat{a}_1$; $\hat{a}_2$; and $\hat{a}_3$ are highly close to those estimated by the augmented Olley–Pakes approach as shown in Table 5. Both exporting and non-exporting firms benefit from trade liberalisation, although exporting benefit less. The negative significant coefficient of $\hat{a}_4$ also suggests that firms that exit from the market are those with low productivity. SOEs firms have lower productivity than those non-SOEs. The only striking finding of Table 11 is that those SOEs controlled by the central government seem to have higher productivity than those controlled by the local governments. Generally speaking, the estimation results are robust to different ways of calculating a firm's productivity.

Table 11 More estimation results using labor productivity

Dependent variable ($\ln TFP_{ijt}^{BB}$)	(1)	(2)	(3)	(4)
Import penetration ($\ln imp_{jt}$)	0.025** (2.72)	0.025** (2.72)	0.025** (2.71)	0.022** (2.37)
Exporting firm (EF_{it})	0.437** (24.81)	0.437** (24.87)	0.442** (25.20)	0.443** (25.23)
$\ln imp_{jt} \times EF_{it}$	− 0.002 (− 0.37)	− 0.002 (− 0.33)	− 0.002 (− 0.36)	− 0.002 (− 0.39)
Firm exit in next year	− 1.303** (− 13.98)	− 1.301** (− 13.95)	− 1.299** (− 13.93)	− 1.301** (− 13.94)
SOE_{it}		− 0.302** (− 6.64)	− 0.315** (− 6.92)	− 0.372** (− 5.70)
$SOE \times central - control_{it}$			0.532** (7.45)	0.530** (7.43)
FDI_{it}				0.038 (0.88)
$SOE_{it} \times \ln imp_{jt}$				0.024 (1.28)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R-squared	0.959	0.959	0.959	0.959

Notes (i) Dependent variable $\ln TFP_{ijt}^{BB}$ is a logarithm of TFP, which is calculated by using the Blundell and Bond (1998) approach. (ii) Robust t-values corrected for clustering at the firm level in parentheses

6 Concluding Remarks

In this paper, we estimate the effect of trade liberalisation on firm productivity by using Chinese plant-level data. After controlling for firms' exits and the endogeneity of trade liberalisation, the effect of trade liberalisation on firm productivity is significantly positive. More interestingly, we find that the improvement in firm productivity induced by trade liberalisation is primarily driven by firms that produce complex goods, and the effect on simple goods producers is the opposite. One implication of these empirical findings is that gradually resources will move out of simple goods production and into complex goods production as a result of higher degree of trade liberalisation in China.

Furthermore, we find that the effect on exporting firms is smaller than on non-exporting firms. Such a finding is consistent with the stylised fact that the processing export is still dominant in China's trade pattern today. It is worthwhile pointing out that although exporting firms benefit less from trade liberalisation in terms of productivity improvement compared to non-exporting firms, exporting firms show a positive increase in productivity. In this sense, the finding of this paper is in line with previous studies, like those of Bernard and Jensen (1999), who showed that good firms export in the US because they have high productivity. However, this result is not necessarily applicable for China since China's economic reform, to some extent, is unique. In any case, whether or not good firms lead to exports in China is a possible future research topic.

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Processing Trade, Export Intensity, and Input Trade Liberalization: Evidence from Chinese Firms

Wei Tian and Miaojie Yu

1 Introduction

Trade liberalization is one of the most important topics in international trade. It is of particular interests for both academia and policy-makers to understand firm's decision in choosing markets when a country experiences gradual trade liberalization. Previous studies mostly focus on how firms realize productivity gains from trade liberalization (see, for example, Amiti & Konings, 2007; Topalova & Khandelwal, 2011; Yu Forthcoming). Still, it is equally interesting to understand how import tariffs reduction on final goods, which is regarded as generating tougher import competition, could in turn force domestic firms to adjust their export intensity the proportion of exports over total sales. More importantly, there is still relatively little research on firm's response to adjust its export intensity upon facing tariffs reductions in input tariffs on intermediate goods. The present paper tries to fill in this gap.

This paper investigates the effects of changing input trade costs on firm's export intensity using a very rich matched Chinese firm-level production data and transaction level trade data. A novel element of the paper is that input trade costs are measured at and tailored to the firm level, which allow us to exactly measure the input trade costs faced by a firm. Firms face declining input trade costs over the sample period 2000 2006. Gradual tariffs reduction in ordinary imports occurs over time after China acceded to the WTO in 2001. More interestingly, a large extent of Chinese firms self-selects to engage in processing trade which has special tariff treatment zero import

W. Tian
School of International Economics and Trade, University of International Business and Economics, Beijing, China
e-mail: weitianpku@163.com

M. Yu (✉)
Center for Economic Research (CCER), National School of Development, Peking University, Beijing, China
e-mail: mjyu@nsd.pku.edu.cn

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tariffs. Further input tariffs reductions have no impact on firms' export intensity for firms that entirely engage in processing trade, but still have some impact on hybrid firms that engage in both ordinary and processing trade. Thus, the impact of input trade liberalization on export intensity for ordinary firms must be larger than its counterpart for hybrid firms. We find strong evidence to support this rationale.

To accurately estimate the impact of input trade cost on export intensity, we also control for the other two types of trade liberalization: import tariffs on final goods and external tariffs set by Chinese trading partners. As mentioned above, output tariffs reduction in final goods also generates tougher import competition, which could in turn change firm's export intensity. Meanwhile, during the sample period over 2000–2006, many Chinese firms export a variety of products to many countries. Chinese exporters also enjoyed large tariffs reductions in their export destinations. With reductions in foreign trade costs, firms are able to access to larger foreign markets which could possibly result in larger export intensity. We hence construct the firm-level external tariffs to measure the weighted tariffs across trading countries and across products over years. However, although the most ideal way is to obtain a corresponding firm-level import output tariffs, data on each product's domestic sales are unavailable, we hence only control for industry-level output import tariffs in the estimates.

We then decompose and identify the sources of variation in firm-level input trade costs. Firms may engage in processing trade or may not. Input tariffs reduction would have a significant effect on non-processing firm's sales decision, but should not be so for pure-processing firms that 100% engage in processing trade since processing trade is already de facto duty-free. Yet, one most interesting case exists: there have some 'hybrid' firms that engage in both processing and ordinary trade. Thus, the variation of hybrid firm's input trade costs could come from two different components: input tariffs reduction in ordinary imports *and/or* the proportion allocation between processing and ordinary import components. Such information is carried to construct the firm-specific input tariffs. Beyond this, we also identify sources of variation in input trade costs by different types of firms: pure ordinary and hybrid firms. Of course, some firms could switch from processing to ordinary trade, or vice versa. We hence also look at the effect of input trade costs on firm's export intensity for such switching firms specifically.

However, in which ways does the reduction in input trade cost affect firm's export intensity? Are they through the extensive margin, or intensive margin, or both? To check this out, we separate exporters to three types: new exporters, exiters, and continuing exporters. In particular, we find that the declining input trade costs not only increase the probability of firm's being new exporters (i.e., extensive margin), but also lead to a higher export intensity (i.e., intensive margin). However, the impact of either extensive margin or intensive margin is insignificant for exiting firms. By contrast, the impact of intensive margin is significant for continuing exporters. Similar findings are present when we turn the interest to the extensive margin firm's export scope.

The endogeneity of firm-specific input trade costs is also carefully discussed and addressed. Three different sources of endogeneity could present for the constructed firm input tariffs. As firm's export intensity is defined as export over sales, the first endogeneity issue is the possible reverse causality of sales on tariffs. Firms with small amount of sales may blame their tough market situation to stronger import competition due to trade liberation. Accordingly, they would lobby the government for protection. We, therefore, adopt an instrumental variable (IV) approach to control for such a possible reverse causality.

The second endogeneity comes from the possible reserve causality of firm's exports on its imports. Firm's exports are highly correlated with its imports. The last endogeneity issue raises from the measure of the input tariffs itself. Suppose that a firm faces a prohibitive tariff line for a product that it wishes to import, such a tariff is not included in firm's input tariffs due to its zero imports. However, the firm indeed faces a very high (but not zero) tariff. To control for these two endogeneity issues, we use firm's imports in the first year of the sample to construct a fixed weight for firm-specific input tariffs following Topalova and Khandelwal (2011) and Yu (Forthcoming). After controlling for a variety of endogeneity issues, we still find robust evidence that input tariffs reduction leads to an increase in export intensity.

Our last robustness check is to adopt the quantile estimates to examine the heterogeneous impact of input trade cost on firm's export intensity by different quantiles. We first look at their response at the four quartiles and then examine them carefully in which quantiles are allowed to be measured at a continuum version. Both types of quantile analysis yield similar results as the standard fixed-effects ordinary least square (OLS) estimates. They also help us understand the economic magnitude of the estimates: A one-point decrease in firm-specific input trade costs would lead to at most a 5.2% increase in its export intensity.

This paper joins a growing literature on both counts. The first is on the topic of export intensity. Previous studies have recognized that firms only sell a small fraction of their output abroad. This is documented by, among others, Bernard and Jensen (1995), Arkolakis and Muendler (2010), and Eaton et al. (2011). Most of such studies focus on interpreting why export intensity is small. Specifically, Bernard et al. (2003) emphasized a key reason for large countries like the United States is the existence of a relatively large domestic market. Brooks (2006) argued the key reason for small countries like Columbia is due to the low quality of their export products. Besides, Bonaccorsi (1992) found evidence that firm's export intensity is positively associated with its size using Italian manufacturing industry-level data. Greenaway et al. (2004) investigated whether spillovers affect firm's export propensity using British firm-level data.

However, there is still limited research for China though it has become the second largest economy and largest exporter in the world. As documented in the later section, although China shares a common phenomenon with other countries in the sense that Chinese firms only export a small proportion of their products, there still exists a sizable proportion of firms that exports all of their products. Such a pattern is known as the U-shape as witnessed by Lu (2011).[1] Therefore, it is worthwhile to ask how

[1] Lu et al. (2010) also use Chinese firm-level data to find that, among foreign affiliates, exporters are less productive than non-exporters. Dai et al. (2012) points out the key reason for such a phenomenon is due to the prevalence of processing trade in China.

the declining input trade costs affect such Chinese firms' export pattern, which hence adds value to the related literature.

Another set of related literature is on input trade liberalization. Among many other papers, Amiti and Konings (2007) found that firm gain from the reduction of input tariffs is at least twice as much as those from cutting output tariffs by using Indonesian firm level data. Topalova and Khandelwal (2011) confirm that such a difference in gains from trade could be exaggerated to ~ 10 times in magnitude in several industries in India. Turning to the application to China, Yu (Forthcoming) found that the declining output tariffs still have a larger impact on firm productivity than the reduction in input tariffs due, in large part, to the fact that processing trade in China is duty-free. However, to our best knowledge, rare studies, if any, consider the impact of input trade cost on firm's export intensity despite both being tropical topics in the field.

The remainder of the paper is organized as follows. Section 2 describes data used in the present paper. Section 3 introduces the measures for key variables and empirical specifications. Section 4 discusses the estimation results and sensitivity analysis. Finally, Sect. 5 concludes.

2 Data

To investigate the impact of trade liberalization on firm's export intensity, this paper uses the following three disaggregated large panel data-sets: tariffs data, firm-level production data, and product-level trade data.

Tariff data can be accessed directly from the WTO.[2] China's tariff data are available at harmonized system (HS) six-digit level over years 2000 2006, which are more disaggregated than HS eight-digit transaction-level trade data. Hence, we first aggregate transaction-level trade data to HS six-digit level to concord with tariff data. The average Ad Valorem duties are used to measure trade liberalization given that our main interest is to estimate the effect of trade liberalization on export intensity.

2.1 Firm-Level Production Data

The sample used in this paper comes from a rich firm-level panel data-set which covers around 230,000 manufacturing firms per year over 2000 2006. The data are collected and maintained by China's National Bureau of Statistics in an annual survey of manufacturing enterprises. It contains entire information of three accounting sheets (i.e., balance sheet, loss and benefit sheet, and cash flow sheet). On average, the annual entire value of industrial production covered in such a data-set accounts for around 95% of China's total industrial production by year. Indeed, aggregated data on the

[2] Source of the data: http://tariffdata.wto.org/ReportersAndProducts.aspx.

industrial sector in the annual China's Statistical Yearbook by the Natural Bureau of Statistics are compiled from this data-set. The data-set includes more than 100 financial variables listed in the main accounting sheets of all these firms. Briefly, it covers two types of manufacturing firms: (1) all state-owned enterprises (SOEs) and (2) non-SOEs whose annual sales are more than five million renminbi (RMB).

However, the raw production data-set is still quite noisy since it still includes many unqualified firms with poor accounting systems.[3] Following Cai and Liu (2009), Feenstra et al. (2014), and Yu (Forthcoming), we delete observations according to the basic rules of Generally Accepted Accounting Principles if any of the following are true: (1) liquid assets are higher than total assets; (2) total fixed assets are larger than total assets; (3) the net value of fixed assets is larger than total assets; (4) number of employees is less than eight people as suggested by Brandt et al. (2012); (4) the firm's identification number is missing; or (5) firm's established time is invalid (e.g., the opening month is later than December or earlier than January). Accordingly, the total number of firms covered in the data-set is reduced to 438,165, around one-third of firms are dropped from the sample after such a filter process.

2.2 Product-Level Trade Data

The disaggregated transaction-level monthly trade data during 2000 2006 are obtained from China's General Administration of Customs. As shown in Column (1) of Table 9, the annual number of observations increases from around 10 million in 2000 to around 16 million in 2006, ending with a huge number of observations, 118,333,831, in total for seven years. Column (2) of Table 9 exhibits that there are 286,819 firms that ever engage in international trade during this period.

For each transaction, the data-set compiles three types of information: (1) basic trade information which includes value (measured at US current dollar), trade status (export or import), quantity, trade unit, and value per unit; (2) trade mode and pattern such as destination country for exports, original country for imports, routing countries (i.e., whether the product is shipped through an intermediate country/regime), customs regime (e.g., processing trade or ordinary trade), transport mode (i.e., by sea, by truck, by air, or by post), and customs port (i.e., where the product departs or arrives); and (3) firm-level transaction information. In particular, it includes seven variables such as firm's name, identification number set by the customs, city where the firm is located, telephone, zip code, name of the manager/CEO, and even ownership type of firm (e.g., foreign affiliate, private, or state-owned enterprises).

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[3] For example, some family-based firms, which usually have no formal accounting system in place, reports their production information based on a unit of one RMB, whereas the official requirement is a unit of 1000 RMB.

Table 1 Comparison of the merged-sample and full-sample trade data

Percentage of firms	Merged sample (%)	Full sample (%)
Ordinary importers	38.1	27.3
Processing importers	61.9	72.7

We then match transaction-level trade data, firm-level production data, and tariffs data together. Since trade data and production data have no common identification numbers, the matching is of particular challenge.[4] Briefly, the matched data account for around 30% of number of exporting firms and around 53% of export value.

2.3 The Matching Results

As shown in Table 1, compared to full-sample trade data-set, the matched data-set has a similar proportion of numbers of ordinary importers and processing importers. Moreover, the merged data-set is skewed toward larger firms in terms of sales, exports, and number of employees, as reported in Yu (Forthcoming). Given that our main interest in the present paper is to investigate Chinese large trading firms, the matched data-set, therefore, is an appropriate data-set to serve for this objective.

Before adopting the matched samples to perform the estimations, it is worthwhile to check whether the distribution of firm's export intensity in the full sample is similar to that in the matched sample. If not, then our estimation results would be a suspect. As seen from Fig. 1, firm's export intensity in the matched sample shows a U-shape in the left-hand-side (LHS) of Fig. 1a, which is very similar to that in the full sample in the LHS of Fig. 1b. Of course, around 72% of firms do not export in the full-sample production firm-level data-set, whereas only 17% of firms do not export in the matched dataset given that the matched data, by construction, only cover trading firms (i.e., either export or import, or both). Therefore, the density for the extreme values of firm's export intensity (i.e., zero and one) would be different. However, their non-parametric kernel density after dropping the two-side extreme values are very similar, as shown in the right-hand-side (RHS) of Fig. 1a, b. Therefore, the matched data-set is a good representative of the full-sample data set even in terms of firm distribution.

[4] The detailed method and technique can be found from Yu (2013).

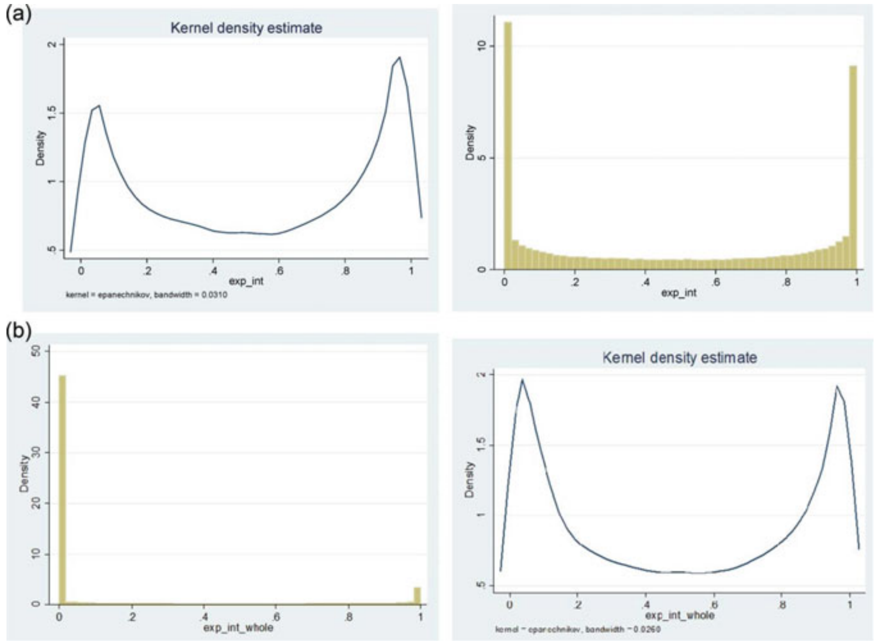

Fig. 1 The distribution of firm's export intensity in the **a** matched-sample data and **b** full-sample data

3 Measures and Empirics

3.1 Firm-Specific Input Tariffs

A firm could import many products in different amounts. Since its imported intermediate input could vary across industries, an aggregated industry-level tariff is insufficient to capture firm heterogeneity within a sector. Therefore, it is essential to construct a firm specific variable of input trade costs.

A special feature of China's import tariffs is that processing imports in China are duty-free. As in Yu (Forthcoming), we construct a firm-specific input tariff index. FIT_{it}/ as follows:

$$\text{FIT}_{it} = \sum_{k \in O} \frac{m_{it}^k}{\sum_{k \in M} m_{it}^k} \tau_t^k \qquad (1)$$

where m_{it}^k is firm i's import value on product k in year t and, as before, τ_t^k is the *ad valorem* tariff of product k in year t. O is the set of firm's ordinary imports, and M is the set of firm's total imports. That is, $O \bigcup P = M$ where P is the set of processing imports and, by definition, is 100% duty free. Thus, this set is not included in Eq. (1).

3.2 *Firm-Specific External Tariffs*

To measure the tariffs reductions in a firm's export destinations, we construct an index of firm-specific external tariffs. FET_{it} as follows:

$$\text{FET}_{it} = \sum_{k}\left[\left(\frac{X_{it}^{k}}{\sum_{k} X_{it}^{k}}\right)\sum_{c}\left(\frac{X_{ikt}^{c}}{\sum_{c} X_{ikt}^{c}}\right)\tau_{kt}^{c}\right] \qquad (2)$$

where τ_{kt}^{c} is product k's ad valorem tariff imposed by export destination country c at year t. A firm may export multiple types of products to multiple countries. The ratio in the second parentheses in Eq. (2), $X_{ikt}^{c}/\sum_{c} X_{ikt}^{c}$, measures the export ratio of product k produced by firm i but consumed in country c, yielding a weighted external tariff across Chinese firms' export destinations. Similarly, the first parenthesis in Eq. (2), $X_{it}^{k}/\sum_{k} X_{it}^{k}$ measures the proportion of product k's exports over firm i's total exports.

As a control variable, we also include import output tariffs in the estimates to capture the possible pro-competition effects. To measure the impact of import competition for each product, it is a need to have information on domestic sales at product level. However, such data are unavailable. As a compromise, we measure the import output tariffs at the HS two-digit industry level. Table 2 reports the summary statistics for such key variables.

Table 2 Summary statistics (2000 2006)

Variables	Mean	SD	Min	Max
Year	2003	1.85	2000	2006
Firm's export intensity	0.488	0.399	0	1
Industry-level output tariffs	12.1	5.91	0	58.7
Firm-level input tariffs	2.56	4.13	0	90
Firm-level input tariffs (fixed weight)	0.577	2.27	0	94.5
Firm-level external tariffs	8.1	17.1	0	2,999
Processing indicator	0.319	0.466	0	1
Predicted processing probability	0.449	0.13	0.026	0.826
Extent to processing imports	0.552	0.474	0	1
Firm's log TFP (Olley-Pakes)	1.27	0.35	1.55	10.4
Log of firm employment	5.35	1.14	2.3	11.9
Firm tenure	10.7	10.3	0	57
Firm scope	6.49	9.84	1	527
SOEs indicator	0.02	0.141	0	1
Foreign indicator	0.615	0.486	0	1

3.3 Estimation Framework

To investigate the effect of input tariffs reductions on firm's export intensity, we then consider an empirical framework as follows:

$$\begin{aligned}\text{Exp\_int}_{ijt} = {} & \alpha_0 + \alpha_1 \text{FIT}_{it} + \alpha_2 \text{FET}_{it} + \alpha_3 \text{FET}_{it} \times \text{PE}_{it} + \alpha_4 \text{OT}_{jt} \\ & + \alpha_5 \text{OT}_{jt} \times \text{PE}_{it} + \alpha_6 \text{PE}_{it} + \theta X_{it} + \eta_i + \zeta_t + \varepsilon_{it} \end{aligned} \tag{3}$$

where Exp_int_{ijt} measures firm's export intensity for firm i in industry j in year t, as discussed above. FIT_{it} and FET_{it} denote firm-specific weighted input tariff and external tariff in year t, respectively. PE_{it} is a processing indicator which equals one, if firm i engages in processing activity in year t, and zero otherwise. OT_{jt} denotes industry-level tariffs for industry j in year t. X_{it} denotes other firm characteristics such as type of ownership (i.e., state-owned enterprises or multinational firms), firm size (i.e., log employment), and firm productivity. Finally, the error term is divided into three components: (1) firm-specific fixed effects hi to control for time-invariant factors such as a firm's location; (2) year-specific fixed effects η_i to control for firm-invariant factors such as China's accession to the WTO in 2001 and Chinese RMB appreciation after 2005; and (3) an idiosyncratic effect ε_{it} with normal distribution $\varepsilon_{it} \sim N\ (0, \sigma^2)$ to control for other unspecified factors.

4 Empirical Results

4.1 Benchmark Results

To investigate the impact of firm-specific input tariffs reduction on export intensity, we start from plotting firm's export intensity against firm-specific input tariffs, which are aggregated in industry level over years. Figure 2a clearly suggests a negative correlation between the average firm-specific export intensity and input tariffs. Admittedly, such a negative correlation could be just driven by other unspecified factors. In addition to the output import tariffs reductions, the tariffs reduction in China's trading partners may also affect Chinese firm's export intensity. Thus, controlling for tariffs reduction in China's export destinations is also worthwhile in obtaining the precise estimate of the effect of import tariffs reductions on a firm's export intensity. We then control for industrial output tariffs and firm-specific external tariffs, as well as firm's type of ownership (i.e., SOEs and foreign firms) and trade regime (i.e., processing and ordinary firms) in all estimates in Table 3.

To understand the overall impact of input tariffs reduction on export intensity, the estimate in Column (1) starts from abstracting away the interaction terms of various tariffs reductions and firm's processing status. After controlling for firm-specific fixed effects and year-specific fixed effects, estimates in Column (1) show that firm's

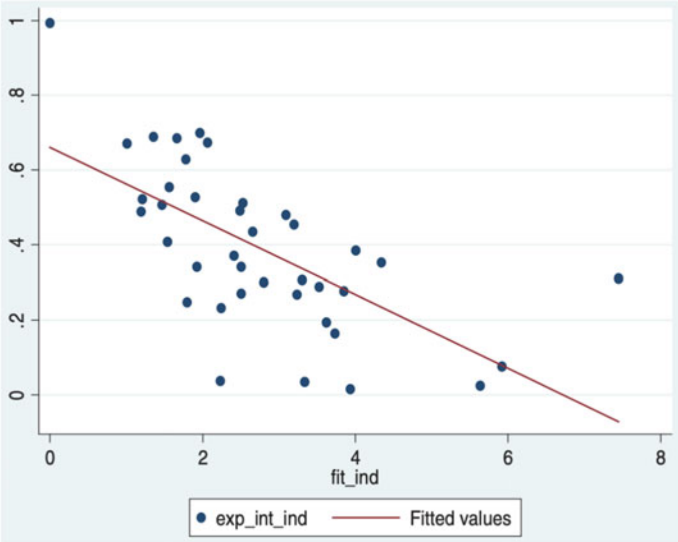

Fig. 2 Firm's export intensity against input tariffs by industry. *Note* The residuals in this figure are obtained from benchmark estimates in the last column of Table 3

input tariffs reduction leads to larger proportion of exports to sales, though the impact of output tariffs and firm-specific external tariffs on export intensity is insignificant. Adding the interaction terms between processing dummy and input tariffs (external tariffs and output tariffs) in Column (2) does not change the estimation results in terms of signs or magnitudes.

One may concern that the large proportion of pure domestic firms which have zero exports may affect our estimation results given that around 17% of Chinese firms have zero exports in our matched data. A similar argument applies to a fairly large proportion of pure exporting firms 12% exporters export all of their products. Meanwhile, as suggested by Ahn et al. (2011), the carry-along trading companies (i.e., intermediaries) notably do not have their own production activity, but only export goods collected from other domestic firms (i.e., 100% export intensity), or import goods abroad and then sell to other domestic companies (i.e., 0% export intensity). Such firms would result in a unit of export intensity. We hence drop firms whose export intensity is zero in Column (3) and one in Column (4). Column (5) goes further to drop observations if export intensity is either zero or one. Neither of such specifications changes our estimation results of the key variable: the coefficient of firm-specific input tariffs is always negative and highly significant at the conventional statistical level.

Table 3 Estimates of tariffs reduction on firm's export intensity

Export intensity (Exp_int)	(1)	(2)	(3)	(4)	(5)
Firm input tariffs	– 0.002*** (−4.75)	– 0.002*** (−4.67)	– 0.002*** (−7.56)	– 0.002*** (−4.83)	– 0.003*** (−7.89)
Industrial tariffs	0.0004 (1.20)	– 0.0001 (−0.17)	– 0.0001 (−0.20)	– 0.0002 (−0.49)	0.0001 (0.01)
Industrial tariffs × processing dummy		0.001*** (2.92)	0.001*** (3.16)	0.001*** (3.11)	0.001*** (3.07)
Firm external tariffs	0 (−1.07)	0 (0.11)	0 (−0.16)	0 (−0.26)	0 (−0.41)
Firm external tariff × processing dummy		0* (−1.92)	0 (−0.44)	0 (−1.16)	0 (−0.88)
Processing dummy	0.001 (0.25)	– 0.013** (−2.27)	– 0.011** (−2.19)	– 0.016*** (−2.71)	– 0.013** (−2.33)
State-owned enterprises	0.019 (0.97)	0.019 (0.98)	0.011 (0.69)	0.017 (0.90)	0.011 (0.62)
Foreign-invested enterprises	0.033*** (2.74)	0.033*** (2.74)	– 0.001 (−0.11)	0.021* (1.65)	– 0.01 (−0.84)
Obs. dropped if Exp_int = 0	No	No	Yes	No	Yes
Obs. dropped if Exp_int = 1	No	No	No	Yes	Yes
Year-specific fixed effects	Yes	Yes	Yes	Yes	Yes
Firm-specific fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	79,212	79,212	67,086	68,420	56,294
R^2	0.01	0.01	0.01	0.01	0.01

Notes Robust *t*-values corrected for clustering at the firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%t levels, respectively

4.2 First-Difference Estimates

Firm's export intensity could be affected by other factors that are unspecified in the estimations above. Although we have employed firm-specific fixed effects and year-specific fixed effects to control for factors that are only variant across firms and over years, respectively. It is still possible that there exist some other omitted factors that change both across firms and over years. For instance, China's government allowed some exportable products to enjoy the privilege of 'export value-added tax rebate'. The value-added tax rebate ratio differs across industries and over year.[5]

[5] Most commodities are mandatory to pay 13 or 17% value-added tax for their value added in China. However, if such commodities are exportable goods, firms can get the value-added tax rebate when

We hence perform the following first-difference estimate to control for such possible unobserved firm heterogeneity as suggested by Trefler (2004) and Amiti and Konings (2007):

$$\Delta \text{Exp\_int}_{ijt} = \alpha_0 + \alpha_1 \Delta \text{FIT}_{it} + \alpha_2 \Delta \text{FET}_{it} + \alpha_3 \Delta \text{FET}_{it} \times \text{PE}_{it} + \alpha_4 \Delta \text{OT}_{jt} + \alpha_5 \Delta \text{OT}_{jt} \times \text{PE}_{it} + \alpha_6 \text{PE}_{it} + \theta X_{it} + \varpi_i + \eta_t + \mu_{it} \quad (4)$$

where Δy_{it} is the first difference of the variable $y_{it} \in \{\text{Exp\_int}_{ijt}; \text{FIT}_{it}; \text{FET}_{it}; \text{OT}_{jt}\}$ denoting y_{it}-y_{it-1}. We also include the firm (year)-specific fixed effects to control for the time-invariant (variant) growth factors.

As shown in Column (1) of Table 4, the variable of first difference in firm input tariffs is still negative and significant. To check whether such results are sensitive to the extreme values of firm's export intensity, we drop samples with zero export intensity in Column (2) and samples with a unit of export intensity in Column (3). Finally, we even drop samples whose export intensity is zero or one. All of such specifications yield a similar result: the reduction in firm-specific input tariffs leads to an increase in export intensity.

4.3 Estimates for Entry and Exit

We have seen much evidence that a reduction in input trade costs leads to an increase in export intensity. But, how does this happen? Are they through the extensive margin, or intensive margin, or both? Previous studies like Blum et al. (2012) found that Chilean firms reduce their domestic sales when they enter foreign markets. For continuing exporters, Chilean firms' foreign and domestic sales are negatively correlated over time. We now go to check whether this is also true for Chinese firms.

Estimates of Column (1) in Table 5 first check the case for starters that include both exporters and non-exporters. The LHS variable in the Probit estimate is a dummy of firm's operation status which takes one if it is a starter and zero otherwise. We see that a reduction in firm input trade costs leads to a higher probability of firms to become new starters. One reason is that the reduction in input trade costs helps firms generate more profit and hence it can overcome the entry fixed costs (Melitz, 2003). Column (2) keeps new exporters only and focuses on the effect of intensive margin. Clearly, the estimate shows that a reduction in input trade costs leads to higher export intensity. For comparison, Columns (3) and (4) include all exiters (i.e., both exporter and non-exporters) and exiting exporters, respectively. It turns out that the reduction in input trade costs does not help much to prevent firms exiting from the market since the coefficient of input trade costs is insignificant. Such an observation also holds for exiting exporters shown in Column (4).

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such products are exported. The value-added tax rate is set as 5, 9, 11, 13, or 17%, which is contingent on products.

Table 4 First-difference estimates of firm input tariffs on export intensity

First difference in export Intensity (ΔExp_int)	(1)	(2)	(3)	(4)
First difference in firm input tariffs	− 0.001 (−1.04)	− 0.001* (−1.88)	− 0.001 (−1.28)	− 0.001** (−2.11)
First difference in industrial tariffs	0 (−0.08)	0.001 (1.01)	0 (−0.31)	0.001 (0.85)
First difference in industrial tariffs × processing dummy	0 (−0.36)	0 (−0.32)	0.001 (0.52)	0 (0.34)
First difference in firm external tariffs	0 (−0.08)	0 (0.01)	0 (−0.30)	0 (−0.03)
First difference in firm external tariffs × processing dummy	0 (−0.76)	0 (1.34)	0 (0.54)	0 (0.9)
Processing dummy	0 (0.04)	0.002 (0.49)	0.002 (0.34)	0.003 (0.61)
State-owned enterprises	0.003 (0.07)	− 0.002 (−0.06)	0.001 (0.02)	− 0.005 (−0.13)
Foreign-invested enterprises	0.04 (1.51)	0.023 (0.97)	0.023 (0.83)	0.001 (0.03)
Obs. dropped if Exp_int = 0	No	Yes	No	Yes
Obs. dropped if Expint = 1	No	No	Yes	Yes
Year-specific fixed effects	Yes	Yes	Yes	Yes
Firm-specific fixed effects	Yes	Yes	Yes	Yes
Observations	36,266	31,623	31,707	27,064
R^2	0.02	0.01	0.01	0.01

Notes Robust *t*-values corrected for clustering at the firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%t levels, respectively

By way of comparison, Columns (5) and (6) just include continuing exporters. The coefficient of firm-specific input trade costs in Column (5) is negative and significant, suggesting that once again the reduction in input trade cost leads to higher export intensity even for continuing firms. Yet, it is still interesting to understand whether the reduction in input trade costs can introduce exporters to export more varieties (i.e., the extensive margin). We hence perform the negative binomial estimate in the last column of Table 5, given that the regressand is a positive integer. Clearly, the negative and significant sign of input trade costs suggests that the reduction in input trade costs also leads to an increase in export scope.

4.4 Sources of the Reduction in Input Trade Costs

It is also worthwhile to ask why firm's input trade costs decline over time. The first natural answer is due to the reduction in import tariffs. In the measure of firm-specific input tariffs (Eq. (1)), if τ_t^k decreases, firm input tariffs FIT_{it} would decrease

Table 5 Estimates of firm input tariffs on export intensity by entry and exit

Type	New exporters		Exiters		Continuing exporters	
Regressand	Export Dummy	Export Intensity	Export Dummy	Export Intensity	Export Intensity	Export Scope
Econometric method	Probit (1)	FE (2)	Probit (3)	FE (4)	FE (5)	Neg. Binomial (6)
Firm input tariffs	− 0.009*** (−6.00)	− 0.002* (−1.77)	0 (−0.24)	− 0.001 (−0.84)	− 0.002*** (−3.15)	− 0.007*** (−4.17)
Industrial tariffs	0.005*** 2.79	− 0.001 (−0.41)	0.004* 1.89	− 0.003* (−1.68)	− 0.001 (−1.33)	− 0.001 (−0.67)
Industrial tariffs xx processing dummy	− 0.004** (−2.08)	0 (−0.04)	− 0.003 (−1.08)	0.003 1.44	0.002*** 2.72	0.002 0.85
Firm external tariffs	− 0.002** (−1.99)	− 0.001 (−0.89)	0 (−0.41)	0 0.57	0 (−0.75)	0.001 0.71
Firm external tariffs × processing dummy	0.001 1.57	0.001 0.94	0.001 1.05	0 0.52	0 0.16	0.001 0.45
Processing dummy	0.128*** 4.65	− 0.017 (−0.65)	0.101*** 3.05	− 0.047* (−1.90)	− 0.022*** (−2.31)	− 0.042 (−1.37)
Firm's TFP	− 0.102*** (−6.56)	− 0.039*** (−2.87)	0.039*** 2.22	− 0.031*** (−2.04)	− 0.042*** (−4.76)	0.054*** 2.95
State-owned enterprises	− 0.202*** (−4.20)	− 0.047 (−1.25)	0.346*** 7.21	0.039 1.28	− 0.001 (−0.02)	− 0.097 (−1.02)
Foreign-invested enterprises	0.089*** 6.95	− 0.075* (−1.66)	0.134*** 8.57	0.006 0.11	− 0.028 (−1.19)	0.258*** 3.8
Observations	65,422	21,624	46,862	32,098	18,053	11,677
R^2	–	0.02	–	0.01	0.02	–
Year-specific fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	No	Yes	No	No	No
Firm-specific fixed effects	No	Yes	No	Yes	Yes	Yes

Notes Robust t-values corrected for clustering at the firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%t levels, respectively

even when other components are unchanged.[6] Meanwhile, there still exists another source for input tariffs reduction. Faced by some negative demand shocks, firms may adjust their production structure between processing and ordinary imports. Since processing activities have a lower threshold to entry, firms may engage in more processing activities when they are low productive (Yu Forthcoming). If firms have more weights in processing activities, they would be able to bear a lower firm-specific input tariff. Of course, in the reality, such two sources are combined automatically. Therefore, it is worthwhile to decompose the two sources and identify their effects one by one.

[6] Of course, when tariff t_t^k decreases, the import weight m_{it}^k for the product k for firm i could change as well. However, change the weight to a fixed weight using the initial year in the period $(m_{i;\,2000}^k)$ or a floating one-period lag weight $(m_{\mathrm{it}\,;\,1}^k)$ does not change our estimation results.

Table 6, therefore, picks up such a task. Column (1) only includes pure ordinary firms. Column (2) covers hybrid firms that have some ordinary imports and some processing imports. However, since the firm-specific input tariffs, as in Eq. (1), still reflect the changes in both processing share and tariffs change, we fix the tariffs by using the tariffs line for products in the initial year (i.e., 2000), so that one can clearly observe the impact of changing processing share on the export intensity. That is, the firm-specific input tariffs in Column (2) are measured as $\sum_{k\in O}\sum_{k\in Mm_{it}^k}^{m_{it}^k}\tau_{2000}^k$. It turns out that the coefficients of firm-specific input tariffs are negative and significant in Columns (1) and (2), indicating that changes in both tariffs and processing share matter for firms to realizing the increase in export intensity. More importantly, the effect of input trade liberalization on export intensity for ordinary firms in Column (1) is larger than its counterpart for hybrid firms in Column (2).

We now go further to explore the transition probability for trade regime switching. The intuition is straightforward. Given that the threshold of processing trade is low in China, pure ordinary firms would engage in processing trade only when the market is tough (Dai et al., 2012). In contrast, pure-processing firms would start to engage in ordinary trade if the market is ease. Columns (3)–(5) hence preform the estimates

Table 6 Estimates for sources of input tariffs variations

Export intensity	Pure ordinary firms	Hybrid firms	Switching firms from		
			Pure ord. to hybrid	Pure proc. to hybrid	Hybrid to non-hybrid
	(1)	(2)	(3)	(4)	(5)
Firm input tariffs	− 0.002*** (−5.21)		− 0.004** (−2.04)	− 0.002 (−0.10)	− 0.001 (−0.39)
Firm input tariffs (fixed tariffs)		− 0.001*** (−2.96)			
Industrial tariffs	− 0.000 (−0.76)	0.000 (0.68)	0.001 (0.66)	0.005 (0.85)	− 0.000 (−0.19)
Firm external tariffs	− 0.000 (−0.50)	0.000 (0.03)	− 0.000 (−0.50)	− 0.001 (−0.68)	0.000 (0.19)
State-owned enterprises	0.008 (0.43)	0.014 (0.47)	0.023 (0.27)	–	0.005 (0.06)
Foreign-invested enterprises	− 0.011 (−0.66)	0.029 (1.63)	0.060 (1.37)	0.416** (2.32)	0.006 (0.07)
Year-specific fixed effects	Yes	Yes	Yes	Yes	Yes
Firm-specific fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	31,740	46,831	12,524	3,644	9,395
R^2	0.01	0.01	0.01	0.03	0.02

Notes Robust *t*-values corrected for clustering at the firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%t levels, respectively for firms that switch from ordinary to hybrid, from pure processing to hybrid, and from hybrid to non-hybrid firms, respectively. It turns out that only the effect of input tariffs on export intensity for firms that switch from ordinary to hybrid is negative and significant.

4.5 Endogeneity of the Measure of Input Tariffs

Furthermore, the weight construction in firm-specific input tariffs in Eq. (1) is still endogenous because goods with high tariffs would be imported less, thus generating a lower import weight in Eq. (1). Taking an extreme example, if China imposes a prohibitive tariff on product k, then its import share on such a good would be zero, because m_{it}^k in Eq. (1) is zero. Meanwhile, firm's exports are also possibly related to its imports since firms with more exports usually use more intermediate imports, as documented by Feng, Li, and Swensen (2012). If so, the LHS variable, firm's export intensity, also reversely affects the import weight in the firm-specific input tariffs FIT_{it}.

Hence, the input tariffs that a firm face may be underestimated. Thus, to avoid such a problem, following Topalova and Khandelwal (2011), we choose firm's import value in the initial year (i.e., 2000) to construct a fixed weight in the firm-specific input tariffs (FIT^{2000}) as follows:

$$\text{FIT}_{it}^{2000} = \sum_{k \in O} \frac{m_{i,2000}^k}{\sum_{k \in M} m_{i,2000}^k} \tau_t^k \tag{5}$$

where $m_{i,2000}^k$ is firm i's imports of product k in 2000. As a result, the import weight is unaffected by tariffs reductions. We then use this measure of tariffs reductions to run regressions as a robustness check.

Table 7 reports the estimates using firm-level tariffs with fixed weights. In all estimates, we use the extent to processing imports to measure firm's processing activities. Columns (1) and (2) first abstracts away the interaction terms between extent to processing and output tariffs (firm external tariffs) for a while, whereas the rest of the table includes such two interaction terms. Estimates in Column (1) confirm that the effect of firm-specific input tariffs on export intensity is negative and significant. It is worthwhile to check whether the effects of firm-level input tariffs on export intensity pick up the role of firm size given that large firms usually have larger export intensity (Bonaccorsi, 1992). We hence include firm size measured by the log of firm's employment since Column (2). It turns out that larger firms usually have higher export intensity. Column (3) drops observations if firms have no foreign sales. Finally, Column (4) only keeps those firms that have both foreign and domestic sales in the estimation. Nevertheless, the effect of firm-specific input tariffs on export intensity is negative and significant in all estimates; more encouragingly, their magnitudes are also close to their counterparts in the previous tables.

Table 7 Estimates using firm-level tariffs with fixed weights

Export intensity (Exp_int)	(1)	(2)	(3)	(4)
Firm input tariffs (fixed weights)	– 0.001* (−1.66)	– 0.001* (−1.66)	– 0.002** (−2.32)	– 0.002** (−1.99)
Industrial tariffs	0 0.65	0 0.65	0 (−0.74)	0 (−0.23)
Industrial tariffs × extent to processing			0.001** 2.5	0.001** 2.13
Firm external tariffs	0 (−1.14)	0 (−1.14)	0 (−0.78)	0 (−0.95)
Firm external tariffs × extent to processing	(−1.81)	(−1.80)	– 0.000*	– 0.000*
Extent to processing	0.017*** 3.85	0.017*** 3.85	0.011 1.63	0.012 1.52
State-owned enterprises	0.043 1.54	0.043 1.54	0.031 1.32	0.031 1.26
Foreign-invested enterprises	0.043** 2.49	0.043** 2.49	0.016 1.1	0.011 0.62
Log employment			0.008** 2.57	0.013*** 3.28
Obs. dropped if Exp_int = 0	No	No	Yes	Yes
Obs. dropped if Exp_int = 1	No	No	No	Yes
Year-specific fixed effects	Yes	Yes	Yes	Yes
Firm-specific fixed effects	Yes	Yes	Yes	Yes
Observations	50,779	50,779	42,819	35,440
R^2	0.01	0.01	0.01	0.01

Notes Robust t-values corrected for clustering at the firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%t levels, respectively

4.6 Further Quantile Estimates

Finally, another possible concern is whether or not the OLS estimates are appropriate for estimation given that the sample of firm's export intensity exhibits a U-shape, which is far from the normal distribution that requires for OLS estimates. However, this is not a problem since that the U-shape of firm's export intensity across firms is due, in large part, to the variation of firm's characteristics. Given that we have already controlled for firm-specific fixed effects and year-specific fixed effects, such omitted characteristics have been well controlled.

Still, the U-shape of firm's export intensity hints us that the response of input trade costs to export intensity may not be identical across all firms. The fixed-effect OLS estimates so far only focus on the mean level of the response of firm input tariff. The rich heterogeneity across all firms is hence abstracted away. To gain a better understanding, the economic magnitude of the effect of input trade costs on firm's export intensity, the quantile estimates would be a plus for us to identify such heterogeneous magnitudes across firms.

The other reason to appeal to the quantile estimates is that, as shown in Fig. 3, the residual obtained from the benchmark estimates in the last column of Table 3 is asymmetric, which deviates from the requirement of standard OLS estimates. Therefore, the quantile analysis is also a need (Koenker-Bassett 1978). Different from minimizing the sum of square errors in the OLS estimates, the quantile estimates propose to minimize the weight of the estimation residual as follows:

$$\beta_q = \operatorname{argmin} \sum\nolimits_{i:y>X_i\beta_q}^{n} q\left|y_i - X_i\beta_q\right| + \sum\nolimits_{i:y<X_i\beta_q}^{n} (1-q)\left|y_i - X_i\beta_q\right| \quad (6)$$

where q is the quantile level, y_i is the LHS variable, and $X_i X\beta_q$ are the fitted values at quantile q. Intuitively, the quantile estimates give much more weights for those observations that are lower than their fitted value at every quantile q. In this way, the estimates would be able to capture the heterogeneous behavior of firm's export intensity.

Table 8, therefore, reports the quantile estimates for the first quantile, median, and the third quantile. To capture the impact of various tariffs reductions on export intensity, we abstract away other control variables but only include firm-specific input tariffs, output import tariffs, and external tariffs. For comparison, we also include the OLS estimate in Column (1). It turns out that the impact of firm-specific input tariffs reduction leads to an increase in export intensity in all estimates.

Finally, we take a step further to perform the quantile estimates in a continuous version that the quantiles vary from zero to one. Figure 4 shows the heterogeneous response of the coefficients for industry-level output tariffs, firm-specific input tariffs,

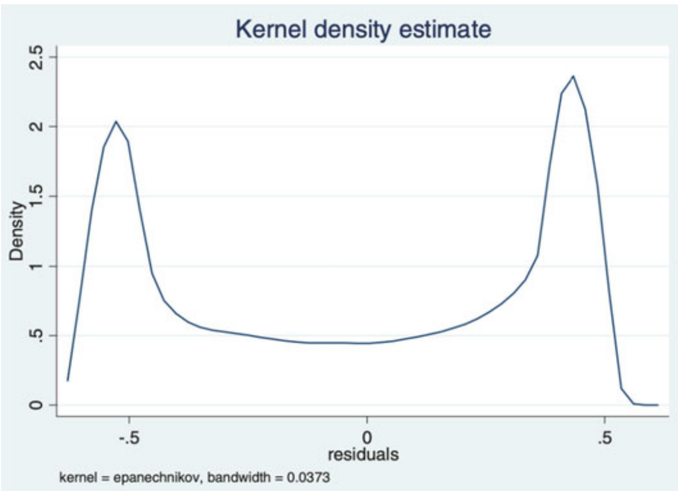

Fig. 3 The distribution of residuals in the benchmark estimates

Table 8 Quantile estimates

Export intensity	OLS	Quantile 25%	Quantile 50%	Quantile 75%
Industrial tariffs	0.010** 40.08	0.010** 38.26	0.020** 45.25	0.005** 41.51
Firm input tariffs	− 0.027** (−55.35)	− 0.016** (−56.49)	− 0.052** (−89.1)	− 0.035** (−189.2)
Firm external tariffs	− 0.0001 (−1.46)	0 (−0.99)	− 0.001** (−10.21)	− 0.001** (−8.45)
Constant	0.469** 120.63	0.0641** 17.39	0.479** 76.47	0.920** 568.6

Notes Robust *t*-values corrected for clustering at the firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% at levels, respectively

firm-specific external tariffs, and the constant intercept term. Clearly, the coefficients of firm-specific input tariffs exhibit a concave shape. Similarly, the coefficients of output tariffs exhibit a hump shape. These two figures suggest that the coefficient of the firm input tariffs should reach its maximum around the median level in an absolute value. This is exactly consistent with the empirical findings shown in Table 8.

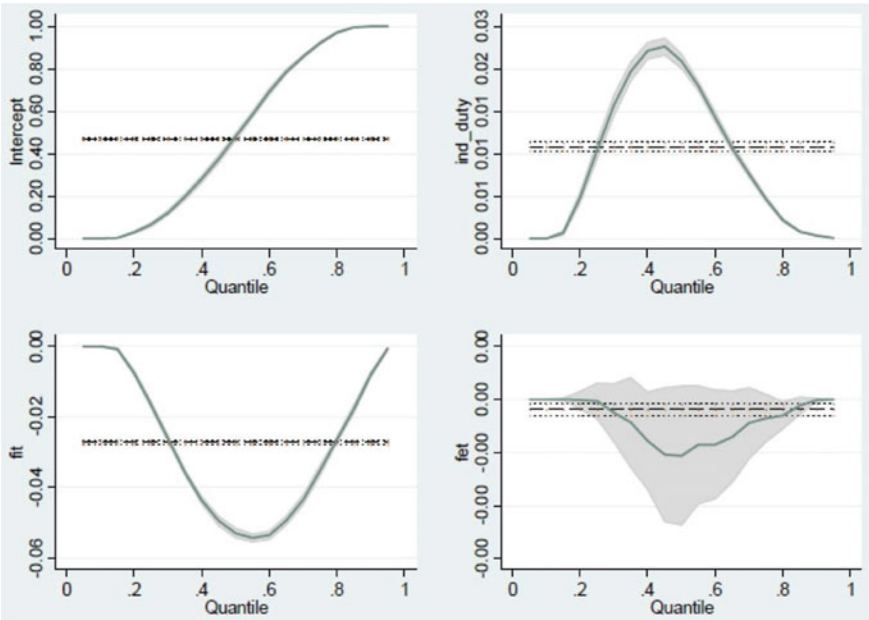

Fig. 4 The quantile estimates of various tariffs reductions

Our final remark is about the economic magnitude of firm's export intensity in response to the input trade costs reduction. As shown in both Fig. 4 and Table 8, the coefficient of input trade costs reaches, in the absolute value, its maximum of 0.052 at the mean level but records a relatively low number of 0.016 at the first-quarter level and of 0.035 at the third-quarter level. This suggests that a one-point declining in input trade costs leads to a 5.2% increase in export intensity for firms with median level of export intensity, and a 1.6 (3.5)% increase in export intensity for firms around the first (third)-quarter level of export intensity. Given that the mean of input trade costs is 2.73% and of export intensity is 48.8% as shown in Table 1, firm's export intensity would increase to around 62.1% if input trade costs were reduced to zero. Such impact indeed is economically sizable.

5 Concluding Remarks

The paper explores how reductions in input trade costs affect firms' export intensity by exploiting the special tariff treatment afforded to the imported inputs by processing firms as opposed to non-processing firms in China. As a popular trade pattern in a large number of Asia-Pacific countries such as China and Indonesia, processing trade plays an important role in firm's decision to choose domestic and foreign markets. By using Chinese firm-level production and transaction-level trade data, an intensive empirical search shows that a reduction in input trade costs leads to an increase in export intensity for Chinese large trading firms. As ordinary import enjoys the free-duty treatment in China, the impact is more pronounced for ordinary firms than that for hybrid firms which engage in both processing and ordinary trades.

The present paper is one of the first to explore the role of processing trade on firm's export share. The rich Chinese data-set enables the determination of whether a firm engages in processing trade and the examination of the effect of the firms' extent of processing trade engagement on export intensity. With such information, firm-specific input tariffs were also constructed, as one of the first attempts in the literature, which, in turn, enriches the understanding of the economic effect of trade liberalization on firm's sales decision.

Our paper also has rich policy implications. Trade liberalization is not only able to boost firm productivity via generating tougher import competition (Yu Forthcoming). Moreover, input trade liberalization can also help firms access to larger foreign market and realize more gains from trade. To maintain comparative advantage of Chinese exportable goods (Yao & Yu, 2009), Chinese government needs to deeply engage in more multinational trade agreements to push further input (and output) trade liberalization in China.

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Conflict of Interest No potential conflict of interest was reported by the authors.

Appendix

See Table 9.

Table 9 Firm's switching by type

Panel A: transition probability from pure-processing firms to non-processing firms			
Pure processing next year			
Pure processing today	0	1	Total
0	45.70	54.30	100.00
1	6.27	93.73	100.00
Total	11.18	88.82	100.00
Panel B: transition probability from ordinary firms to non-ordinary firms			
Ordinary next year			
Ordinary today	0	1	Total
0	85.23	14.77	100.00
1	34.08	65.92	100.00
Total	67.85	32.15	100.00
Panel C: transition probability from hybrid firms to non-hybrid firms			
Hybrid next year			
Hybrid today	0	1	Total
0	81.45	18.55	100.00
1	52.06	47.94	100.00
Total	73.46	26.54	100.00

Notes Panel A: 0 means pure-processing firms, 1 means non-pure processing firms
Panel B: 0 means ordinary firms, 1 means non-ordinary firms
Panel C: 0 means hybrid firms, 1 means non-hybrid firms

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Processing Trade, Tariff Reductions and Firm Productivity: Evidence from Chinese Firms

Miaojie Yu

The effect of trade liberalisation on firm productivity is one of the most important topics in empirical trade research. Initially, trade economists primarily focused on the effect of cutting tariffs on final goods. At present, research interest has shifted to exploration of the effect of tariff reductions on imported intermediate inputs, which is usually greater than the effect on final goods (Amiti & Konings, 2007; Goldberg et al., 2010; Topalova & Khandelwal, 2011). Amiti and Konings (2007) analyse Indonesian firm-level data and find that firms' gains from reduction of input tariffs are at least twice as much as those from reduction of output tariffs. Furthermore, Topalova and Khandelwal (2011) find that Indian firms' gains from input tariff reduction could be ten times greater than those from output tariff reduction in several industries. They forcefully argue that the primary reason for this result is that access to better intermediate inputs through the reduction of input tariffs is more important than the pro-competitive effect of the reduction of output tariffs.

Different from such findings, the present article shows that reducing output tariffs has had a greater effect on productivity improvement than reducing input tariffs for large Chinese trading firms in the new century. A 10 percentage point fall in output (input) tariffs leads to a productivity gain of 9.2 (5.1)%. The positive impact of both types of tariff reductions on productivity improvement is weaker as the firm's share of processing imports grows. Such results are primarily attributable to the special tariff treatment afforded to imported inputs by processing firms as opposed to non-processing firms in China. Processing imports, which account for half of total imports in China, have zero tariffs. Further tariff reductions on imported intermediate inputs have no impact on firms that entirely engage in processing trade but still have some impact on firms that engage in both processing and non-processing trade. As the firm's processing share grows, input tariff reductions have a smaller impact on productivity

M. Yu (✉)
China Centre for Economic Research (CCER), National School of Development, Peking University, Beijing 100871, China
e-mail: mjyu@ccer.pku.edu.cn

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gains. Similarly, as firms' processing share increases, the share of domestic sales decreases accordingly; and the pro-competition effects from the reductions in output tariffs are hence weaker.

The current article contributes to the literature in at least three important ways. First, it enriches the understanding of the economic growth of China, the second largest economy and the largest exporter of goods in the world. It is widely believed that China's huge foreign trade volume, a 10% of world trade, is a fundamental cause of the country's rapid economic growth. However, this conjecture is rarely supported by using Chinese micro firm-level data.[1] This study aims to fill in this gap. Using highly disaggregated transaction-level customs data and firm-level production data from 2000 to 2006, the article thoroughly explores the nexus between foreign trade and firm productivity.

Second, processing trade is an important type of trade in many developing countries, such as Indonesia, Mexico and Vietnam. Processing trade is the process by which a domestic firm initially obtains raw materials or intermediate inputs from abroad and, after local processing, exports the value-added final goods (Feenstra & Hanson, 2005). Governments typically encourage processing trade by offering tariff reductions or even exemptions on the processing of intermediate goods. Although there are some studies on trade reform in both developed and developing countries,[2] the interaction between trade reform and processing trade is rarely explored. Hence, understanding the productivity gains from trade reform under the special tariff treatments afforded to processing trade is essential.

Last but not least, aside from adopting the widely accepted method of measuring tariffs at the sector level, I take a step forward to measure both output tariffs and input tariffs at the firm level. Perhaps because of data restrictions, previous studies have usually measured tariffs at the industrial level by using input–output tables, as in Amiti and Konings (2007), or by measuring effective tariff protection as in Topalova and Khandelwal (2011). However, such a convenient approach might face a possible pitfall because input–output tables mix up both imported intermediate inputs and domestic intermediate inputs that are not directly relevant to tariff reductions. Using input–output tables may not accurately measure the level of trade protection faced by firms. Thanks to the rich information covered by both Chinese firm-level production data and transaction-level trade data, I am able to construct novel measures of firm-specific input and output tariffs to estimate the effect of trade reforms on firm productivity. To my knowledge, this is the first attempt to measure tariffs at the firm level in the literature, although it is worthwhile to stress that my estimation results remain robust when using conventional industry-level measures of tariffs.

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[1] Brandt et al. (2012) is an outstanding exception.

[2] The studies focusing on developed countries, among others, include Bernard et al. (2003) for the US and Trefler (2004) for Canada. However, more evidence has been found for developing countries, such as Bustos (2011) for Argentina, Schor (2004) for Brazil, Pavcnik (2002) for Chile, Fernandes (2007) for Colombia, Harrison (1994) for Côte d'Ivoire, Krishna and Mitra (1999) and Topalova and Khandelwal (2011) for India, Amiti and Konings (2007) for Indonesia and Levinsohn (1993) for Turkey. Other research, such as that of Lu et al. (2010), Lu (2011) and Ma et al. (2011), also explores the nexus between export growth and productivity improvement in China.

I also carefully control for two sets of endogeneity issues of firm-level tariffs and firms' self-selection to processing activities. Several endogeneity problems plague the firm-level input and output tariffs. The first one results from tariff measures themselves. Because a firm may import multiple products, it is useful to construct an import-based weight to reflect the importance of products for the firm. However, imports and tariffs are negatively correlated. In the extreme case, imports and their associated import shares are zero for prohibitive tariffs. As a result, the measure of input tariffs faces a downward bias. To address this endogeneity problem, throughout all the estimation, firm-level tariffs are constructed using time-invariant weights based on the firm's imports in the first year it appears in the sample. The second endogeneity problem relates to a possible reverse causality of tariffs with respect to productivity. Tariffs may be granted in response to domestic special interest groups, the pressure of which could be significant in countries such as India (Topalova & Khandelwal, 2011) or low in countries such as Indonesia (Amiti & Konings, 2007). Given that China acceded to the WTO in 2001, domestic pressure might not have played a key role during 2000–2006. However, for the sake of completeness, an (IV) approach is adopted to control for possible reverse causality.

Another set of endogeneity issues is of firms' self-selection to processing activities. Observing that some Chinese firms are involved in both processing and ordinary trade, whereas others are only involved in one type of trade, I measure the processing variable in two ways. First, I use a processing indicator to identify whether a firm engages in processing trade. If a firm imports any products for processing purposes, as revealed in the customs data, such a firm is defined as a processing firm. However, the firm's processing share is endogenous. A firm would first decide whether to engage in processing trade and, if so, the extent to which it will engage in processing imports. To address such self-selection behaviour, I rely on a type-2 Tobit model. In the first-step probit estimates, I find that low-productivity firms self-select to engage in processing trade, possibly to enjoy the free duty on imported intermediate inputs. After obtaining the firm's fitted extent of processing imports from the second-step Heckman estimates, I use it as a measure of the processing indicator in the main estimates of the effects of tariffs on firm productivity to control for the endogeneity of the firm's processing decision. All else being constant, a high degree of engagement in processing trade is shown to reduce firm productivity.

To explore the relationship between firm productivity and output and input tariffs, I follow the standard procedure to investigate the nexus in two steps. First, the firm's total factor productivity (TFP) is measured based on a production function using the methodology of Olley and Pakes (1996), with a number of necessary modifications and extensions to fit the Chinese context. As processing firms and non-processing firms could use different technologies to produce products even within an industry, I estimate firm TFP for processing firms and non-processing firms separately within an industry. I also take the firm's learning from processing trade into account (De Loecker, 2013). Although the augmented Olley–Pakes approach is capable of controlling for the possible simultaneity bias and selection bias caused by regular OLS estimates, it relies on the important assumption that capital is more actively responsive to unobserved productivity. However, China is a labour-abundant country and hence has relatively low labour costs. In the face of a productivity shock, Chinese usually adjust their labour input to re-optimise production behaviour (Blomström & Kokko, 1996). Therefore, I adopt three alternative approaches to measure firm TFP:

(i) labour productivity;
(ii) the Levinsohn–Petrin (2003) TFP; and
(iii) the Blundell and Bond (1998) system-GMM TFP.

Given that the system-GMM TFP has an additional advantage in controlling for the role of lagged firm productivity to avoid possible serial correlation in the TFP estimation (Fernandes, 2007), I use it as the main measure of firm TFP.

It is also important to understand the mechanisms through which firm productivity improves in response to trade reforms. Inspired by previous studies, such as Amiti and Konings (2007), Goldberg et al. (2010) and Bustos (2011), the impact of input tariffs on productivity is straightforward, as lower tariffs induce a larger variety of inputs. By contrast, the impact of output tariffs on productivity could work directly by pressuring firms to be more productive, and/or indirectly by weeding out less-productive firms. This article finds that the pro-competition effect is mostly through the channels that pressure firms to be more productive, which is in line with the findings of Horn et al. (1995). Several possible channels—such as import scope and research and development (R&D)—are also discussed. Unlike Amiti and Konings (2007), my data set includes information that allows the firm's product scope (in export markets) to be directly measured as in Goldberg et al. (2010). In addition, similar to Bustos (2011), the analysis takes into consideration information on R&D expenses.

Finally, as economy-wide productivity is an essential measure of a country's welfare, my final step is to add firm productivity to economy-wide productivity by using Domar's (1961) weight, which corrects for possible aggregation bias due to the ignorance of vertical integration in an open economy. In brief, I find that both output and input tariff reductions contribute at least 14.5% to economy-wide productivity growth during the sample period.

The remainder of the article is organised as follows. Section 1 introduces the special tariff treatment on Chinese processing trade. Section 2 describes the unique data used in the analysis. Section 3 discusses key variables and the econometric method. Section 4 presents the empirical evidence. Finally, Sect. 5 concludes.

1 Special Tariff Treatment on Processing Trade

Processing trade in China began in the early 1980s. As an important means of trade liberalisation, the government encourages Chinese firms to import all or part of the raw materials and intermediate inputs, and re-export final value-added goods after local processing or assembly. As of 2012, the General Administration of Customs reports 16 specific types of processing trade in China.[3]

Among these types of trade, two are the most important, namely, processing with assembly and processing with inputs.[4] Both types of processing trade are duty-free but they are characterised by an important difference. For processing with assembly, a domestic Chinese firm obtains raw materials and parts from its foreign trading partners without any payment. However, after local processing, the firm has to sell its products to the same foreign trading partner by charging an assembly fee. By contrast, for processing with inputs, a domestic Chinese firm pays for raw materials from a foreign seller. After local processing, the Chinese firm can then sell its final goods to other foreign countries.

Figure 1 shows that, compared with ordinary imports, processing imports in China accounted for just a small proportion of total imports in the early 1980s. However, China's processing imports dramatically increased in the early 1990s and began to dominate ordinary imports in 1992, when China officially announced the adoption of a market economy. Going forward, processing imports accounted for more than 50% of the country's total imports. Interestingly, processing imports with assembly were more popular in the 1980s because most Chinese firms lacked the capital needed to import. Since the 1990s, processing imports with inputs have been more prevalent. This trend can be seen clearly in Fig. 2: within processing imports, the ratio of processing with assembly over processing with inputs declined from 0.41 in 2000 to 0.32 in 2006.

The primary objective of the current article is to determine how a firm's TFP reacts to output and input tariff reductions in the presence of special tariff treatments on processing trade. Therefore, understanding whether a firm engages in processing activities is important. All Chinese firms are classified into four types, namely, non-importing firms and three types of importing firms: ordinary importers, hybrid processing importers and pure processing importers. As shown in Fig. 3, non-importing firms do not have any imports; all raw materials and intermediate inputs are locally acquired. However, non-importing firms can sell their final goods domestically and internationally (as shown by arrow (1)).

Among the three types of importers, ordinary importers are firms that do not use any processing of imported intermediate inputs, although they import non-processing intermediate inputs and could sell their final goods in both domestic and foreign markets (arrow (2)).[5] In sharp contrast, pure processing importers are firms engaged

[3] Such types of processing trade include, among others, foreign aid (code: 12), compensation trade (13), assembly (14), processing with inputs (15), goods on consignment (16), goods on lease (17), border trade (19), contracting projects (20), outward processing (22), barter trade (30), customs warehouse trade (33) and entrepôt trade by bonded area (34).

[4] Processing with assembly is also referred to as 'processing with supplied materials', as stated in the official customs reports, or 'pure assembly' as adopted in Feenstra and Hanson (2005). Correspondingly, processing with inputs is also referred to as 'processing with imported materials' or 'input and assembly'.

[5] Different from processing importers, non-processing importers have to pay import tariffs for their imported intermediate inputs, although such imported goods are possibly used as inputs to produce

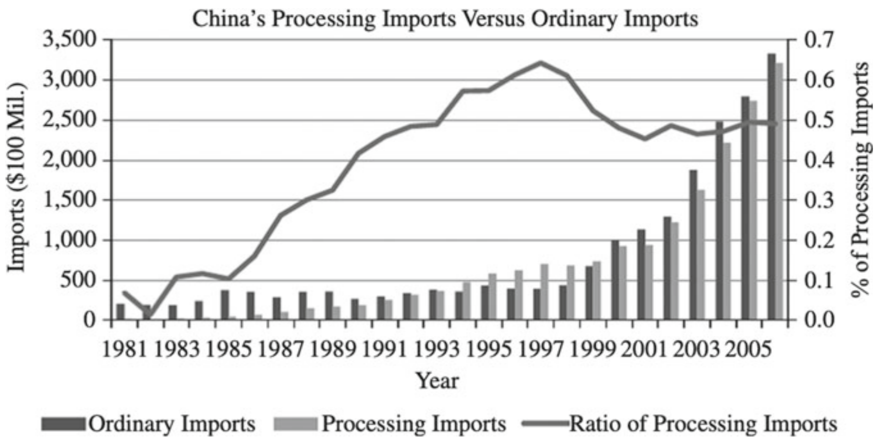

Fig. 1 China's processing imports versus ordinary imports

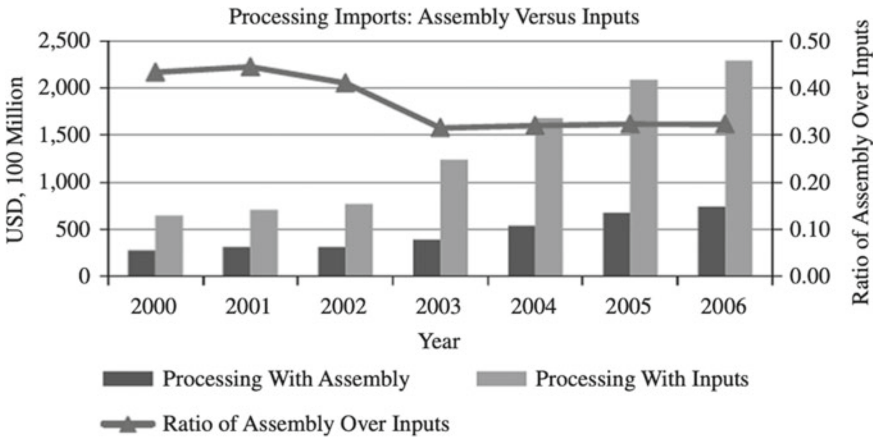

Fig. 2 China's processing imports: assembly versus inputs. *Source* Customs trade data (2000–2006), author's own compilation

only in processing activities, shown by the dotted lines in the figure. Pure processing importers purchase 100% of their raw materials and intermediate inputs abroad and re-export their final value-added goods (arrow (5)). Such firms clearly enjoy the privilege of duty-free imports. Finally, and perhaps the most interesting type of firm, hybrid processing importers engage in both ordinary imports (arrow (3)) and processing imports (arrow (4)). Such firms enjoy free duties for their processing imports, but still pay duties for ordinary imports. Here it is important to stress that

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final exportable goods. The key difference is that non-processing firms cannot show processing contracts/licences to the customs to enjoy the privilege of free duty.

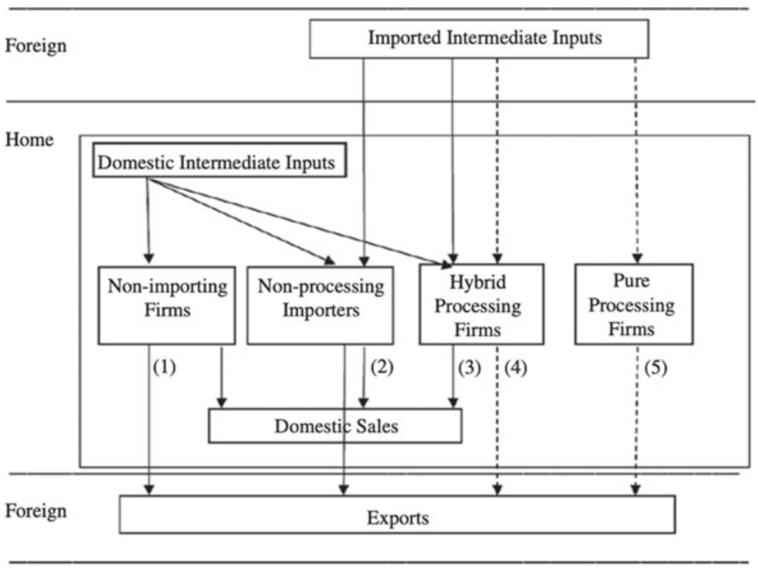

Fig. 3 Four types of Chinese firms. *Note* Dotted lines denote firms' processing imports/exports; solid lines represent firms' non-processing imports/exports

the processing trade of both hybrid and pure processing importers could include any processing type, such as assembly and processing with inputs.

2 Data

To investigate the impact of trade liberalisation on firm productivity, I rely on the following three disaggregated, large panel data sets: tariff data, firm-level production data and product-level trade data.

Tariff data can be accessed directly from the WTO and the trade analysis and information system (TRAINS).[6] China's tariff data are available at the Harmonised System (HS) six-digit disaggregated level for 2000–2006. Given that the product-level trade data are at the HS eight-digit level, the product-level trade data are aggregated to the HS six-digit level to correspond with the tariff data. As I am interested in measuring the average effect of trade liberalisation on firm productivity, I use the *ad valorem* duty at the six-digit level to measure trade liberalisation.

[6] The data are from WTO webpage http://tariffdata.wto.org/ReportersAndProducts.aspx. Note that TRAINS data generally suffer from missing values, particularly regarding the tariffs imposed by other countries for Chinese exports. The product-destination-year combinations that have missing tariffs are hence dropped. All data sets and programmes that allow the replication of the results in the article are available online.

2.1 *Firm-Level Production Data*

The sample is derived from a rich firm-level panel data set that covers between 162,885 firms (in 2000) and 301,961 firms (in 2006). The data are collected and maintained by China's National Bureau of Statistics (NBS) in an annual survey of manufacturing enterprises. Complete information on the three major accounting statements (i.e. balance sheet, profit and loss account, and cash flow statement) is available. In brief, the data set covers two types of manufacturing firms—all state-owned enterprises (SOEs) and non-SOEs whose annual sales exceed RMB 5 million ($770,000).[7] The data set includes more than 100 financial variables listed in the main accounting statements of these firms.

Although the data set contains rich information, some samples are still noisy and are therefore misleading, largely because of misreporting by some firms.[8] Following Cai and Liu (2009), I clean the sample and omit outliers by using the following criteria. First, observations with missing key financial variables (such as total assets, net value of fixed assets, sales and gross value of the firm's output productivity) are excluded. Second, I drop firms with fewer than eight workers as they fall under a different legal regime, as mentioned in Brandt et al. (2012).

Following Feenstra et al. (2013a), I delete observations according to the basic rules of the Generally Accepted Accounting Principles (GAAP) if any of the following are true:

(i) liquid assets are greater than total assets;
(ii) total fixed assets are greater than total assets;
(iii) the net value of fixed assets is greater than total assets;
(iv) the firm's identification number is missing; or
(v) an invalid established time exists (e.g. the opening month is later than December or earlier than January).

After applying such a stringent filter to guarantee the quality of the production data, the filtered firm data are reduced by about 50% in each year, as shown in columns (3) and (4) of Appendix Table 14.

Note that, in China's customs data set, some Chinese firms do not have their own production activity but only export goods collected from other domestic firms or import goods from abroad and then sell them to other domestic companies (Ahn et al., 2010).[9] To ensure the preciseness of the estimates, I exclude such trading companies from the sample in all the estimates. In particular, firms with names

[7] Aggregated data on the industrial sector in the annual *China's Statistical Yearbook* by the NBS are compiled from this data set.

[8] For example, information on some family-based firms, which usually have no formal accounting system in place, is based on a unit of one RMB, whereas the official requirement is a unit of RMB 1000.

[9] Note that in the firm-level production data, a firm's sales to trade intermediaries are accounted for as domestic sales but not exports, following the requirement of the GAAP.

Table 1 Chinese transaction-level trade data by shipment and year

Imports by shipment	2000	2001	2002	2003	2004	2005	2006	Total
Percentage of number of observations (HS eight-digit)								
Ordinary imports	2.57	3.54	3.77	5.17	6.04	6.80	7.30	35.19
Processing imports with assembly	2.46	2.72	2.37	2.59	2.77	2.79	2.77	18.47
Processing imports with inputs	3.90	4.14	3.57	4.67	5.33	5.74	5.61	32.95
Other types of processing imports	1.42	1.55	1.70	1.71	2.03	2.24	2.77	13.40
Total	10.34	11.95	11.41	14.13	16.16	17.57	18.44	100
Percentage of import value								
Ordinary imports	3.12	3.87	3.71	5.87	7.74	8.86	10.46	43.64
Processing imports with assembly	0.87	0.98	0.98	1.22	1.68	2.11	2.31	10.16
Processing imports with inputs	2.02	2.21	2.39	3.87	5.24	6.52	7.15	29.40
Other types of processing imports	1.01	1.24	1.43	1.93	2.85	3.35	4.99	16.80
Total	7.02	8.30	8.52	12.89	17.51	20.85	24.91	100

including any Chinese characters for Trading Company or Importing and Exporting Company are excluded from the sample.[10]

2.2 Product-Level Trade Data

The extremely disaggregated product-level trade transaction data are obtained from China's General Administration of Customs. It records a variety of information for each trading firm's product list, including trading price, quantity and value at the HS eight-digit level. More importantly, this rich data set not only includes both import and export data but also breaks down the data into several specific types of processing trade, such as processing with assembly and processing with inputs.

Table 1 reports a simple statistical summary for Chinese product-level trade data by shipment and year for 2000–2006. Overall, when focusing on the highly disaggregated HS eight-digit level, approximately 35% of the 18,599,507 transaction-level observations are ordinary trade and 65% refer to processing trade. Similar proportions are obtained when measuring by trade volume: around 43% of trade volume comprises ordinary trade. Processing with inputs accounts for around 30%, whereas processing with assembly only is around 10%. The remaining 17% represents other types of processing trade, aside from assembly and processing with inputs.

[10] In China, pure trading companies are required to register with a name containing Chinese characters for 'trading company' or 'importing and exporting company'.

2.3 *Merged Data Set*

Firm-level production data are crucial in measuring TFP, whereas product-level trade transaction data are non-substitutable in identifying a processing firm. However, researchers face some technical challenges in merging the two data sets. Although the data sets share a common variable (i.e. the firm's identification number), the coding system in each data set is completely different.[11] Hence, the firm's identification number cannot serve as a bridge to match the two data sets.

To address this challenge, following Yu and Tian (2012), I use two methods to match the two data sets by using other common variables. First, I match the two data sets by using each firm's Chinese name and year. That is, if a firm has an exact Chinese name in both data sets in a particular year, it should be the same firm.[12] As described carefully in Appendix 1, I obtain 83,679 matched firms in total by using the raw production data set and the number is reduced to 69,623 in total by using the more accurate filtered production data set as described above. To increase the number of qualified matching firms as much as possible, I then use another matching technique to serve as a supplement. Namely, I rely on two other common variables to identify the firms: postal code and the last seven digits of the firm's phone number. The rationale is that firms should have a unique phone number within a postal district. Although this method seems straightforward, there are subtle technical and practical difficulties.[13] The detailed merging procedures are explained in Appendix 1. After merging both product-level trade data and firm-level production data, I finally obtain 76,823 common trading firms, including both importers and exporters.[14] Briefly, the merged data set accounts for around 40% of the filtered full-sample, firm-level production data set in terms of the number of exporters, and around 53% in terms of export value. By way of comparison, my matching success rate is highly comparable to that in other studies that use the same data sets, such as Ge et al. (2011) and Wang and Yu (2012).

How successful is the matching using this technique? Table 2 first compares the merged data and the full-sample customs trade data sets. Of the total 56,459 importing firms in the merged data, ordinary importers account for 38.1% whereas processing importers account for 61.9%. These numbers are close to their counterparts from the full-sample customs data—27.3% for ordinary importers and 72.7% for processing

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[11] In particular, the firm's codes in the product-level trade data are at the ten-digit level, whereas those in the firm-level production data are at the nine-digit level, with no common elements inside.

[12] The year variable is necessary as an auxiliary identification variable as some firms could change their name in different years and newcomers could possibly take their original name.

[13] For example, the phone numbers in the product-level trade data include both area phone codes and a hyphen, whereas those in the firm-level production data do not.

[14] Note that in the merged sample shown in column (7) of Appendix Table 14, exports for some firms reported from the customs trade data set are larger than total sales reported from the NBS production data set. I also drop such firms from the sample in column (8) of Appendix Table 14 to guarantee the quality of my merged data set.

Table 2 Merged importers by firm type

Percentage	Merged sample								
	2000	2001	2002	2003	2004	2005	2006	Total	Full sample
Total importers	8.8	9.9	10.6	12.4	19.4	18.0	21.0	100.0	100.0
Ordinary importers	2.4	3.0	3.7	5.0	7.5	7.3	9.1	38.1	27.3
Processing importers	6.4	6.9	6.9	7.4	12.0	10.7	11.8	61.9	72.7
Hybrid processing importers	3.0	3.2	3.5	3.9	5.8	5.3	6.0	30.7	53.0
Pure processing importers	3.4	3.6	3.4	3.5	6.2	5.4	5.9	31.2	19.7

Note There are 56,459 importers in total in the matched data whereas 217,372 firm importers are included in the full-sample trade data

importers—as shown in the last column of Table 2.[15] The proportions of hybrid processing importers and pure processing importers by year in both the merged data and the full-sample data sets are also reported in the bottom two rows of Table 2.

Given that the firm-level production data set is crucial for the construction of the regressand (i.e. firm TFP), Table 3 shows how much of total sales and total employment are accounted for by the merged data set each year during 2000–2006. In particular, the proportion of exports in the merged sample over exports in the full-sample production data varies from 50% to around 58% during the sample period, suggesting that some firms enter and exit in the merged sample that is used for the estimation. The merged data set includes both exporters and importers.[16] Moreover, Table 4 compares the differences between the merged data set and the full-sample firm-level data set. The merged sample has clearly higher means of sales, exports and number of employees than those in the full-sample firm-level data set. These findings suggest that the merged sample is skewed towards large firms. Thus, my findings are valid for large Chinese trading firms.

[15] Note that the percentages for ordinary importing firms and processing firms in Table 2 are different from the import volumes for ordinary imports and processing imports shown in Table 1, as a processing importing firm (except pure processing firms) usually also has both processing imports and ordinary imports.

[16] Around 60% of firms are exporters whereas the other 40% are importers. The merged sample also includes entry and exit of firms. The last paragraph of Appendix 1 provides more detailed descriptions on this.

Table 3 Firm-level production information in merged versus full-sample data by year

Types of firms (%)	2000	2001	2002	2003	2004	2005	2006	Average
Sales	23.7	24.0	23.8	24.6	27.8	25.8	28.3	25.5
Exports	51.9	50.1	52.9	50.0	55.2	51.6	57.9	52.8
Number of employees	20.2	20.9	21.6	23.0	26.5	25.5	28.7	23.8

Notes The values in this panel are the proportions that were obtained by dividing sales/exports/number of employees in the matched data by their counterparts in the full-sample data, respectively. The last column reports the year-average percentage over 2000–2006

Table 4 Comparison of the merged data set and the full-sample production data set

Variables	Merged data			Full-sample data		
	Mean	Min.	Max.	Mean	Min.	Max.
Sales (RMB 1000)	150,053	5000	1.57e+08	85,065	5000	1.57e+08
Exports (RMB 1000)	53,308	0	1.52e+08	16,544	0	1.52e+08
Number of employees	478	8	157,213	274	8	165,878

3 Measures and Empirics

In this section, I first introduce the measures of the three key variables: firm TFP, firm-specific output tariffs and firm-specific input tariffs. For comparison, I also introduce the measure of industry-specific output and input tariffs. Finally, I discuss my empirical investigation of the effect of tariff reductions on productivity.

3.1 TFP Measures

I use the augmented Olley and Pakes (1996) approach to construct measures of Chinese firm-level TFP following Amiti and Konings (2007). Assuming a Cobb–Douglas production function, the usual estimation equation is as follows:

$$\ln Y_{it}^{j} = \beta_0^j + \beta_m^j \ln M_{it}^j + \beta_k^j \ln K_{it}^j + \beta_l^j \ln L_{it}^j + \varepsilon_{it} \quad (1)$$

where Y_{it}^j, M_{it}^j, K_{it}^j and L_{it}^j refer to firm i's output, materials, capital and labour in industry j in year t, respectively. Traditionally, TFP is measured by the estimated Solow residual which is the difference between the true data on output and the fitted value using the OLS approach. However, the OLS approach suffers from two problems: simultaneity bias and selection bias. At least some shocks to TFP changes could be observed by the firm early enough for it to change its input decisions to maximise profit. Thus, firm TFP could have a reverse endogeneity on firm input choices. Moreover, firms with low productivity that have collapsed and exited the market are excluded from the data set, indicating that the samples used for the regression are not randomly selected, which, in turn, results in estimation bias. Olley and Pakes (1996) successfully provide a semi-parametric approach to address those two biases. Subsequently, numerous studies, such as those by De Loecker (2011, 2013) and De Loecker et al. (2012), among others, have modified and tailored their approaches to calculating TFP. In the present article, I adopt the Olley–Pakes approach to estimate and calculate a firm's TFP with some extensions. Appendix 2 provides the detailed estimation procedure.

First and foremost, I estimate the production function for processing and non-processing firms separately in each industry. The idea is that different industries may use different technologies; hence, firm TFP (denoted TFP^{OP1}) is estimated separately for each industry. Equally important, even within an industry, processing firms (especially those firms engaged in processing with assembly) may use completely different technologies than non-processing firms, given that processing firms with assembly receive only imported material passively without making any profit-maximising input choices (Feenstra & Hanson, 2005). For the non-processing firm TFP estimates, since a non-processing importing firm may or may not export its final goods, I also include an export dummy to allow different TFP realisation between exporting non-processing firms and non-exporting non-processing firms. By the same token, I include an import dummy in the control function to allow different TFP realisation between non-processing importers and non-processing non-importers (but exporters). Note that two such dummies are not necessary for processing firms as, by definition, processing firms must import inputs and sell their products abroad.

Possibly, firms could learn by processing imports. If productivity gains from processing imports occur simultaneously with investment, TFP^{OP1} may have a bias on the estimated capital coefficient. Thus, ignorance of controlling for the effect of the previous period's processing activity on firm productivity may cause another bias of measured productivity. Inspired by De Loecker (2013), as an alternative approach to estimate TFP (denoted by TFP^{OP2}), I consider another control function in which both processing and non-processing firms are pooled together. More importantly, a processing dummy (i.e. a dummy that takes the value one if a firm has any processing imports and zero otherwise) is also incorporated in the control function (see Appendix 2 for details). This is done because processing imports may affect firm productivity and, accordingly, the TFP trajectory of a processing firm is endogenously different compared with the trajectory of a non-processing firm.

Second, I use deflated prices at the industry level to measure TFP. The measured TFP is expected to capture the firm's true technical efficiency only. However, here the measured TFP is also likely to pick up differences in price, price–cost markups and even input usage across firms (De Loecker, 2011; De Loecker & Warzynski, 2012). Admittedly, an ideal way to remove price differences across firms would be to adopt firm-specific price deflators (Foster et al., 2007). However, as in many other studies, such price data are unavailable.[17] Following De Loecker et al. (2012), I

[17] The customs trade data provide information on unit-value, which could serve as a proxy for the price for each imported good. However, the prices of imported intermediate inputs could be much

use the industrial price to deflate the firm's output.[18] Turning to the issue of price–cost markups, as stressed by Bernard et al. (2003), once the price–cost markup is positively associated with true efficiency, even revenue-based productivity can work well to capture the true efficiency, as is done with physical efficiency.

Third, I take China's WTO accession in 2001 into account, as such a positive demand shock would push Chinese firms to expand their economic scales, which, in turn, would exaggerate the simultaneous bias of their measured TFP. In particular, a WTO dummy (i.e. equal to one after 2001 and zero otherwise) is included in the estimation of the capital coefficient, as discussed in Appendix 2.

Fourth, the prevalence of SOEs also affects firm productivity. SOEs in China are usually accompanied by state intervention and do not necessarily make profit-maximising choices (Hsieh & Klenow, 2009). Therefore, it is important to construct an SOE indicator and add it to the control function in the first-step Olley–Pakes estimates.[19]

Finally, it is necessary to construct a real investment variable when using the Olley and Pakes (1996) approach. I adopt the perpetual inventory method as the law of motion for real capital and real investment. Nominal and real capital stocks are constructed as in Brandt et al. (2012). Rather than assigning an arbitrary number for the depreciation ratio, I use the exact firm's real depreciation provided by the Chinese firm-level data set. Appendix Table 15 presents the estimated coefficients for the production function and the associated log of TFP by industry for processing firms and non-processing firms, respectively. The implied scale elasticities are quite close to constant returns-to-scale elasticities for both processing firms and non-processing firms within each industry.

The augmented Olley–Pakes approach assumes that capital responds to the unobserved productivity shock with a Markov process, whereas other input factors respond without any dynamic effects. However, labour may also be correlated with an unobserved productivity shock. As highlighted by Ackerberg et al. (2006), it is unlikely that there is enough variation left to identify the labour coefficient by using the Olley–Pakes approach. This consideration may fit China's case more closely, given that the country is labour abundant. When facing an unobserved productivity shock, firms might re-optimise their production behaviour by adjusting their labour rather than their capital. I use the Blundell and Bond (1998) system-GMM approach to capture the dynamic effects of other input factors. By assuming that the unobserved

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different from those of domestic intermediate inputs (Helpern et al., 2010). Using the imported intermediate inputs as a proxy for all intermediate inputs may generate another unnecessary estimation bias. This bias may be exaggerated when the scope of domestic inputs is much different from the scope of foreign inputs.

[18] As in Brandt et al. (2012), the output deflators are constructed using 'reference price' information from China's Statistical Yearbooks, whereas input deflators are constructed based on output deflators and China's national input–output table (2002).

[19] By the official definition reported in the *China City Statistical Yearbook* (2006), SOEs include firms such as domestic SOEs (code: 110), state-owned joint venture enterprises (141), and state-owned and collective joint venture enterprises (143) but exclude state-owned limited corporations (151). Appendix Table 18 presents the transitional probability for all SOEs.

productivity shock depends on a firm's previous periods realisations, the system-GMM approach models TFP as affected by all types of inputs in both current and past realisations.

In particular, this model has the following dynamic representation:

$$\begin{aligned}\ln y_{it}^{j} &= \gamma_0^j + \gamma_1^j \ln L_{it}^j + \gamma_2^j \ln L_{i,t-1}^j + \left(\gamma_3^j \ln L_{it}^j + \gamma_4^j \ln L_{i,t-1}^j\right) PE_{it} \\ &+ \gamma_5^j \ln K_{it}^j + \gamma_6^j \ln K_{i,t-1}^j + \left(\gamma_7^j \ln K_{it}^j + \gamma_8^j \ln K_{i,t-1}^j\right) PE_{it} \\ &+ \gamma_9^j \ln M_{it}^j + \gamma_{10}^j \ln M_{i,t-1}^j + \left(\gamma_{11}^j \ln M_{it}^j + \gamma_{12}^j \ln M_{i,t-1}^j\right) PE_{it} \\ &+ \gamma_{13}^j \ln y_{i,t-1}^j + \gamma_{14}^j \ln y_{i,t-1}^j PE_{it} + \gamma_{15}^j PE_{it} + \varsigma_i + \zeta_t + \omega_{it} \qquad (2)\end{aligned}$$

where ς_i is firm i's fixed effect, f_t is the year-specific fixed effect, and PE_{it} is a processing indicator that takes the value one if a firm has any processing imports and zero otherwise. The idiosyncratic term x_{it} is serially uncorrelated if no measurement error exists.[20] Consistent estimates of the coefficients in the model can be obtained by using a system-GMM approach. The idea is that labour and material inputs are not taken as exogenously given but are instead allowed to change over time as capital grows. Appendix Table 16 presents the estimated coefficients for system-GMM firm TFP by industry.[21] Overall, the estimated log TFP increases 0.17 log points (from 2.28 in 2001 to 2.45 in 2006), registering a 2.62% annual growth rate, which is very close to the findings in Brandt et al. (2012).

3.2 *Firm-Specific Tariffs*

A firm could produce multiple products and, thus, its productivity could be affected by multiple tariff lines. Hence, it is important to properly measure the input tariff level faced by firms. As mentioned above, processing imports are duty-free in China. Given that a firm could engage in both processing imports (P) and non-processing imports (O), I construct a firm-specific input tariff index (FIT_{it}) as follows:

$$FIT_{it} = \sum_{k \in O} \frac{m_{i,initial\_year}^k}{\sum_{k \in M} m_{i,initial\_year}^k} \tau_t^k \qquad (3)$$

[20] As discussed by Blundell and Bond (1998), even if transient measurement error exists in some of the series (i.e. x_{it} MA(1)), the system-GMM approach can still provide consistent estimates of the coefficients in (2).

[21] Appendix Table 16 reports the associated specification tests for system-GMM estimates including AR(1) and AR(2) tests and Hansen over-identification tests. For most Chinese two-digit level industries, the system-GMM estimates have first-order serial autocorrelation but not second-order serial autocorrelation. The Hansen over-identification tests also suggest that the instruments are valid for most industries.

where $m^k_{i,initial\_year}$ is firm i's imports of product k in the first year the firm appears in the sample. Note that $O \cup P = M$ where M is the set of the firm's total imports. The set of processing imports does not appear in (3) because processing imports, again, are duty-free. The firm's input tariffs are constructed by using time-invariant weights to avoid the well-known endogeneity of weighted tariffs: imports are negatively associated with tariffs. For products with prohibitive tariffs, their imports and the associated import share would be zero. Accordingly, if the import weight is measured in the current period, the measure of firm tariffs would face a downward bias. Therefore, following Topalova and Khandelwal (2011), I measure the import weight for each product using data for the firm's first year in the sample.

Turning to the construction of firm-level output tariffs, product-level domestic sales would be an ideal proxy for capturing the role of each product within a firm. However, such data are unavailable. Hence, I rely on an index to circumvent this data restriction. As a more productive firm is not only capable of selling its products domestically, but also internationally (Melitz, 2003), a product would, in general, be sold domestically if it is sold abroad. Assuming a product is sold domestically and internationally in the same proportions, I consider a following weighted output tariff index (FOT_{it}) for firm i in year t:

$$FOT_{it} = \sum_k \left(\frac{X^k_{i,initial\_year}}{\sum_k X^k_{i,initial\_year}} \right) \tau^k_t \tag{4}$$

where s^k is the *ad valorem* tariff of product k in year t. The ratio in the parentheses is the value weight of product k, measured by the firm's exports of product k in its initial year in the sample, $X^k_{i,initial\_year}$, over the firm's total exports in the initial year. Inspired by i; initial year Topalova and Khandelwal (2011), exports for each product are fixed at the initial period to avoid possible reverse causality in firm productivity with respect to measured output tariffs.

This measure suffers from two important caveats. First, a firm may sell a product at home but not abroad (i.e. it is a pure domestic firm), which could be fairly reasonable as recent studies show that multi-product firms often sell different products at home and abroad (Arkolakis & Muendler, 2012; Bernard et al., 2011). In this case, the export weight for such a product in (4) is zero and the firm's output tariff measure fails to capture any pro-competition effects. This argument also holds for pure exporting firms that sell their products abroad only (around 12.2% of firms are pure exporters in my matched data). To ensure that my main estimation results are not biased by such firms, I drop pure domestic firms and pure exporting firms from the sample in all regressions. Second, the exported and domestic shares of a product are assumed to be equal. Note that this is a strong assumption indeed as the product composition of exports may be very different from the composition of domestic sales. This is especially true for China, which holds an important position in global supply chains (GSCs) and produces some intermediates that cannot be used

Table 5 China's output tariffs and input tariffs by year

Year	Firm output tariffs		Firm input tariffs		Industry output tariffs		Industry input tariffs	
	Mean (1)	SD (2)	Mean (3)	SD (4)	Mean (5)	SD (6)	Mean (7)	SD (8)
2000	15.57	12.03	2.54	4.9	21.43	8.78	3	3.63
2001	12.39	9.4	2.37	5.06	17.77	6.07	2.98	3.78
2002	9.63	8.22	1.68	3.53	14.28	6.05	1.41	1.66
2003	8.82	7.51	1.94	3.7	12.46	5.21	0.41	0.27
2004	7.59	7.08	1.87	3.59	11.27	4.6	0.36	0.25
2005	7	6.78	1.71	3.53	10.49	4.46	0.34	0.21
2006	7.46	6.46	2.18	3.72	10.27	4.2	0.35	0.18
All years	8.29	7.65	1.98	3.82	11.88	5.63	0.69	0.15

Notes Columns (1)–(4) report the mean and standard deviation of firm output tariffs and firm input tariffs with initial time-invariant weights as described in (4) and (3), in the text. Columns (5) and (6) report the mean and standard deviation of industry-level output tariffs and columns (7)–(8) report the mean and standard deviation of industry-level input tariffs that are constructed using the 2002 input–output table for China

in the domestic production sector.[22] Because of data restrictions, I am not able to check this out directly. However, as this problem would bias the measure of firm output tariffs differently depending on the industry and depending on the intensity of the sector of processing firms, I run further regressions by distinguishing more integrated industries from less integrated industries and by separating the sample by the intensity of the sector in processing firms. As shown in the text later, all such robustness checks suggest that my main results are still valid even considering such within-firm differences in product composition.

Columns (1)–(4) in Table 5 report firm-specific input and output tariffs computed using (3) and (4), respectively. The average firm-specific output tariffs were cut in half from around 15.6% in 2000 to 7.4% in 2006, and their standard deviation also dropped by around 50% over the same period. Firm-specific input tariffs are much lower than output tariffs. Input tariffs also exhibit a sharp declining trend during the sample period.

[22] Besides, when firms sell in both the domestic and export markets, the quality of the products is likely to be different, with better quality products sold to the export markets. As data on unit-price, a common proxy of product quality, are unavailable for domestic products, here I am not able to distinguish the quality difference between domestic products and exportable products, which is a future research topic once data are available. I thank a referee for correctly pointing this out.

3.3 Industry-Specific Tariffs

Similar to Amiti and Konings (2007), the sector output tariffs at the two-digit Chinese industry classification (CIC) level are obtained by taking a simple average of the HS six-digit codes within each two-digit CIC industry code.[23] The industry-level input tariff index is measured by

$$IIT_{ft} = \sum_{n} \left(\frac{input_{nf}^{2002}}{\sum_{n} input_{nf}^{2002}} \right) \tau_{nt} \tag{5}$$

where IIT_{ft} denotes the industry-level input tariffs facing firms in industry f in year t. s_{nt} is the import tariff of input n in year t. The weight in parentheses is measured as the cost share of input n in the production of industry f, for which data can be obtained from by China's input–output table for 2002.[24]

As shown in columns (5)–(8) in Table 5, the information in these columns is in line with that obtained by using the firm-level tariffs in columns (1)–(4): both output and input tariffs dramatically fell over the sample period. Similar patterns can be found from their standard deviations. Firm-specific output tariffs seem to be lower than industrial output tariffs. In sharp contrast, firm-specific input tariffs are higher than industry-specific input tariffs. One possible reason for the under-measurement of industrial input tariffs is that the inclusion of non-importing firms in intermediate input industries biases the industrial input weight in (5) which does not show up in the corresponding firm-specific input tariffs.[25] The simple correlations reported in Table 6 confirm this point: industry-specific input tariffs are only weakly correlated to firm-specific input tariffs ($|corr.| = 0.06$), whereas industry-specific output tariffs are strongly correlated to firm-specific output tariffs, as expected ($|corr.| = 0.48$).

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[23] The reason for not using weighted import tariffs, again, is to avoid the endogeneity of tariffs: imports are negatively correlated to tariffs.

[24] China's input–output table is compiled every five years; the most recent updates were in 2007. As my data sample is between 2000 and 2006, I adopt the input–output table from 2002. In particular, I proceed with the following steps to calculate the industry-specific tariffs. As there are 71 manufacturing sectors reported in China's input–output table (2002) and only 40 manufacturing sectors reported in the CIC, the first step is to find the correspondence between sectors in the input–output table and the CIC. The second step matches the CIC sectors with the International Standard Industrial Classification (ISIC, rev. 3). Note that China's government adjusted its CIC in 2003. I make the same adjustment in the sample. The third step is to link the ISIC and the HS six-digit classification to find the corresponding tariffs from the WTO. The final step calculates the average industry-level tariffs, which are aggregated to the CIC sector level.

[25] For example, if firm i in industry f uses 50% lumber with 1% tariffs and 50% steel with 10% tariffs, then the firm-specific input tariff is 5.5%. However, if industry f uses more domestic lumber, the industrial weight of lumber increases to 70%. Accordingly, the industry-specific input tariffs are reduced to 9 1% + 0.3 9 10% = 3.7%, which is significantly lower than its counterpart of firm-specific input tariffs.

3.4 Empirical Specification

To investigate the effects of input and output tariff reductions on firm productivity, I consider the following empirical framework:

$$\begin{aligned}\ln TFP_{it} = \beta_0 + \beta_1 FOT_{it} + \beta_2 FOT_{it} \times PE_{it} + \beta_3 FIT_{it} + \beta_4 FIT_{it} \times PE_{it} \\ + \beta_5 PE_{it} + \boldsymbol{\theta X_{it}} + \varpi_i + \eta_t + \mu_{it}\end{aligned} \quad (6)$$

where ln TFP_{it} is the logarithm of firm i's measured TFP in industry j in year t, whereas FIT_{it} and FOT_{it} denote firm-level input tariffs and output tariffs as measured in (3) and (4), respectively. The augmented Olley–Pakes TFP is adopted for the baseline estimates, but the system-GMM TFP is adopted as the main measure, given that it enjoys rich, measured flexibility. PE_{it} is a processing indicator that equals one if firms import any processing products in year t, and zero otherwise. An interaction term between the firm's output (input) tariff and the processing indicator is also included to capture a possible heterogeneous effect of output (input) tariff reductions on firm productivity between processing and ordinary firms.

In addition, b_5 in (6) measures other possible gains from processing trade not caused by trade liberalisation. X_{it} denotes other firm characteristics, such as type of ownership (i.e. SOEs or multinational firms). SOEs are traditionally believed to have relatively low economic efficiency and, hence, low productivity (Hsieh & Klenow, 2009). By contrast, multinational firms have higher productivity in part because of international technology spillovers (Keller & Yeaple, 2009) or fewer financial constraints (Manova et al., 2009). Therefore, I construct two indicators to measure the roles of SOEs and multinational firms. In particular, a firm is classified as a foreign firm if it has any investments from other countries (regimes). A large proportion of the inflow of foreign investment comes from Hong Kong/Macao/Taiwan, so these investments are considered in the construction of such an indicator.[26] As a result, 77% of trading firms are classified as multinational affiliates.[27] Similarly, I construct an indicator for SOEs, which is one if a firm has any investment from the government, and zero otherwise.

[26] Specifically, foreign-invested enterprises (FIEs) include the following firms: foreign-invested joint-stock corporations (code: 310), foreign-invested joint venture enterprises (320), fully FIEs (330), foreign-invested limited corporations (340), Hong Kong/Macao/Taiwan (henceforth, H/M/T) joint-stock corporations (210), H/M/T joint venture enterprises (220), fully H/M/T-invested enterprises (230) and H/M/T-invested limited corporations (240). Appendix Table 19 presents the transitional probability for such foreign firms.

[27] At first glance, these ratios are significantly higher than their counterparts reported in other studies, such as Feenstra et al. (2013a). However, this finding simply reflects the fact that the present article covers only large trading firms. Large, non-trading firms have been excluded.

Finally, the error term is divided into three components:

(i) firm-specific fixed effects ϖ_i to control for time-invariant but unobservable factors such as managerial ability;
(ii) year-specific fixed effects η_t to control for firm-invariant factors such as an appreciation of the *renminbi* (RMB); and
(iii) an idiosyncratic effect μ_{it} with normal distribution μ_{it} ~ N $(0, \sigma^2)$ to control for other unspecified factors.

However, the empirical specification above faces an identification challenge. The processing indicator in (6) is a relatively crude measure of processing activity, which may overestimate the role of processing firms. For example, if a firm has only a very small proportion of processing imports over total imports, it is still classified as a processing firm, yet its primary operation remains in ordinary trade. To overcome this challenge, I consider a continuous measure of the extent to which a firm is engaged in processing trade to replace the processing indicator, and the extent of processing engagement ($Pext_{it}$) is measured through firm i's total processing imports over total imports in year t. In particular, I consider the following specification for my main estimation:

$$\begin{aligned}\ln TFP_{it} = \beta_0 + \beta_1 FOT_{it} + \beta_2 FOT_{it} \times Pext_{it} + \beta_3 FIT_{it} + \beta_4 FIT_{it} \times Pext_{it} \\ + \beta_5 Pext_{it} + \boldsymbol{\theta X_{it}} + \varpi_i + \eta_t + \mu_{it} \qquad (7)\end{aligned}$$

Yet, a new identification challenge arises from the coefficients of the variable Pextit itself and its interaction terms: β_2, β_4 and β_5. These coefficients differ across industries as different industries use different technologies (Pavcnik, 2002). More importantly, even within an industry, the decision to engage in processing trade is endogenous to firms. Previous works, such as Dai et al. (2012), find that less-productive firms self-select to engage in processing trade. If so, a firm's extent of processing engagement is also endogenous as firms with a high extent of processing engagement may be less productive. That is, β_2, β_4 and β_5 vary across firms. My estimating equation thus has random coefficients that are correlated with the endogenous extent of processing engagement, so it is a correlated random coefficients (CRC) model (Wooldridge, 2008).

Heckman and Vytlacil (1998) recommend replacing the endogenous variable in a CRC model—or the extent of processing engagement in my case—with its predicted value.[28] In the next section, I estimate the extent of processing engagement with a Heckman procedure, or type-2 Tobit model, using the exogenous variables Z_{it} which is be specified in the next section. In particular, I have

$$Pext_{it} = E(Pext_{it}|\boldsymbol{Z_{it}}) + \varepsilon_{it} \quad with\ E(\varepsilon_{it}|\boldsymbol{Z_{it}}) = 0 \qquad (8)$$

[28] Feenstra et al. (2013a) also apply this method to estimate the impact of credit constraints on firm's exports.

By substituting (8) into (7), I obtain:

$$\begin{aligned}\ln TFP_{it} = \beta_0 + \beta_1 FOT_{it} + \beta_2 FOT_{it} \times E(Pext_{it}|\mathbf{Z_{it}}) + \beta_3 FIT_{it} \\ + \beta_4 FIT_{it} \times E(Pext_{it}|\mathbf{Z_{it}}) + \beta_5 E(Pext_{it}|\mathbf{Z_{it}}) \\ + \boldsymbol{\theta} \boldsymbol{X_{it}} + \varpi_i + \eta_t + \mu_{it}\end{aligned} \tag{9}$$

where the error term is $\varepsilon_{it} = (b_2 FOT_{it} + b_4 FIT_{it} + b_5)\varepsilon_{it} + \mu_{it}$.[29] All the terms appearing within this error have zero expected value conditional on Z_{it}, so that e_{it} is conditionally uncorrelated with these exogenous variables and they can be used for estimation. Finally, as suggested by Wooldridge (2008), a correction to the standard errors must be made to reflect the use of estimated regressors in (9), which I implement by bootstrapping.

4 Estimation Results

4.1 Baseline Results

As described above, the merged data set is skewed towards large trading firms, which are the main focus of the present article. Still, it is worthwhile checking whether the relatively high attrition rate of the merged data set affects the estimation results. Hence, my estimation begins with a comparison between the full-sample data set and the merged data set.

I start off the estimation in Table 7 by using conventional industry-level tariffs, as introduced in Sect. 4.3. Columns (1) and (2) first run regressions using full-sample firm data. As processing information is not included in the full-sample firm data, it is ignored in the estimation. As firms in different industries would adopt different technologies, it would be inappropriate to combine firms across all industries without controlling for industrial differences (Pavcnik, 2002). Therefore, I control for industry-level fixed effects at the two-digit CIC level in the estimates in column (1). It turns out that both industrial output tariffs and input tariffs are negatively and statistically significantly correlated with firm productivity, which is consistent with the findings of many other studies. Column (2) takes a step forward to control for firm-specific fixed effects and year-specific fixed effects. The coefficient of industry output tariffs is still negative and significant. Strikingly enough, the coefficient of industry input tariffs is positive. However, this is not a worry as the coefficient is

[29] Similar to Heckman and Vytlacil (1998), the conditional homoscedasticity of covariance assumption for the term $e_{it} l_{it}$ is needed to ensure that it would not bias the estimates.

statistically insignificant. One possible reason for such an unanticipated finding is the inclusion of non-importing firms that appeared in the full-sample firm data set but did not directly benefit from reductions in tariffs on the imported intermediate inputs.

The rest of the regressions reported in Table 7 use the merged data set, which only includes large trading firms. For a close comparison with columns (1) and (2), the estimates in column (3) control for industry-level fixed effects, whereas those in column (4) control for firm-specific and year-specific fixed effects. The coefficients of both industry output tariffs and input tariffs are found to be negative and significant.[30] I include the processing indicator (i.e. one if a firm has any processing imports and zero otherwise) in the first three columns of Table 8, given that processing information is available in the merged data set. To check whether the estimation results are sensitive to different TFP measures, column (1) uses TFP^{OP1} in which the productivities of processing firms and non-processing firms are estimated using different control functions, whereas column (2) uses TFP^{OP2} in which productivities of processing firms and non-processing firms are jointly estimated as the regressand. In addition, columns (1) and (2) abstract from the interaction term between output (input) tariffs and the processing indicator. After controlling for firm-specific and year-specific fixed effects, both industry output tariffs and industry input tariffs are negatively correlated with firm productivity. Their coefficients are statistically significant. Meanwhile, the coefficient of the processing indicator is negative and significant, indicating that processing firms have low productivity.

However, the Olley–Pakes TFP measure that is used in columns (1) and (2) of Table 8 still suffers from three possible pitfalls. First, the Olley–Pakes approach does not allow output to exhibit any serial correlation, which is likely. Second, it assumes that firms will mostly adjust their capital usage when facing an exogenous shock. However, this may not be the case for China, given that Chinese firms are able to access relatively cheap labour. Finally, there are many missing values for investment in the Chinese firm data, which are essential for computing the Olley–Pakes TFP.[31] By way of comparison, the system-GMM TFP measure is better at overcoming such pitfalls: It has enough flexibility to allow for possible serial autocorrelation and to allow firms to adjust all inputs including not only capital, but also labour and materials. In addition, the computation of system-GMM TFP no longer relies on investment as a proxy variable. I therefore use the system-GMM TFP as the main measure of firm productivity from column (3) of Table 8 to the rest estimates in the article.

To examine the possibly heterogenous impact of tariff reductions on firm productivity, column (3) of Table 8 includes interaction terms for the processing indicator and industry output and input tariffs. The coefficients of output tariffs and input tariffs themselves and their interaction with the processing indicator are still statistically significant. However, the processing indicator exhibits an erratic sign, although

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[30] As in common, the R^2 in all estimates with firm-specific and year-specific fixed effects in the article is exclusive of both firm-specific and year-specific dummies.

[31] Around 40% of the observations are missing investment data.

Table 8 Preliminary estimates

Tariffs measure	Industry tariffs			Firm tariffs		
Processing measure	Processing dummy			Extent of processing imports		
Regressand	$\ln TFP_{ijt}^{OP1}$ (1)	$\ln TFP_{ijt}^{OP2}$ (2)	$\ln TFP_{ijt}^{GMM}$ (3)	$\ln TFP_{ijt}^{GMM}$ (4)	$\ln TFP_{ijt}^{GMM}$ (5)	$\ln TFP_{ijt}^{GMM}$ (6)
Output tariffs	− 0.161** (− 1.98)	− 0.715*** (− 12.53)	− 1.010*** (− 25.17)	− 1.074*** (− 11.20)	− 1.069*** (− 9.92)	− 0.315*** (− 4.61)
Output tariffs × processing variable			− 0.099** (− 1.79)	− 0.614*** (− 4.92)	− 0.604*** (− 4.21)	− 0.234*** (− 2.69)
Input tariffs	− 1.468*** (− 3.57)	− 1.332*** (− 5.19)	− 0.656*** (− 5.13)	− 1.667*** (− 2.90)	− 1.379** (− 2.26)	− 0.572*** (− 5.37)
Input tariffs × processing variable			0.561*** (3.26)	2.233*** (3.56)	2.251*** (3.33)	2.409*** (8.01)
Processing variable	− 0.010* (− 1.76)	− 0.011** (− 2.53)	0.001 (0.14)	− 0.097*** (− 6.66)	− 0.077*** (− 4.62)	− 0.180*** (− 17.54)
Year-specific fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm-specific fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Pure domestic firms	Yes	Yes	Yes	Yes	No	No
Pure exporting firms	Yes	Yes	Yes	Yes	No	No
Observations	82,558	82,314	97,299	35,172	24,457	27,679
R^2	0.02	0.01	0.03	0.12	0.12	0.09

Notes Robust t values are in parentheses. Significant at * 10%, ** 5% and *** 1%. Regressions in columns (1)–(5) use industry-level output tariffs and input tariffs, which are calculated using the 2002 time-invariant input–output matrix for China's described in (6) in the text. Regressions in column (6) use firm-specific output tariff and input tariffs which are computed using the time-invariant weight in the initial period that the firm first appears in the data set. Columns (1)–(3) use a processing dummy (one if a firm has any processing imports and zero otherwise), whereas columns (4)–(6) use the extent of processing imports as a proxy for the processing variable. Regressands in columns (1)–(2) are Olley–Pakes TFP with different first step control functions as introduced in Appendix 2, whereas those in columns (3)–(6) are system-GMM TFP it is insignificant. I suspect this is because the processing indicator is a relatively crude measure of processing activity, which may overestimate the role of processing firms. For example, if a firm has only a very small proportion of processing imports over total imports, it is still classified as a processing firm, yet its primary operation remains in ordinary trade. I then consider a continuous measure of the extent to which a firm is engaged in processing trade to replace the processing indicator in the rest of Table 8; the extent of processing engagement is measured by the firm's total processing imports over total imports each year.

Column (4) of Table 8 gives the results of a regression of system-GMM firm TFP on industry-level input and output tariffs. The coefficients of the output and input tariffs are still negative and statistically significant. The variable for the extent of processing imports turns out to be negative and significant. As one of the novel measures of the present article is firm-specific output and input tariffs, I now turn to compare the estimation results using industry-level tariffs and firm-level tariffs. Because firm-specific output tariffs, as introduced in (4), cannot apply to pure domestic firms or pure exporting firms, I drop such firms in column (5) with measures of industry-level output and input tariffs and in column (6) with measures of firm-specific output and input tariffs for comparison.

The coefficients of output (input) tariffs in columns (5) and (6) are all negative and statistically significant. In terms of economic magnitudes, the differences in the coefficients of output (input) tariffs between the two columns are sizable. When moving from the industry-level measure of output tariffs in column (5) to the firm-specific measure of input tariffs in column (6), the coefficient is reduced from − 1.07 to − 0.32. Likewise, the point estimate of the input tariffs is reduced more than half moving from the measure of industrial input tariffs to the measure of firm-specific input tariffs.

Such sizable differences indicate the pitfalls of using industry-level measures of tariffs. First, output tariff reductions for some products in an industry are not directly relevant to a firm in the same industry if the firm never produces such products. Thus, the pro-competitive effects would be overestimated if output tariffs were measured at the industry level. By the same token, the cost-saving effects of cutting input tariffs are also overstated with the industry measure of input tariffs. Second, compared with output tariffs, the estimation bias for input tariffs could be more severe as the industry measure of input tariffs is also contaminated by the use of an input–output matrix, which also mixed up both imported intermediate inputs and domestic intermediate inputs that are not directly relevant to the cut in tariffs. Finally, ignorance of the 'free-duty' phenomenon for processing imports generates an additional measurement error in industrial input tariffs for Chinese firms. To avoid such possible estimation bias, I use a firm-specific measure of tariffs in the rest of the article.

4.2 Self-selection to Processing

Columns (4) and (5) of Table 8 use the extent of processing imports and its interaction with output and input tariffs, but the processing imports variable is endogenous. As shown in column (1) of Table 8, processing firms are associated with low productivity. Thus, it is interesting to compare the TFP trajectories of processing firms with those of non-processing firms. As shown in the last column of Table 9, processing firms, overall, are less productive than non-processing firms. Interestingly, the productivity difference between processing and non-processing firms roughly decreases over the years, suggesting that a catching-up process of processing firms may take place.[32] Such comparisons are straightforward. However, they bear a cost because processing firms may be very different from non-processing firms in terms of size. To overcome such a pitfall, as suggested by Imbens (2004), I perform the nearest-neighbour matching between the treatment group (i.e. processing firms) and the control group (i.e. non-processing firms) by choosing the number of firm employees and firm sales as covariates. Each processing firm would find its most similar non-processing firm. Table 9 reports both the estimates for average treatment for the treated (ATT) and average treatment for the control (ATC). For instance, the coefficient of ATT for all processing firms is 0.037 and highly statistically significant, suggesting that, overall, productivity for processing firms is lower than that for similar non-processing firms.

The estimates in Table 9 hint that low-productivity firms may self-select to engage in processing trade. To control for this, I introduce a type-2 Tobit model or, equivalently, a bivariate sample selection model (Cameron & Trivedi, 2005). The type-2 Tobit specification includes:

(i) a processing participation equation,

$$Processing_{it} = \begin{cases} 0 & if\ V_{it} < 0 \\ 1 & if\ V_{it} \geq 0 \end{cases} \tag{10}$$

where V_{it} denotes a latent variable faced by firm i; and

(ii) an 'outcome' equation whereby the firm's extent of processing imports is modelled as a linear function of other variables.

In particular, I estimate the following selection equation using a probit model:

$$\begin{aligned} Pr(Processing_{it} = 1) &= Pr(V_{it} \geq 0) \\ &= \boldsymbol{\Phi}(\alpha_0 + \alpha_1 \ln TFP_{it-1} + \alpha_2 SOE_{it-1} + \alpha_3 FIE_{it-1} \\ &\quad + \alpha_4 \ln L_{it-1} + \alpha_5 Tenure_{it-1} + \lambda_j + \varsigma_i\big) \end{aligned} \tag{11}$$

where $\Phi(.)$ is the cumulative density function of the normal distribution. In addition to the logarithm of the firm's TFP, a firm's decision to engage in processing trade

[32] Appendix Table 20 also reports the transitional probability for processing firms. The switching of processing firms is an interesting topic for future research, although it is beyond the scope of the present article.

Table 9 TFP trajectories of processing versus non-processing firms by year

Firm productivity $\ln TFP_{ijt}^{GMM}$	2001	2002	2003	2004	2005	2006	Overall
Non-processing firms	2.458	2.465	2.518	2.544	2.585	2.625	2.576
Processing firms	2.416	2.432	2.462	2.539	2.575	2.629	2.551
Difference	0.042*** (2.90)	0.033*** (2.57)	0.056*** (4.98)	0.005 (0.64)	0.010* (1.74)	– 0.003 (– 0.58)	0.025*** (7.63)
Comparisons using nearest-neighbour matching							
Average treatment on the treated	0.040*** (3.64)	0.032*** (3.08)	0.014 (1.30)	0.034*** (5.08)	0.032*** (5.88)	0.051*** (9.24)	0.031*** (10.13)
Average treatment on the control	0.031*** (2.60)	0.018*** (2.18)	0.004 (0.46)	0.037*** (4.92)	0.027*** (5.57)	0.041*** (7.86)	0.027*** (9.60)

Notes t-values corrected for clustering at the firm level are in parentheses. Significant at * 10%, ** 5% and *** 1%. Estimates for both average treatment on the treated (i.e. processing firms) and average treatment on the control (i.e. non-processing firms) are obtained by using the nearest-neighbour matching approach in which firm size and firm sales are chosen as covariates

is also affected by other factors, such as its ownership (whether it is an SOE or a multinational firm) and size (measured by the logarithm of the number of employees). Note that the bivariate sample selection estimation require an excluded variable that affects the firm's processing decision but does not appear in the extent of processing equation (Cameron & Trivedi, 2005). Here the firm's age ($Tenure_{it-1}$) serves this purpose, as previous studies have found that a firm's export probability is higher for older firms (Amiti & Davis, 2011). By contrast, my sample also reveals that the simple correlation between a firm's extent of processing imports and the firm's age is close to nil (– 0.04), suggesting that the firm's age can be excluded in the second-step Heckman estimates.[33] All regressors in the type-2 Tobit selection model are of a one-period lag as it usually takes time for such factors to affect a firm's processing choice. Finally, I include the three-digit CIC industrial dummies, k_j, and year dummies, ς_t, to control for other unspecified factors.

Table 10 reports the estimation results for the type-2 Tobit selection model. From the first-step probit estimates (11), low-productivity firms are more likely to engage in processing trade. Similarly, large and foreign firms are more likely to engage in processing trade. However, SOEs are less likely to become processing firms. Finally, as predicted, firms that were established earlier are more likely to engage in processing trade. I then include the computed inverse Mills ratio obtained in the first-step probit estimates in the second-step Heckman estimation as an additional

[33] Note that even when the firm's age is included, its coefficient in the second-step Heckman estimate is also statistically insignificant.

Table 10 The Heckman two-step estimates of bivariate selection model

Heckman two-step	1st step		2nd step	
Regressand	Processing indicator		Extent of processing	
One-period lag of log TFP $\ln TFP_{ijt}^{GMM}$	− 0.126***	(− 7.23)	− 0.176***	(− 15.17)
One-period lag of log labour	0.152***	25.55	0.031***	3.23
One-period lag of SOEs indicator	− 0.160***	(− 2.82)	− 0.039	(− 1.47)
One-period lag of foreign indicator	0.978***	68.97	0.299***	5.05
One-period lag of firm tenure	0.004***	5.02	–	
Inverse Mills ratio	–		0.172**	2.1
Year-specific fixed effects	Yes		Yes	
Industry-specific fixed effects	Yes		Yes	
Observations	58,629		21,232	

Notes t-values corrected for clustering at the firm level are in parentheses. Significant at * 10%, ** 5% and *** 1%. The sample selection model is presented in (10) and (11) in the text. The regressand in the first-step is the firm's processing dummy, whereas that in the second step is the firm's extent of processing imports. Firm-level system-GMM TFP is adopted as a measure of firm productivity. Firm tenure is used as an exclusion variable that appeared in the first step but not the second step. The three-digit Chinese industry-specific fixed effects and year-specific fixed effects are also included in the estimation

regressor. It turns out that the estimated coefficients have exactly identical signs as obtained in the first-step estimates. Thus, after controlling for the endogenous selection of processing, I obtain the fitted value of the firm's extent of processing, which is used to replace the firm's actual extent of processing in the rest of estimates, as discussed above.

4.3 Endogeneity Issues

The specifications in Tables 7 and 8 face three possible endogeneity problems. The first one relates to the measure of firm input tariffs, because imports and tariffs are strongly correlated. This problem is essentially solved by using measures of tariffs based on time-invariant weights. The second relates to the possible reverse causality between firm productivity and exports. As the firm's productivity improves, its exports may grow faster for some products than for others. The disproportional growth in exports of some products would challenge the validity of a time-variant measure of firm output tariffs. To avoid this possibility, measures of tariffs based on time-invariant weights, as in (4), have been used in all specifications.

However, there is still another possible reverse causality problem. Although tariff reductions are regulated by the GATT/WTO agreements, they are still, to some extent, endogenous because firms in low-productivity sectors would lobby the government for protection (Grossman & Helpman, 1994), that is, to maintain related internationally negotiated tariffs at a relatively high level. I control for such reverse causality by using an IV approach.

Identifying a good instrument for tariffs is challenging. Inspired by Amiti and Konings (2007), here I construct a one-year lag of firm-specific output tariffs and input tariffs as instruments.[34] The economic rationale is as follows. The government generally has difficulty in removing the high protection status quo from an industry with high tariffs, possibly because of domestic pressure from special interest groups. Hence, compared with other sectors, industries with high tariffs one year ago would still be expected to have relatively high tariffs at present.

Column (1) of Table 11 presents 2SLS fixed-effects estimates using the previous tariffs with time-invariant weights as instruments.[35] After controlling for reverse causality, reductions in both firm input tariffs and firm output tariffs lead to firm productivity growth. As noted before, the measure of firm output tariffs may suffer from a pitfall because of the assumption of equal shares between domestic sales and exports for each product produced, as the product composition of exports may be different from that of domestic sales by the sector integration of GSCs and by the intensity of the sectors in processing firms. To address this concern, besides dropping pure domestic firms and pure exporters from the sample, I run two sets of auxiliary regressions. First, all industries are classified into two groups (more integrated and less integrated) according to their 'production depth' of engaging (GSCs) which is measured by the value-added ratio to gross industrial output (OECD, 2010). By taking the mean of such ratios across two-digit level industries as a cut-off, columns (2) and (3) regress the impact of tariff reductions on firm productivity by the extent of GSCs integrating. Second, columns (4) and (5) run regressions for sectors with high (low) intensity of the sectors in processing firms, respectively, in which the intensity is measured by share of number of processing firms over number of total firms in each industry and the mean of the ratios across industries is taken as the cut-off. In all cases, the coefficients of output and input tariffs are significant and in line with my previous findings.

[34] Accordingly, the interaction between the firm's input and output one-period tariff with the time-invariant weight and the fitted extent of processing trade are adopted as additional instruments in all IV estimates.

[35] Note that adopting firm-specific fixed effects here would cause a huge loss of observations as most of the firms do not have a continuous panel in the sample. Such a pattern is more pronounced in the 2SLS estimates when using the one-year lagged tariffs as instruments. I therefore include the disaggregated three-digit CIC industry-specific fixed effects and year-specific fixed effects in all 2SLS estimates.

Table 11 IV estimates with measure of system-GMM TFP

Regressand: $\ln TFP_{ijt}^{GMM}$	All sample (1)	GSCs integrated		Processing intensity	
		Less (2)	More (3)	Low (4)	High (5)
Firm output tariffs	− 1.319*** (− 4.60)	− 0.825*** (− 2.13)	− 1.962*** (− 3.66)	− 1.657**** (− 3.98)	− 1.941*** (− 4.47)
Firm output tariffs × fitted extent of processing	0.817* (1.72)	0.802 (1.18)	1.184 (1.41)	1.321 (1.53)	1.765*** (2.67)
Firm input tariffs	− 1.712*** (− 3.46)	− 2.821*** (− 3.57)	− 1.519*** (− 2.76)	− 1.883** (− 3.50)	− 3.447** (− 2.32)
Firm input tariffs × fitted extent of processing	2.460*** (2.54)	2.497* (1.75)	2.818** (2.71)	3.478** (2.65)	3.546** (1.72)
Fitted extent of processing	− 0.740*** (− 17.66)	− 1.005*** (− 15.99)	− 0.778*** (− 10.28)	− 0.944*** (− 12.28)	− 0.833*** (− 11.95)
Kleibergen–Paap rank LM χ^2 statistic	87.75	428.5	961.9	883.6	639.1
Kleibergen–Paap rank Wald F statistic	95.94	112.0	257.1	234.2	171.3
Year-specific fixed effects	Yes	Yes	Yes	Yes	Yes
Industry-specific fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	22,812	8374	14,438	13,633	9179
R^2	0.17	0.18	0.16	0.16	0.23
First-stage regressions					
IV1: firm output tariffs with a lag	0.004*** (12.03)	0.005*** (9.91)	0.003*** (9.38)	0.003*** (8.40)	0.004*** (4.19)
IV2: firm output tariffs with a lag × fitted extent of processing	0.004*** (19.15)	0.004*** (12.67)	0.004*** (5.92)	0.005*** (11.72)	0.004*** (7.69)

(continued)

Table 11 (continued)

Regressand: $\ln TFP_{ijt}^{GMM}$	All sample (1)	GSCs integrated		Processing intensity	
		Less (2)	More (3)	Low (4)	High (5)
IV3: firm input tariffs with a lag	0.005*** (8.89)	0.004*** (19.62)	0.005*** (4.22)	0.005*** (7.95)	0.005*** (3.82)
IV4: firm input tariffs with a lag × fitted extent of processing	0.008*** (14.31)	0.008*** (9.02)	0.008*** (7.85)	0.007*** (10.33)	0.010*** (9.01)

Notes t-values in parentheses are obtained using bootstrapped standard errors. Significant at * 10%, ** 5% and *** 1%. Column (1) includes the entire sample in the regression. Columns (2) and (3) include sectors that are less (more) integrated in global supply chains (GSCs), respectively, using the industrial average ratio of value-added to gross industrial output as cut-offs. Columns (4) and (5) include the sectors with low (high) intensity of the sectors in processing firms, respectively, in which the intensity is measured by share of number of processing firms over number of total firms in each industry. † (‡) indicates significance of the p-value at the 1 (5)% level. In the first-stage regressions, IV1 reports the coefficient of the firm output tariffs with initial time-invariant weight and one-period lag of tariffs, using firm output tariffs with initial time-invariant weight and current tariffs as the regressand. IV2 reports the coefficient of the interaction between fitted extent of processing obtained from the second-step Heckman estimates in Table 8 and firm output tariffs with initial time-invariant weight and one-period lag of tariffs, using the interaction between fitted extent to processing and current tariffs as the regressand. Similarly, IV3 reports the coefficient of the firm input tariffs with initial time-invariant weight and one-period lag of tariffs using firm input tariffs with initial time-invariant weight and current tariffs as the regressand. IV4 reports the coefficient of the interaction between fitted extent of processing and firm input tariffs with initial time-invariant weight and one-period lag of tariffs, using the interaction between fitted extent of processing and firm output tariffs with initial time-invariant weight and current tariffs as the regressand. Pure domestic firms and pure exporters are dropped from the sample in all estimates

Several tests were performed to verify the quality of the instruments. First, I use the Kleibergen–Paap LM v^2 statistic to check whether the excluded instruments are correlated with the endogenous regressors. As shown in Table 11, the null hypothesis that the model is under-identified is rejected at the 1% significance level. Second, the Kleibergen–Paap (2006) F-statistics provide strong evidence for rejecting the null hypothesis that the first stage is weakly identified at a highly significant level.[36] Finally, the first-stage estimates reported in the lower module of Table 11 offer strong evidence to justify such instruments. In particular, all the t-values of the instruments are significant. Finally, standard errors are corrected for the use of the estimated regressors by bootstrapping.[37]

4.4 Further Robustness Checks of 2SLS Estimates

It is also worthwhile checking whether the effects of firm-level input and output tariffs on firm productivity pick up only the role of firm size, given that large firms usually have high productivity, or whether the effects are sensitive to the inclusion of the firm's type of ownership. I therefore include an SOE indicator, a foreign indicator, and the log of labour (i.e. a measure of firm size) in all the 2SLS estimates in Table 12.

Because measured TFP may also pick up the difference in prices and price–cost mark-ups across firms, column (1) of Table 12 performs the 2SLS estimates using the logarithm of the firm's labour productivity as the regressand. As the log of firm labour is already used as the denominator of the regressand, it is no longer appropriate to include it as a control variable for firm size in the regression. I instead use the log of the firm's capital-labour ratio as a proxy.

To check further whether my main findings are sensitive to the measure of firm TFP and the empirical specifications, column (2) also uses the Levinsohn–Petrin (2003) TFP as the regressand while controlling for other variables as in column (1). Column (3) still uses the system-GMM as the regressand but includes the above-mentioned controlling variables. Overall, the main findings of the estimates in these columns are highly consistent with those in Table 11: the impact of input tariff reductions on productivity improvement, overall, is weaker than that of output tariff reductions. The firm's gains from tariff reductions are diminishing as the firm's processing imports share increases.

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[36] Note that the Cragg and Donald (1993) F-statistic is no longer valid because it only works under the i.i.d. assumption. As here I have four (more than three) endogenous variables, STATA does not report the critical values for the Kleibergen–Paap (2006) weak instruments test. In this case, Baum et al. (2007) suggest that one can safely adopt 10 as a critical value as initiated by Staiger and Stock (1997). As all my Kleibergen–Paap (2006) F-statistics are one-order much higher than 10, it is safe to reject the null hypothesis of weak instruments in all estimates.

[37] There are in fact four steps to my estimation: the selection (11); the second-step Heckman equation used to obtain the predicted extent of processing; the first-step of 2SLS where the predicted extent of processing is a regressor; and the second-step of 2SLS estimates. Panel bootstrapping by randomly drawing firms is done in the last two steps.

Table 12 More robust IV estimates

Regressand	$\ln LP_{ijt}$	$\ln TFP_{ijt}^{LevP}$	$\ln TFP_{ijt}^{GMM}$		Weighted $\ln TFP_{ijt}^{GMM}$
	(1)	(2)	(3)	(4)	(5)
Firm output tariffs	– 1.980*** (– 3.49)	– 1.217** (– 2.02)	– 1.100*** (– 4.51)	– 1.096*** (– 4.62)	– 1.159*** (– 4.47)
Firm output tariffs xx fitted extent of processing	2.260** (2.03)	– 0.106 (– 0.08)	0.677 (1.63)	0.675 (1.47)	0.812** (1.96)
Firm input tariffs	– 3.866** (– 2.30)	– 5.069*** (– 2.69)	– 1.380*** (– 2.66)	– 1.378*** (– 2.47)	– 1.589*** (– 2.57)
Firm input tariffs xx fitted extent of processing	8.610*** (2.36)	10.309*** (2.59)	2.448** (2.12)	2.435** (2.09)	2.664** (2.06)
Fitted extent of processing	– 2.737*** (– 22.42)	– 2.901*** (– 23.00)	– 1.251*** (– 26.78)	– 1.251*** (– 23.61)	– 1.311***** (– 27.83)
SOEs indicator	– 0.619*** (– 11.60)	– 0.369*** (– 5.15)	– 0.187*** (– 7.71)	– 0.187*** (– 7.51)	– 0.188*** (– 7.81)
Foreign ownership indicator	0.493*** (19.38)	0.475*** (24.15)	0.220*** (27.24)	0.220*** (32.40)	0.229*** (28.84)
Firm size	0.325*** (51.51)	0.559*** (81.26)	0.068*** (34.23)	0.068*** (29.81)	0.072*** (24.59)
Firm external tariffs				0.001 (1.09)	0.001 (1.22)
Kleibergen–Paap rank LM χ^2 statistic	106.5†	92.00†	105.4†	105.4†	105.5†
Kleibergen–Paap rank Wald F statistic	54.98†	47.78†	55.18†	55.10†	55.10†
Year-specific fixed effects	Yes	Yes	Yes	Yes	Yes
Industry-specific fixed effects	Yes	Yes	Yes	Yes	Yes

(continued)

Table 12 (continued)

Regressand	$\ln LP_{ijt}$	$\ln TFP_{ijt}^{LevP}$	$\ln TFP_{ijt}^{GMM}$		Weighted $\ln TFP_{ijt}^{GMM}$
	(1)	(2)	(3)	(4)	(5)
Observations	19,296	15,759	19,283	19,283	19,283
R^2	0.4	0.53	0.3	0.3	0.65

Notes t-values in parentheses are obtained using bootstrapped standard errors. Significant at * 10%, ** 5% and *** 1%. † Indicates significance of *p*-value at the 1% level. The regressand is log of value-added labour productivity ($\ln LP_{ijt}$) in column (1) and Levinsohn–Petrin (2003) TFP ($\ln TFP_{ijt}^{LevP}$) in column (2), and conventional measure of system-GMM TFP $\ln TFP_{ijt}^{GMM}$ in columns (3) and (4). The regressand in column (5) is weighted system-GMM TFP which is calculated by multiplying $\ln TFP_{ijt}^{GMM}$ with their relative standard deviations across firms within an industry at the two-digit level. In all IV estimates, I control for year-specific fixed effects and time-invariant two-digit level Chinese industry fixed-effects. Firm size in columns (2)–(5) is proxied by log of firm labour, whereas in column (1) it is proxied by firm's capital-labour ratio. All instruments used are the same as those in Table 9. Pure domestic firms and pure exporters are dropped from the sample

Thus far, the effect of China's import tariff reductions on firm efficiency has been carefully investigated. However, although China has substantially reduced its import tariffs in the new century, Chinese exporters have also enjoyed large tariff reductions in their export destinations. Access to large foreign markets could possibly create incentives for productivity upgrading, especially if such investments require substantial fixed costs. Thus, controlling for tariff reductions in China's export destinations is also worthwhile to obtain a precise estimate of the effect of import tariff reductions on firm TFP.

To measure tariff reductions in a firm's export destination markets, I construct an index of firm-specific external tariffs (FET_{it}) as follows[38]:

$$FET_{it} = \sum_k \left[\left(\frac{X_{it}^k}{\sum_k X_{it}^k} \right) \sum_c \left(\frac{X_{ikt}^c}{\sum_c X_{ikt}^c} \right) \tau_{kt}^c \right] \tag{12}$$

where τ_{kt}^c is product k's ad valorem tariff imposed by export destination country c in year t. A firm may export multiple types of products to multiple countries. The ratio in the second set of parentheses in (12), $X_{ikt}^c / \sum_c X_{ikt}^c$, measures the export ratio of product k produced by firm i but consumed in country c, yielding a weighted external tariff across Chinese firms' export destinations. Similarly, the first term in parentheses in $X_{it}^c / \sum_k X_{ikt}^c$ measures the proportion of product k's exports over firm i's total exports. The mean of the firm-specific external tariff is only 0.9%, which is significantly lower than its counterpart for firm-specific import tariffs on final goods

[38] Note that all the main findings are not changed if firm external tariffs are measured using time-invariant export weights. The reason for choosing a time-variant export weight is to allow a dynamic response of the firm's exports to a reduction in foreign tariffs.

(8.3%). This makes good economic sense. The most important export destinations for Chinese firms are developed countries, such as the US and the countries of the EU, which usually set substantially lower import tariffs on exporters from developing countries like China. Column (4) of Table 12 presents the estimation results including a variable for the firm's external tariffs in the regressions. The coefficient of firm external tariffs is statistically insignificant. One possible reason for this is that Chinese firms had already entered foreign markets before 2000. Thus, tariff reductions in Chinese firms' export destinations have no statistically significant effect in reducing the fixed costs of exports.

Still, the regressand used in all the estimation is a measure of TFP, estimated in various ways. As the observations are estimated but not observed, it is worthwhile controlling for the fact that some observations are estimated more precisely than the others. Therefore, I compute the standard deviation of system-GMM TFP both across firms within an industry and across all firms and divide its sector average by the total average to multiply the firm's system-GMM TFP as the regressand in the last column of Table 12.[39] I obtain similar results as before: the effect of firm tariffs on productivity declines as the firm's processing imports grow. The overall impact of output tariff reductions is stronger than that of input tariff reductions.

Finally, the great flexibility of the system-GMM estimation method indeed provides a unique opportunity to obtain the effects of tariff reduction on firm productivity using a one-step approach. That is, the coefficients of both input coefficients for the production function and tariffs are obtained simultaneously. I hence experiment with this in Appendix Table 17, as additional robustness checks.[40]

4.5 Discussion of Channels

The article has presented rich evidence that both output and input tariff reductions boost firm productivity. However, we still have little understanding about the channels through which these effects occur. The impact of input tariffs on productivity is relatively direct, as lower tariffs induce access to a larger variety of imported intermediate inputs (Helpern et al., 2010).[41] Reductions in output tariffs are found to have

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[39] See columns (5) and (6) of Appendix Table 16. I thank a referee for suggesting this point.

[40] Using the log of firm output as the regressand, both the current period and a one-period lag realisation of firm inputs—labour, capital and materials—are included as regressors. Simultaneously, firm output and input tariffs based on time-invariant weights, the extent of processing imports and its interaction with tariffs are included as another set of regressors. To control for possible endogeneity, I adopt a one-period lag of firm output (input) tariffs with time-invariant weights as instruments as before. Appendix Table 17 reports the 2SLS fixed-effects estimates using the one-step system-GMM approach. All estimation results are highly consistent with the previous findings: the impact of tariff reductions on productivity improvement shrinks as the firm's processing imports grow. Overall, firm output tariff reduction leads to stronger productivity gains than firm input tariff reductions.

[41] Besides variety, Amiti and Konings (2007) highlight two other possible channels through which cheaper imported inputs can raise productivity: learning and quality effects.

a pro-competitive effect. However, it is less clear whether such a pro-competitive effect is realised through improvement in the efficiency of firms that are present in the market, or through weeding out the less-productive firms from the market.

To test these two possible channels, I first include an always-present firms indicator (i.e. it equals one if the firm is present in all years during 2000–2006 and otherwise zero) in column (1) of Table 13. The always-present indicator has a positive and significant sign, suggesting that always-present firms are more productive. To check whether low-productivity firms collapse and exit from the market, column (2) includes an exit indicator that takes the value one if firms exit from the market in the next year and zero otherwise. The insignificant sign of the exiting dummy suggests that exiters do not have a significant productivity difference compared with non-exiting firms. This finding is different from the predictions in Melitz (2003).

Amiti and Konings (2007) argue that tariff reductions could result in firms switching their scope from low to high-productivity products. However, they do not have information on firm scope because of Indonesian data restrictions. Thus, they use a switching dummy as a compromise. However, my merged data set includes information on exporters' scope. Many Chinese firms export multiple products, with the maximum reaching 745 export products. The logarithm of the firm's export scope is included in column (3) of Table 13, and its coefficient is positive and significant, suggesting that firms exporting more products have higher productivity. In column (4), the log of the firm's scope is then interacted with firm-specific input and output tariffs. The interaction of output tariffs and log scope is found to be significant, whereas that of input tariffs and log scope is insignificant, indicating that at least a few gains from output tariff reductions are attributable to product switching, as also found by Amiti and Konings (2007) with their more limited data. However, this channel is not important for input tariff reductions.

Last but not least, firms' productivity gains from trade reform may also result from the channel of investing in new technologies (Bustos, 2011). Firms with higher R&D expenses are expected to have higher productivity. This conjecture is verified in column (5) of Table 13 by including a variable for the firm's log R&D. In the last column, the logarithm of R&D is also interacted with the firm-specific input and output tariffs. Interestingly, the interaction coefficients of the output and input tariffs and R&D are insignificant, showing that the gains from both output and input tariff reductions do not result from investing in new technologies. One reason is the limited firm R&D data in my sample: around 80% of the observations do not contain valid R&D expenses,[42] thus the effect of R&D is under-estimated for firms to realise gains from tariff reductions.

[42] In particular, R&D in 2004 is completely missing. Moreover, around 50% of firms report negative or zero R&D expenses in my sample.

Table 13 IV estimates for channels

Regressand: ln TFP_{ijt}^{GMM}	Firm's selection		Multi-product firms		R&D expenses	
	(1)	(2)	(3)	(4)	(5)	(6)
Firm output tariffs	– 1.081*** (– 4.10)	– 1.086*** (– 3.44)	– 0.838*** (– 3.51)	– 0.468 (– 1.54)	– 1.119*** (– 2.16)	– 1.628 (– 1.17)
Firm output tariffs × fitted extent of processing	0.934** (2.03)	0.934* (1.82)	1.026** (2.30)	1.139*** (2.38)	0.421 (0.37)	0.785 (0.51)
Firm output tariffs × log of firm's scope				– 0.263*** (– 3.45)		
Firm output quad tariffs × log of firm's R&D						0.061 (0.40)
Firm input tariffs	– 1.671*** (– 4.10)	– 1.672*** (– 2.88)	– 1.267*** (– 3.36)	– 1.199*** (– 3.31)	– 2.060* (– 1.73)	– 0.899 (– 0.52)
Firm input tariffs × fitted extent of processing	3.557*** (4.07)	3.575*** (2.94)	4.065*** (4.33)	3.486*** (4.29)	4.711 (1.53)	3.889 (1.35)
Firm input tariffs × log of firm's scope				0.224 (1.08)		
Firm input quad tariffs × log of firm's R&D						– 0.150 (– 0.73)
Fitted extent of processing	– 1.500*** (– 40.41)	– 1.501*** (– 29.71)	– 1.467*** (– 35.02)	– 1.461*** (– 32.76)	– 1.471*** (– 10.87)	– 1.476*** (– 9.16)
SOEs indicator	– 0.249*** (– 12.94)	– 0.238*** (– 12.89)	– 0.216*** (– 9.87)	– 0.217*** (– 8.38)	– 0.245*** (– 8.56)	– 0.244*** (– 6.80)
Foreign ownership indicator	0.281*** (40.84)	0.282*** (39.83)	0.228*** (28.95)	0.229*** (29.88)	0.310*** (18.64)	0.309*** (19.74)
Log of labour	0.079*** (34.27)	0.079*** (31.90)	0.061*** (35.40)	0.061*** (27.95)	0.078*** (14.85)	0.078*** (13.77)
Log of capital-labour ratio	0.033*** (18.21)	0.033*** (15.31)	0.021*** (8.82)	0.019*** (8.68)	0.044*** (6.97)	0.045*** (8.74)
Firm exits next year		0.009 (0.92)				
Always-present firm indicator	0.013* (1.89)					
Log of firm's scope			0.042*** (19.57)	0.059*** (8.16)		
Log of R&D					0.028*** (11.33)	0.028*** (2.18)
Year-specific fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-specific fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,190	19,190	19,190	19,190	3331	3331
R^2	0.38	0.38	0.4	0.4	0.47	0.47

Notes t-values in parentheses are obtained using bootstrapped standard errors. Significant at * 10%, ** $5% and *** 1%. The two-digit Chinese industry-specific fixed effects are included in the estimation

4.6 Economic Magnitudes and Welfare Contributions

This section discusses the economic magnitudes of tariff reductions. As shown in the IV estimates in column (1) of Table 11, the regressand is in logarithms whereas the regressors are in levels. Thus, the estimated key coefficients can be interpreted as semi-elasticities. With tariffs as natural numbers used in the regressions (e.g. the mean of firm output tariffs is 0.083, as reported in Table 5), the own coefficient of the firm output (input) tariffs is − 1.32 (− 1.71). Measuring tariffs in percentage points (so the mean of firm output tariffs in the sample is 8.3 percentage points), such coefficients are changed to − 0.0132 (− 0.0171), implying that a 10 percentage point fall in output tariffs for non-processing firms leads to a 0.132 (0.171) increase in log TFP, or equivalently, a productivity gain of 13.2 (17.1)%.[43]

Equally important, the firm's productivity gains from cutting input and output tariffs become smaller as the firm's processing imports share grows. On average, the impact of the output tariff reductions on productivity improvement is − 0.013 + 0.008 9 0.49 = − 0.0092, given that the mean of the fitted extent of processing is 0.49, implying that a 10 percentage point fall in output tariffs leads to a productivity gain of 9.2%. Analogously, the average impact of a reduction in input tariffs is − 0.017 + 0.025 9 0.49 = − 0.0051, indicating that a 10 percentage point fall in input tariffs leads to a productivity gain of 5.1%, almost 56% as high as the gains from reducing output tariffs.[44] Average firm output tariffs were cut 8.2 percentage points (from 15.6% in 2000 to 7.4% in 2006), which thus predicts 0.00998.2 = 7.4% productivity gain and contributes 44.4% of the 0.17 log point increase in firm productivity covered in the sample. By the same token, the average firm input tariffs were cut 0.36 percentage points (from 2.54% in 2000 to 2.18% in 2006), which thus predict 0.005 9 0.36 = 0.18% productivity gain and contributes 1.1% of the 0.17 log point increase in log of TFP. Adding these numbers, tariff reductions, overall, contribute around 45.5% to productivity growth for the firms covered in the sample.

As economy-wide productivity growth is one of the best measures of a country's standard of living, my final step is to offer a more intuitive economic interpretation for the contribution of tariff reductions to China's aggregated productivity growth. The adding-up of firm productivity to economy-wide productivity is non-trivial as, because of the presence of vertical integration, intermediate inputs across firms (sectors) contribute to aggregated productivity by allowing productivity gains

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[43] My estimates are also close to other studies such as Amiti and Konings (2007), who find that a 10 percentage point fall in output (input) tariffs leads to a productivity gain of 6.4 (12.7)% using data on Indonesian firms.

[44] It is also interesting to check the productivity gains from tariff reductions for pure processing firms, for which the ratio of processing imports to total imports equals one. As firm input tariffs for pure processing firms reduce to zero, given that processing imports are duty-free, one cannot directly calculate such productivity gains from column (1) of Table 11. However, as the impact of the input tariff reductions is given by 0:0171 0:0246 E $Pext_{it}$ Z$_{it}$, by using a sufficiently high value for the extent of processing (e.g. the 90th percentile of E $Pext_{it}$ Z$_{it}$ 0:69) as a proxy of pure processing firms, the impact of input tariff reductions is close to zero, confirming that heavy processing firms rarely gain from input tariff reductions.

in successive firms (sectors) to augment one another (OECD, 2001).[45] As initiated by Domar (1961) and later elaborated by Hulten (1978) and Feenstra et al. (2013b), the economy-wide TFP can be aggregated by using the 'Domar weight' which is defined by each firm's gross output relative to economy-wide absorption (i.e. total gross output minus trade surplus). I then calculate the aggregated TFP using Domar weights for each year. It turns out that aggregated log of TFP increases around 0.53 log points (from 0.56 in 2000 to 1.09 in 2006).[46] As described before, both output and input tariff reductions, on average, lead to productivity gains of $7.54\% + 0.11\% = 0.076$, and thus contribute to 14.5% of the 0.53 log point increase in economy-wide log productivity. A final remark is that the calculation here presumes that tariff cuts have no impact on firm productivity beyond the sample. As tariff reductions still, in reality, have beneficial ripple effects beyond the set of firms in the sample, the calculated contribution to the whole economy should be interpreted as a lower-bound number.

5 Concluding Remarks

To explore how reductions in tariffs on imported inputs and final goods affect firm productivity, the article has exploited the special tariff treatment afforded to imported inputs by processing firms as opposed to non-processing firms in China. As a popular trade pattern in a large number of developing countries, including China, processing trade plays an important role in the realisation of productivity gains. Overall, I find that the impact of output tariff reduction is greater than that of input tariff reduction for large Chinese trading firms. More interestingly, the positive impact of reduction in input (output) tariffs on firm productivity is weaker as firms' processing import share grows.

This article is one of the first to explore the role of processing trade in Chinese firms' productivity gains. The rich data set enables the determination of whether a firm engages in processing trade and the examination of the effect of the firm's extent of processing trade engagement on productivity. With such information, firm-level input and output tariffs were also constructed, as one of the first attempts in the literature, which, in turn, enriches the understanding of the economic effects of China's special tariff reforms in processing trade.

[45] For example, if TFP growth for both shoe and rubber firms is 1%, the simple average of such firms' TFP growth will be 1%. However, productivity growth of the integrated rubber and shoe industry will be more than 1%, as the shoe firms' productivity gains cumulate with those of the rubber firms as the latter sells inputs to the former.

[46] To calculate Domar-weight TFP, the Domar weight is multiplied by four since the gross output of my merged sample only accounts for a quarter of total gross output in the full-sample data set, as shown in Table 3. See also Appendix 3 for a careful derivation of the Domar-weight aggregate productivity.

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Appendix 1: Matching Production and Trade Data Sets

My discussion on matching the two data sets (i.e. firm-level production data and firm-customs data) here draws heavily from Yu and Tian (2012). As mentioned in the text, I go through two steps to merge transaction-level trade data with firm-level production data. In the first step, I match the two data sets by firm name and year. The year variable is necessarily an auxiliary identifier because some firms could have different names across years and newcomers could possibly take their original names. Using the raw (i.e. unfiltered) production data set, I come up with 83,679 merged firms; this number is further reduced to 69,623 with the more accurately filtered production data set.

In the second step, I use another matching technique as a supplement. In particular, I adopt two other common variables to identify firms: postal code and the last seven digits of a firm's phone number. The rationale is that firms should have different and unique phone numbers within a postal district. Although this method seems straightforward, subtle technical and practical difficulties still exist. For instance, the production-level trade data set includes both area codes and a hyphen in the phone numbers, whereas the firm-level production data set does not. Therefore, I use the last seven digits of the phone number to serve as the proxy for firm identification for two reasons. First, in 2000–2006, some large Chinese cities (e.g. Shantou in Guangdong province) added one more digit at the start of their seven-digit phone numbers. Therefore, using the last seven digits of the number will not confuse firm identification. Second, in the original data set, phone numbers are defined as a string of characters with the phone postal code; however, it is inappropriate to de-string such characters to numerals because a hyphen is used to connect the postal code and phone number. Using the last seven-digit sub-string neatly solves this problem.

A firm might not include information on its name in either the trade or the production data set. Similarly, a firm could lose its phone and/or postal code information. To be sure that the merged data set can cover as many common firms as possible, I then include observations in the matched data set if a firm occurs in either the name-adopted matched data set or the phone- and post-adopted matched data set.

As shown in Appendix Table 14, column (1) reports the number of observations of HS eight-digit monthly transaction-level trade data from China's General Administration of Customs by year. As shown at the bottom of column (1), there are more than 118 million monthly trade transactions conducted by 286,819 firms during the seven years, as shown in column (2). Meanwhile, if no further data cleaning and stringent filter criteria are adopted as introduced in the text, column (3) shows that there are 615,591 large manufacturing firms in China. However, after stringent filtering according to GAAP requirements, around 70% of them survive-number of the filtered firms is 438,165 as seen at the bottom of column (4). Accordingly, column (5) reports the number of matched firms using exactly identical company names in both trade data set and raw production data set. By contrast, column (6) reports number of matched firms using exactly identical company names in both the trade data set and the filtered production data set, which results in 69,623 matched firms.

Column (7) reports the number of matched firms using exactly identical company names and exactly identical postal codes and phone numbers in both the trade and raw production data sets. The number of merged firms increases to 91,299. By way of comparison, my matching performance is highly comparable with that of other similar studies. For example, Ge et al. (2011) use the same data sets and similar matching techniques and end up with 86,336 merged firms. Finally, if I match the

Table 14 Matched statistics-number of firms

Year	Trade data		Production data		Matched data			
	Transactions	Firms	Raw firms	Filtered firms	w/Raw firms	w/ Filtered firms	w/Raw firms	w/ Filtered firms
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2000	10,586,696	80,232	162,883	83,628	18,580	12,842	21,425	15,748
2001	12,667,685	87,404	169,031	100,100	21,583	15,645	24,959	19,091
2002	14,032,675	95,579	181,557	110,530	24,696	18,140	28,759	22,291
2003	18,069,404	113,147	196,222	129,508	28,898	21,837	33,901	26,930
2004	21,402,355	134,895	277,004	199,927	44,338	35,007	49,891	40,711
2005	24,889,639	136,604	271,835	198,302	44,387	34,958	49,891	40,387
2006	16,685,377	197,806	301,960	224,854	53,748	42,833	49,680	47,591
All years	118,333,831	286,819	615,951	438,165	83,679	69,623	91,299	76,823

Notes Column (1) reports number of observations of HS eight-digit monthly transaction-level trade data from China's General Administration of Customs by year. Column (2) reports number of firms covered in the transaction-level trade data by year. Column (3) reports number of firms covered in the firm-level production data set compiled by China's National Bureau of Statistics without any filter and cleaning. By contrast, column (4) presents number of firms covered in the firm-level production data set with careful filtering according to GAAP requirements. Accordingly, column (5) reports number of matched firms using exactly identical company names in both the trade data set and the raw production data set. By contrast, column (6) reports number of matched firms using exactly identical company names in both the trade data set and the filtered production data set. Column (7) reports number of matched firms using exactly identical company names and exactly identical postal codes and phone numbers in both the trade data set and the raw production data set. By contrast, column (8) reports number of matched firms using exactly identical company names and exactly identical postal codes and phone numbers in both the trade data set and the filtered production data set more stringent filtered production data set with the firm-level data set using exactly identical company names and postal–phone code numbers but drop firms whose customs-reported exports are higher than NBS-reported firm sales, I end up with 76,823 firms in total, as shown in the last column of Appendix Table 14. I use these firms to run the regressions because they are the most reliable firms that can pass various stringent filtering processes in the firm production data.

After merging both the product-level trade data and the firm-level production data, the 76,823 common trading firms account for approximately 27% of the 286,819 firms in the product-level trade data set and approximately 17% of the 438,146 valid firms in the firm-level production data set (11% of the valid firms are exporters, whereas 6% of them are importers). Given that only 27% of firms are exporters in the firm-level production data set (Feenstra et al., 2013b), the merged data set hence accounts for around 40% of the filtered full-sample firm-level production data set in terms of number of exporters, and around 53% of exports in terms of export value.

Appendix 2: The Augmented Olley–Pakes TFP Measures

In this Appendix, I estimate the measured Olley–Pakes TFP by taking the role of processing trade into account. In the article, the Olley–Pakes TFP is estimated in three ways:

(i) TFP^{OP} which is used in the full-sample estimates in columns (1) and (2) in Table 7;
(ii) TFP^{OP1} which separates processing firms and non-processing firms into two groups and uses different control function approaches, as discussed below, and is used in columns (3) and (4) in Table 7 and column (1) in Table 8; and
(iii) TFP^{OP2} which pools processing firms and non-processing firms together for estimation and is used in column (2) in Table 8.

It is important to stress that different versions of Olley–Pakes TFP do not qualitatively change my estimation results.

By assuming that the expectation of future realisation of the unobserved productivity shock, υ_{it}, relies on its contemporaneous value, firm i's investment is modelled as an increasing function of both unobserved productivity and log capital, $k_{it} \equiv \ln K_{it}$. Following previous works, such as Amiti and Konings (2007), the Olley–Pakes approach was revised by adding other control variables as extra arguments of the investment function as follows:

$$I_{it} = \tilde{I}(\ln K_{it}, \upsilon_{it}, FX_{it}, WTO_t, SOE_{it}) \tag{13}$$

where FX_{it} is a dummy to measure whether firm i exports in year t as firm's export decision may affect firm investment. As my firm data set is from 2000 to 2006, I include a WTO dummy (i.e. one for a year after 2001 and zero for before) in the investment function. Finally, given the importance of state intervention, SOEs would have different decision behaviour than non-SOEs. I therefore include an SOE dummy in the investment function as well. Therefore, the inverse function of (13) is $\upsilon_{it} = \tilde{I}^{-1}(\ln K_{it}, I_{it}, FX_{it}, WTO_t, SOE_{it})$. The unobserved productivity also depends on log capital and other arguments. The estimation specification (M.1) in the text can now be written as follows:

$$\ln Y_{it} = \beta_0 + \beta_m \ln M_{it} + \beta_l \ln L_{it} + g(\ln K_{it}, I_{it}, FX_{it}, WTO_t, SOE_{it}) + \varepsilon_{it} \tag{14}$$

where $g(\cdot)$ is defined as $\beta_k \ln K_{it} + \tilde{I}^{-1}(\ln K_{it}, I_{it}, FX_{it}, WTO_t, SOE_{it})$. Following Olley and Pakes (1996), fourth-order polynomials in log-capital, log-investment, firm's export dummy and import dummy are used to approximate $g(\cdot)$.[47] With this specification, the coefficient of labour b_l and that of materials b_m can be estimated as the first-step procedure.

The three different versions of Olley–Pakes TFP use different control functions. The control function of TFP^{OP} which is used in the full-sample estimates cannot control for the firm's import status, as the full-sample production data set does not report import status. However, the import dummy is incorporated in the other two approaches (TFP^{OP1} and TFP^{OP2}) when using a matched sample to estimate. The difference between TFP^{OP1} and TFP^{OP2} is whether processing firms are separated from non-processing firms.

TFP$^{\mathbf{OP}}$ *Used in the Full-Sample Data Set*

In the full-sample data set, information on the firm's import status and processing status is unavailable. I hence adopt the following functional form

$$g(\ln K_{it}, I_{it}, FX_{it}, WTO_t, SOE_{it}) = (\alpha_0 + \alpha_1 WTO_t + \alpha_2 FX_{it} + \alpha_3 SOE_{it}) \sum_{h=0}^{4} \sum_{q=0}^{4} \delta_{hq} (\ln K_{it})^h I_{it}^q \tag{15}$$

In the first step, I obtain estimates of $\hat{b}_m$ and $\hat{b}_l$ for non-processing (ordinary) firms. I then calculate the residual R_{it} which is defined as $R_{it} = \ln Y_{it} - \hat{b}_m \ln M_{it} - \hat{b}_l \ln L_{it}$.

[47] Using higher-order polynomials to approximate $g(\cdot)$ does not change the estimation results.

The next step is to obtain an unbiased estimated coefficient of b_k. To correct the selection bias as mentioned above, Amiti and Konings (2007) suggest estimating the probability of a survival indicator on a high-order polynomial in log-capital and log-investment. One can then accurately estimate the following specification:

$$R_{it} = \beta_k \ln K_{it} + \tilde{I}^{-1}\left(g_{i,t-1} - \beta_k \ln K_{i,t-1}, \hat{pr}_{i,t-1}\right) + \varepsilon_{it} \tag{16}$$

where $\hat{pr}_i$ denotes the fitted value for the probability of the firm's exit in the next year. As the specific 'true' functional form of the inverse function $\tilde{I}^{-1}(\cdot)$ is unknown, it is appropriate to use fourth-order polynomials in $g_{i,t-1}$ and $\ln K_{i,t-1}$ to approximate it. In addition, (16) also requires the estimated coefficients of the log-capital in the first and second terms to be identical. Therefore, non-linear least squares seems to be the most desirable econometric technique.

Finally, the Olley–Pakes type of TFP for ordinary firm i in industry j is obtained once the estimated coefficient $\hat{\beta}_k$ is obtained:

$$\ln TFP_{ijt}^{OP} = \ln \mathrm{Y_{it}} - \hat{\beta}_m \ln \mathrm{M_{it}} - \hat{\beta}_l \ln \mathrm{L_{it}} - \hat{\beta}_k \ln \mathrm{K_{it}} \tag{17}$$

TFP^{OP1} *with Separate Estimates for Processing and Non-processing Firms*

By contrast, the control functions used in TFP^{OP1} for processing firms and non-processing firms are different. If a firm is engaged in any processing imports, it is defined as a processing firm; otherwise it is defined as a non-processing (ordinary) firm. I first separate all firms in the sample into two groups—non-processing (ordinary) firms and processing firms. The control function for non-processing firms in the first-step estimates takes the following form:

$$\begin{aligned} g^{ord}(\ln K_{it}, I_{it}, FX_{it}, WTO_t, SOE_{it}) = (&\theta_0 + \theta_1 WTO_t + \theta_2 FX_{it} \\ &+ \theta_3 IM_{it} + \theta_4 SOE_{it}) \sum_{h=0}^{4}\sum_{q=0}^{4} \delta_{hq}^{ord} (\ln K_{it})^h I_{it}^q \end{aligned} \tag{18}$$

where IM_{it} denotes the import dummy that takes the value one if firm i in year t is an importer, and zero otherwise. The estimates in the second step are identical to the corresponding estimates in the first approach TFP^{OP}. The Olley–Pakes type of TFP for ordinary firm i in industry j is obtained once the estimated coefficient $\hat{\beta}_k^{ord}$ is obtained:

$$\ln TFP_{ijt}^{ord} = \ln \mathrm{Y_{it}} - \hat{\beta}_m^{ord} \ln \mathrm{M_{it}} - \hat{\beta}_l^{ord} \ln \mathrm{L_{it}} - \hat{\beta}_k^{ord} \ln \mathrm{K_{it}} \tag{19}$$

The estimates for processing firms have two important differences from those for ordinary firms. First, the coefficients of all inputs are allowed to be different because processing firms could use different technologies from ordinary firms. Second, because processing firms, by definition, are both importers and exporters, I do not need to introduce the export dummy or the import dummy in their investment function or the fourth-order polynomials. That is, the polynomials for processing firms are as follows:

$$g^{ord}(\ln K_{it}, I_{it}, FX_{it}, WTO_t, SOE_{it}) = (\gamma_0 + \gamma_1 WTO_t + \gamma_2 SOE_{it}) \sum_{h=0}^{4}\sum_{q=0}^{4} \delta_{hq}^{proc} (\ln K_{it})^h I_{it}^q \tag{20}$$

The rest of the procedures for processing firm TFP are the same as their counterparts for non-processing firms. The Olley–Pakes type of TFP for processing firm i in industry j is obtained as follows:

$$\ln TFP_{ijt}^{proc} = \ln \mathrm{Y_{it}} - \hat{\beta}_m^{proc} \ln \mathrm{M_{it}} - \hat{\beta}_l^{proc} \ln \mathrm{L_{it}} - \hat{\beta}_k^{proc} \ln \mathrm{K_{it}} \tag{21}$$

I hence obtain two different sets of TFP for ordinary firms and processing firms. Their estimated input coefficients and measured TFP are shown in Appendix Table 15. The series of TFP^{OP1} is obtained by stacking them together.

$\mathbf{TFP^{OP2}}$ *with Learning from Processing*

Following De Loecker (2013), I now allow firms to learn from processing trade. Therefore, the export dummy is endogenously correlated with firm investment.

To obtain TFP^{OP2}, the difference from standard Olley–Pakes estimates is the first-step estimation. I first insert the processing dummy, PE_{it}, into the investment function as follows:

$$I_{it} = \tilde{I}(\ln K_{it}, \upsilon_{it}, FX_{it}, IM_{it}, WTO_t, SOE_{it}, PE_{it}) \tag{22}$$

Therefore, the inverse function of (22) is $\upsilon_{it} = \tilde{I}^{-1}(\ln K_{it}, I_{it}, FX_{it}, IM_{it}, WTO_t, SOE_{it}, PE_{it})$. To capture the possible learning effects from processing, the export decision was presumed to be made prior to the realisation of firm productivity. Hence, the productivity processing function $g(\cdot)$ is defined as $\beta_k \ln K_{it} + \upsilon_{it+1}$ where the productivity realisation υ_{it+1} uses the following polynomial specification as in De Loecker (2013):

$$\upsilon_{it+1} = \sum_{s=0}^{4}\sum_{m=0}^{4} \beta_{sm} PE_{it}^{s} \upsilon_{it}^{m} + \zeta_{it+1} \tag{23}$$

Table 15 Estimates of Olley–Pakes TFP by processing and ordinary firms separately

Chinese industry	Ordinary firms			Processing		
	Labour	Materials	Capital	Labour	Materials	Capital
13	0.242	0.875	0.052	0.116	0.884	0.066
14	0.023	0.926	0.050	0.037	0.925	0.074
15	0.185	0.508	0.268	0.243	0.505	0.088
17	0.017	0.884	0.059	0.089	0.834	0.041
18	0.054	0.858	0.076	0.177	0.669	0.142
19	0.126	0.895	0.023	0.118	0.808	0.000
20	0.126	0.895	0.023	0.044	0.913	0.003
21	0.055	0.917	0.042	0.101	0.873	0.103
22	0.111	0.907	0.008	0.027	0.896	0.063
23	0.023	0.821	0.039	0.105	0.836	0.025
24	0.068	0.764	0.123	0.104	0.863	0.036
26	0.086	0.795	0.063	0.007	0.927	0.024
27	0.108	0.862	0.040	0.038	0.860	0.038
28	0.116	0.789	0.033	0.016	0.837	0.041
29	0.061	0.569	0.174	0.073	0.938	0.032
30	0.118	0.633	0.182	0.125	0.696	0.114
31	0.073	0.851	0.047	0.050	0.870	0.035
32	0.046	0.976	0.051	0.038	0.961	0.010
33	0.053	0.815	0.080	0.055	0.850	0.076
34	0.041	0.867	0.048	0.044	0.883	0.026
35	0.065	0.875	0.024	0.032	0.917	0.026
36	0.090	0.823	0.076	0.038	0.869	0.111
37	0.058	0.888	0.047	0.054	0.924	0.029
39	0.013	0.830	0.103	0.102	0.826	0.000
40	0.071	0.831	0.072	0.086	0.878	0.086
41	0.081	0.906	0.015	0.139	0.567	0.168
42	0.055	0.917	0.045	0.142	0.818	0.094

Notes This table reports the estimates of log of Olley–Pakes TFP ($\ln TFP^{OP1}$) by separating ordinary firms and processing firms. The Chinese industries and associated codes are classified as follows: processing of foods (13), manufacture of foods (14), beverages (15), textiles (17), apparel (18), leather (19), timber (20), furniture (21), paper (22), printing (23), articles for cultures and sports (24), petroleum (25), raw chemicals (26), medicines (27), chemical fibres (28), rubber (29), plastics (30), non-metallic minerals (31), smelting of ferrous metals (32), smelting of non-ferrous metals (33), metal (34), general machinery (35), special machinery (36), transport equipment (37), electrical machinery (39), communication equipment (40), measuring instruments (41) and manufacture of artwork (42). I do not report the standard errors for each estimated coefficient to save space, although they are available upon request with $\mathrm{E}(\zeta_{it+1} PE_{it}) = 0$. Note that firm innovation ζ_{it+1} thus is different from the standard Olley–Pakes step where $\zeta_{it+1} = \upsilon_{it+1} - \upsilon_{it}$. Compared with other dummies, such as the exporting dummy, the processing dummy is not only used in the second-step estimates, but also in the first-step estimates. Similarly, the inverse investment function can be characterised as the following control function:

$$\upsilon_{it} = (\lambda_0 + \lambda_1 WTO_t + \lambda_2 FX_{it} + \lambda_3 IM_{it} + \lambda_4 PE_{it} + \lambda_5 SOE_{it}) \sum_{h=0}^{4}\sum_{q=0}^{4} \delta_{hq} (\ln K_{it})^h I_{it}^q$$

The second-step estimates are standard as above. After obtaining the coefficients of capital, labour and materials, the *TFP*^{OP2} is calculated as follows:

$$\ln TFP_{ijt}^{OP2} = \ln \mathrm{Y_{it}} - \hat{\beta}_m \ln \mathrm{M_{it}} - \hat{\beta}_l \ln \mathrm{L_{it}} - \hat{\beta}_k \ln \mathrm{K_{it}} \tag{24}$$

Appendix 3: Derivation of Domar-Aggregation Productivity

This Appendix interprets how to add firm productivity to economy-wide aggregate productivity using Domar's (1961) weight under an open-economy set-up. The Appendix draws heavily from OECD (2001) and Feenstra et al. (2013a). The challenging part of the aggregation comes from the fact that domestic intermediate inputs used by firms do not show up in the economy-wide production possibility frontier (PPF), as they represent intra-industry flows that are absorbed in a process of vertical integration. To concretise this idea, consider the following PPF:

$$T(FA, N, IM, \pi) = 0 \tag{25}$$

where *FA* denotes China's final absorption (or equivalently, final demand), *N* denotes all domestic primary inputs such as capital and labour, *IM* is imported intermediate inputs and π is aggregate TFP. By assuming inputs are homogenous of degree zero in *FA*, *N*, *IM* and π and perfectly competitive markets, the productivity change can be traced as follows:

$$\frac{d\ln\pi}{dt} = \frac{d\ln FA}{dt} - \frac{P_N N}{P_{FA}FA}\frac{d\ln N}{dt} - \frac{P_{IM}IM}{P_{FA}FA}\frac{d\ln IM}{dt} \tag{26}$$

where $(P_N\ N) = (P_{FA}\ FA)$ is the share of primary inputs in total final absorption and $(P_{IM}\ IM)/(P_{FA}\ FA)$ is the share of imported intermediate inputs in total final absorption. Both terms sum to unity because of zero profit in a perfectly competitive set-up. To link the aggregate economy with firm-level economic activities, each term in (26) can be decomposed as follows:

$$\begin{aligned}
\frac{d\ln FA}{dt} &= \sum_i \frac{P_{FA}^i FA^i}{P_{FA}FA}\frac{d\ln FA^i}{dt} \\
\frac{d\ln N}{dt} &= \sum_i \frac{P_N^i N^i}{P_N N}\frac{d\ln N^i}{dt} \\
\frac{d\ln IM}{dt} &= \sum_i \frac{P_{IM}^i IM^i}{P_{IM}IM}\frac{d\ln IM^i}{dt}
\end{aligned} \tag{27}$$

That is, aggregated final demand (aggregated primary inputs, aggregated imported intermediate inputs) can be written as a weighted average of firms' demand (primary inputs, imported intermediate inputs). By inserting (27) back into (26), I obtain:

$$\begin{aligned}
\frac{d\ln\pi}{dt} = {} & \sum_i \frac{P_{FA}^i FA^i}{P_{FA}FA}\frac{d\ln FA^i}{dt} - \frac{P_N N}{P_{FA}FA}\left(\sum_i \frac{P_N^i N^i}{P_N N}\frac{d\ln N^i}{dt}\right) \\
& - \frac{P_{IM}IM}{P_{FA}FA}\left(\sum_i \frac{P_{IM}^i IM^i}{P_{IM}IM}\frac{d\ln IM^i}{dt}\right)
\end{aligned} \tag{28}$$

Turning to measures of firm productivity, consider the following production function, which is homogenous of degree one:

$$Y^i = \pi^i f\left(N^i, M^i, IM^i\right) \tag{29}$$

where Y^i, N^i, M^i, and IM^i denote firm i's output, primary inputs, domestic intermediate inputs and imported intermediate inputs, respectively. π^i is the Hicks-neutral TFP. Total differentiate (29) to obtain the following equation:

$$\begin{aligned}
\frac{d\ln\pi^i}{dt} = {} & \frac{d\ln Y^i}{dt} - \frac{P_N^i N^i}{P^i Y^i}\frac{d\ln N^i}{dt} \\
& - \frac{P_M^i M^i}{P^i Y^i}\frac{d\ln M^i}{dt} - \frac{P_{IM}^i IM^i}{P^i Y^i}\frac{d\ln IM^i}{dt}
\end{aligned} \tag{30}$$

Note that each firm gets zero profit as the market structure is perfect competition, which implies:

$$P^i Y^i = P_N^i N^i + P_M^i M^i + P_{IM}^i IM^i \tag{31}$$

Thus, the input shares in the last three terms in (30) sum to unity. Meanwhile, the firm's total demand (i.e. demand for intermediate goods and final goods) is equal to its production value (i.e. supply):

$$P^i Y^i = \sum_k P^i Y^{ki} + P^i FA^i$$

where prices for intermediate demand use and for final use are assumed to be equal for simplicity and Y^{ki} denotes firm i's deliveries of its product to firm k. Totally differentiate the above equation to obtain:

$$\frac{d\ln FA^i}{dt} = \frac{P^iY^i}{P^iFA^i}\left(\frac{d\ln Y^i}{dt} - \sum_k \frac{P^iY^{ki}}{P^iY^i}\frac{d\ln Y^{ki}}{dt}\right) \tag{32}$$

By inserting (32) into (28), I obtain:

$$\begin{aligned}\frac{d\ln \pi}{dt} = \sum_i \frac{P^iY^i}{P^iFA^i}\Bigg(&\frac{d\ln Y^i}{dt} - \sum_k \frac{P^iY^{ki}}{P^iY^i}\frac{d\ln Y^{ki}}{dt}\\ &-\frac{P_N^iN^i}{P^iY^i}\frac{d\ln N^i}{dt} - \frac{P_M^iM^i}{P^iY^i}\frac{d\ln M^i}{dt}\Bigg)\end{aligned} \tag{33}$$

Finally, by definition, each delivery of firm k to firm i is also the intermediate input for firm i. That is, $Y^{ki} = M^{ik}$. Or equivalently, d ln Y^{ki}/dt = dM^{ik}/dt. Then I have:

$$\sum_i\sum_k \frac{P^iY^{ki}}{P_{FA}FA}\frac{d\ln Y^{ki}}{dt} = \sum_k\sum_i \frac{P^iM^{ik}}{P_{FA}FA}\frac{d\ln M^{ik}}{dt} \tag{34}$$

The aggregated productivity measure can be readily obtained by inserting (34) into (33):

$$\begin{aligned}\frac{d\ln \pi}{dt} = \sum_i \frac{P^iY^i}{P_{FA}FA}\Bigg(&\frac{d\ln Y^i}{dt} - \frac{P^iM^i}{P^iY^i}\frac{d\ln M^i}{dt}\\ &-\frac{P_N^iN^i}{P^iY^i}\frac{d\ln N^i}{dt} - \frac{P_{IM}^iIM^i}{P^iY^i}\frac{d\ln IM^i}{dt}\Bigg)\end{aligned} \tag{35}$$

All terms in the parentheses of (35) are the change in firm productivity, as seen from (30). Therefore, I have:

$$\frac{d\ln \pi}{dt} = \sum_i \frac{P^iY^i}{P_{FA}FA}\frac{d\ln \pi^i}{dt} \tag{36}$$

That is, the economy-wide productivity change can be represented as a weighted sum of firm productivity change in which the weight is calculated by the firm's gross output value divided by the economy-wide total absorption (i.e. total gross output minus total trade surplus in an open economy like China). As this is initiated by Domar (1961), I hence call (36) the Domar-weight aggregated productivity (Tables 16, 17, 18, 19 and 20).

Additional Supporting Information may be found in the online version of this article: Data S1.

Table 16 Estimates of system-GMM firm TFP by industry

Chinese industry	Estimated coefficients			TFP	SD	Weighted TFD TFP	Tests (p-value)		
	Labour	Materials	Capital				AR(1)	AR(2)	Hansen
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
13	0.094	0.718	0.010	2.575	0.387	2.884	0.000	0.987	0.443
14	0.089	0.828	0.003	2.528	0.380	2.776	0.000	0.396	0.603
15	0.077	0.677	0.152	2.677	0.465	3.599	0.063	0.724	1.00
17	0.065	0.748	0.002	2.523	0.298	2.175	0.007	0.389	0.569
18	0.068	0.724	0.020	2.447	0.326	2.303	0.000	0.317	0.834
19	0.050	0.868	0.029	2.488	0.323	2.320	0.015	0.858	0.676
20	0.015	0.844	0.010	2.851	0.412	3.398	0.011	0.510	0.548
21	0.114	0.795	0.001	2.650	0.309	2.367	0.000	0.051	0.808
22	0.151	0.655	0.011	2.705	0.338	2.644	0.424	0.570	1.00
23	0.178	0.474	0.051	2.618	0.341	2.578	0.036	0.059	0.846
24	0.098	0.609	0.058	2.485	0.281	2.018	0.030	0.411	0.990
25	0.017	0.700	0.173	2.865	0.498	4.127	0.156	0.744	1.00
26	0.142	0.701	0.034	2.669	0.353	2.721	0.000	0.868	0.222
27	0.014	0.748	0.054	2.764	0.350	2.797	0.008	0.988	0.712
28	0.052	0.812	0.088	2.674	0.326	2.520	0.082	0.280	1.00
29	0.165	0.633	0.025	2.593	0.348	2.606	0.015	0.691	0.899
30	0.128	0.865	0.022	2.690	0.335	2.605	0.000	0.303	0.371
31	0.105	0.769	0.019	2.626	0.343	2.600	0.000	0.936	0.034
32	0.001	0.876	0.001	2.864	0.388	3.212	0.060	0.233	0.909
33	0.068	0.805	0.057	2.592	0.386	2.888	0.914	0.682	0.896
34	0.022	0.840	0.021	2.480	0.318	2.279	0.009	0.161	0.788

(continued)

Table 16 (continued)

Chinese industry	Estimated coefficients			TFP	SD	Weighted TFD TFP	Tests (p-value)		
	Labour	Materials	Capital				AR(1)	AR(2)	Hansen
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
35	0.108	0.782	0.003	2.527	0.313	2.286	0.000	0.473	0.726
36	0.091	0.719	0.089	2.604	0.356	2.681	0.000	0.845	0.537
37	0.103	0.813	0.034	2.637	0.359	2.737	0.090	0.893	0.393
39	0.309	0.628	0.101	2.503	0.394	2.847	0.049	–	0.743
40	0.158	0.729	0.021	2.833	0.451	3.692	0.013	–	0.368
41	0.061	0.889	0.012	2.682	0.465	3.603	0.028	0.281	0.767
42	0.088	0.667	0.012	2.450	0.295	2.090	0.041	–	0.564

Notes The Chinese industries and associated codes are classified as follows: processing of foods (13), manufacture of foods (14), beverages (15), textiles (17), apparel (18), leather (19), timber (20), furniture (21), paper (22), printing (23), articles for culture and sports (24), petroleum (25), raw chemicals (26), medicines (27), chemical fibres (28), rubber (29), plastics (30), non-metallic minerals (31), smelting of ferrous metals (32), smelting of non-ferrous metals (33), metal (34), general machinery (35), special machinery (36), transport equipment (37), electrical machinery (39), communication equipment (40), measuring instruments (41) and manufacture of artwork (42). I do not report the standard errors for each coefficient in first three columns to save space, which are available upon request. In all estimates, I include a one-period lag of capital, labour and materials. I also include a pure assembly dummy and its interaction with both current period and a one-period lag of capital, labour and materials. After obtaining system-GMM TFP in column (4), I compute the standard deviation of system-GMM TFP both across firms within an industry and across all firms, divide the industrial average to total average and multiply TFP in column (4) to obtain the weighted TFP in column (5). Numbers are p-values in columns (6)–(8), which report various tests for the system-GMM TFP estimates

Table 17 .

Regressand: log of output ln y_{it}	(1)	(2)	(3)	(4)
Firm output tariffs	− 3.272** (− 2.15)	− 3.044** (− 2.11)	− 2.389* (− 1.85)	− 2.726** (− 2.03)
Firm output tariffs × fitted extent of processing	5.350** (2.03)	5.012**** (2.03)	3.837 (1.63)	4.408* (1.87)
Firm input tariffs	− 2.700*** (− 2.83)	− 2.707*** (− 2.78)	− 2.121** (− 2.43)	− 2.453** (− 2.57)
Firm input tariffs × fitted extent of processing	6.408*** (3.06)	6.035*** (3.02)	4.212** (2.29)	4.826**** (2.19)
Extent of processing	− 1.062** (− 2.03)	− 1.055** (− 2.11)	− 0.749** (− 1.65)	− 0.933* (− 1.96)
Log of output at one lag (ln y_{it-1})	0.376*** (2.90)	0.357*** (2.81)	0.414*** (3.31)	0.358*** (2.80)
Log of materials (ln M_{it})	0.553*** (15.79)	0.565*** (14.60)	0.563*** (15.28)	0.578*** (13.91)
Log of materials at one lag (ln M_{it-1})	− 0.147 (− 1.62)	− 0.137 (− 1.50)	− 0.161* (− 1.86)	− 0.128 (− 1.44)
Log of labour (ln L_{it})	0.145*** (9.19)	0.145*** (8.44)	0.130*** (7.75)	0.129*** (6.75)
Log of labour at one lag (ln L_{it-1})	− 0.016 (− 0.43)	− 0.014 (− 0.41)	− 0.028 (− 0.89)	− 0.013 (− 0.39)
Log of capital (ln K_{it})	0.069*** (5.13)	0.066*** (4.22)	0.071*** (4.95)	0.065*** (3.75)
Log of capital at one lag quad (ln K_{it-1})	− 0.003 (− 0.36)	− 0.002 (− 0.26)	− 0.010 (− 1.06)	− 0.007 (− 0.70)
SOE indicator	− 0.171*** (− 3.12)	− 0.183*** (− 3.15)	− 0.143*** (− 2.88)	− 0.171*** (− 2.95)
Foreign ownership indicator	0.113 (1.62)	0.117** (1.73)	0.082 (1.38)	0.109* (1.73)
Year-specific fixed effects	Yes	Yes	Yes	Yes
Industry-specific fixed effects	Yes	Yes	Yes	Yes
Pure domestic firms dropped	No	Yes	No	Yes
Pure exporting firms dropped	No	No	Yes	Yes
Observations	15,308	13,675	13,383	11,750

Notes This table reports the one-step system-GMM dynamic panel-data estimation. t-values in parentheses are obtained using bootstrapped standard errors, corrected for clustering at the firm level. Significant at * 10%, ** 5% and *** 1%. Year-specific fixed effects and industry-level fixed effects are included. Column (1) includes the whole sample. Column (2) drops pure domestic firms. Column (3) drops pure exporting firms. Column (4) drops both pure domestic firms and pure exporting firms. As in Table 11, firm output (input) tariffs with initial time-invariant weight and one-period lag of tariffs are used as instruments for firm output (input) tariffs with initial time-invariant weight. Similarly, the interactions between fitted extent of processing obtained from the second-step Heckman estimates in Table 10 and firm output (input) tariffs with initial time-invariant weight and one-period lag of tariffs are used as instruments for the interaction between fitted extent of processing and firm output (input) tariffs

Table 18 Transitional probability for state-owned enterprises (SOEs)

Probability (%) current period	Next period		Total
	SOEs	Non-SOEs	
SOEs	99.87	0.13	100
Non-SOEs	13.01	86.99	100
Total	98.21	1.79	100

Table 19 Transitional probability for foreign firms

Probability (%) current period	Next period		Total
	Foreign firms	Non-foreign firms	
Foreign firms	98.32	1.62	100
Non-foreign firms	0.96	99.04	100
Total	38.22	61.78	100

Table 20 Transitional probability for processing firms

Probability (%) current period	Next period		Total
	Non-processing	Processing	
Non-processing firms	85.90	14.10	100
Processing firms	34.14	65.86	100
Total	69.11	30.89	100

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Firm R&D, Processing Trade and Input Trade Liberalisation: Evidence from Chinese Firms

Wei Tian and Miaojie Yu

1 Introduction

The nexus between firm innovation and trade liberalisation is an important research subject in the empirical trade literature, as firm innovation is an important channel for firms to realise productivity gains from trade. Some work in this area has focused on how output trade liberalisation affects firm research and development (R&D) inputs (Iacovone et al., 2013; Bloom et al., forthcoming). Since tariff reductions usually happen bilaterally, other research has concentrated on how cuts in foreign tariffs boost firm R&D activity (Aw et al., 2007, 2011; Bustos, 2011; Lileeva & Trefler, 2010). Some researchers have been paying more attention to the role of imported intermediate inputs by exploring how input trade liberalisation affects firm R&D behaviour (Goldberg et al., 2010; Griffith et al., 2004; Hu et al., 2005; Kim & Nelson, 2000).

The present paper examines the effect of input trade liberalisation on firm R&D by taking into account China's special treatment on imported intermediate inputs. After China's accession to the World Trade Organization (WTO) in 2001, the country experienced significant trade liberalisation in final outputs and intermediate inputs (Yu, 2015). Different from ordinary imports, processing imports in China enjoy zero

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W. Tian
School of International Trade and Economics, University of International Business and Economics (UIBE), Beijing, China

M. Yu (✉)
China Center for Economic and Research (CCER), National School of Economics, Peking University, Beijing, China
e-mail: mjyu@nsd.pku.edu.cn

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tariffs and were not affected by the input trade liberalisation caused by the WTO accession. We thus take China's accession to the WTO as a quasi-natural experiment and perform difference-in-difference (DID) analysis by taking processing import firms as a control group. We also carefully deal with the possible endogeneity and serial correlation problems. We identify and drop imported capital goods to avoid potential contamination of our estimates. Overall, we find strong evidence that input trade liberalisation due to the WTO accession significantly fosters firm R&D activity.

This paper contributes to the literature in three important ways. First, it enriches our understanding of China's innovation activity in the new century. As China's labour costs have increased in recent years, the country's apparent comparative advantage based on its abundant labour endowment is shrinking. As a result, Chinese firms are eager to invest more in R&D to boost firm productivity to maintain their international competitiveness. Aggregated data from the *China Statistical Yearbook on Science and Technology* ascertain this conjecture. For example, the share of R&D in GDP rose from 0.6% in 1995 to 1.23% in 2004. The number of employees in the R&D sectors increased over 77% during the same period. However, this idea is rarely supported by Chinese micro firm-level production data. This paper aims to fill this gap. We use disaggregated and firm-level production data and highly disaggregated transaction-level customs data from 2000 to 2006, to explore the relationship between firm R&D and input trade liberalisation.

Second, the paper contributes to understanding the channels and mechanisms of the effects of trade liberalisation on firm performance. Although firm innovation is a crucial channel to realise firm productivity gains from trade, previous studies have mostly focused on output trade liberalisation. A fall in domestic output tariffs generates tougher import competition, which in turn forces firms to invest more in R&D activities. By contrast, a reduction in foreign tariffs creates a large foreign market, which could make firms more profitable, so that they can invest more in R&D activities. Few papers have considered the impact of input trade liberalisation on firm R&D. However, import trade liberalisation plays a substantial role in firms' ability to realise productivity gains from trade (Amiti & Konings, 2007; Goldberg et al., 2010; Tian & Yu, 2015; Topalova & Khandelwal, 2011; Yu, 2015). The present paper thus picks up this job.

Third, the paper makes a contribution to the issue of empirical identification. Firm R&D activity may be endogenous to import tariffs. Usually firms with lower R&D investment are less productive. Accordingly, they could lobby the government for temporary protection (Bown & Crowley, 2013). It is well recognised that it is a challenging job to find an ideal instrument for import tariffs. However, China has special, zero-tariff treatment on processing imports. Further trade liberalisation has not impacted processing imports. Thus, we are able to take advantage of this situation using processing import firms as a control group to mitigate the endogeneity problem, and hence to explore the causal relation between input trade liberalisation and firm R&D.

The paper is related to two strands of the growth literature. The first strand is on the nexus between firm R&D and external trade liberalisation from trading partners. Grossman and Helpman (1991) was one of the pioneering works to model the impact of foreign trade liberalisation on firm R&D. In line with this idea, Yeaple (2005) shows that firms have a greater incentive to increase investment in technology in response to a fall in trade costs under a framework in which firms choose either high or low technology according to the observed random ability of workers. Verhoogen (2008) examines the impact of currency validity on firm R&D activity using Mexican data. By assuming that more productive firms choose to produce higher quality products and pay higher wages, he shows that home currency depreciation forces high-productivity firms to invest more in improving product quality, which is accompanied by greater within-industry wage discrepancies. Lileeva and Trefler (2010) forcefully argue that foreign tariff reduction leads to more exports from high-productivity Canadian firms; the increase in exports is associated with more R&D inputs in new product innovation. By comparison, we also control for foreign market size, but focus on input trade liberalisation.

The second strand of literature examines the impact of output trade liberalisation on firm R&D. Iacovone et al. (2013) study the impact of China entering the WTO on Mexican firms, and they find that more productive firms invest more in R&D. Bloom et al. (forthcoming) find that the elimination of import quotas on Chinese goods in Europe since 2001 has increased domestic competition, which in turn has improved firm-level technology upgrading as well as the mobility of labour towards more productive firms. Finally, some other research explores reductions in foreign tariffs and import tariffs. Bustos (2011) studies the effect of bilateral trade liberalisation and finds that bilateral tariff reductions in import tariffs and external tariff encourage firms to use high technology and improve productivity. Yu (2015) examines the impact of three types of tariff reductions: import tariffs on output goods, import tariffs on imported intermediate inputs and foreign tariffs. However, his focus is the effect of trade liberalisation on firm productivity. In this paper, we explore the impact of input trade liberalisation on firm innovation, controlling for the size of foreign market access and output trade liberalisation.

The rest of the paper is organised as follows. Section 2 describes the data and measures of the key variables. Section 3 presents our empirical strategy and reports our estimation results. Section 4 concludes.

2 Data

To investigate the impact of intermediate trade liberalisation on firm R&D, we use the following highly disaggregated large, panel data set: firm-level production data, transaction-level trade data and tariff data.

The firm-level production data come from a large firm-level data set that covers around 230,000 manufacturing firms per year over 2000–2006. The data are collected and maintained by China's National Bureau of Statistics in an annual survey of manufacturing enterprises. Briefly, the survey covers two types of manufacturing firms: all state-owned enterprises (SOEs); non-SOEs with annual sales more than 5 million RMB (or equivalently, $730,000). The survey reports more than 100 financial

Table 1 Key firm characteristics by pure and non-pure exporters

Firm log R&D	All firms		Pure exporter		Non-pure exporter	
Year	Mean	Std	Mean	Std	Mean	Std
	(1)	(2)	(3)	(4)	(5)	(6)
2001	11.71	2	11.49	1.62	11.72	2.01
2002	11.76	2.01	11.04	1.86	11.78	2.01
2003	11.78	2.03	11.29	1.79	11.8	2.03
2005	12.36	2.16	11.51	1.93	12.38	2.16
2006	12.62	2.2	11.81	1.99	12.64	2.2
All years	12.13	2.13	11.46	1.88	12.14	2.14
Other firm characteristics						
Labour	4.91	1.08	5.29	1.03	4.89	1.08
Sales	103,751	876,144	56,855	214,120	105,652	892,633
TFP (Olley-Pakes)	1.17	0.34	1.15	0.23	1.17	0.34

variables listed in three accounting sheets (i.e. balance sheet, loss and benefit sheet and cash flow sheet) and covers all the required variables used in the analysis, such as number of employees, firm sales, firm R&D and firm exports.

However, such a raw data set could be noisy, in the sense that it includes some unqualified samples.[1] Following Feenstra et al. (2014) and Yu (2015), we delete observations according to the basic rules of the generally accepted accounting principles. Accordingly, the total number of observation is reduced to 438,165 for 2000–2006. Around one-third of the firms were dropped from the sample after the screening process.[2]

Data on firm R&D are available from 2001 to 2006 but are missing for 2004. As shown in Table 1, firm R&D expenses increased during the sample years. The main interest of this paper is to examine changes in firm R&D in response to changes in trade liberalisation, for two types of firms: processing firms and non-processing firms. Unfortunately, firm processing information is not available from the firm-level data. However, as Dai et al. (2012) point out, processing firms are usually pure exporters that sell all their products abroad. We instead break all firms into the two categories: pure exporters and non-pure exporters. Columns (3) and (5) report firm R&D for pure exporters and non-pure exporters, respectively. By way of comparison, non-pure exporters invest more in R&D than pure exporters do during the sample years, suggesting that processing exporters are less innovative. This observation is consistent with the finding that processing firms are usually less productive (Dai et al., 2012; Tian & Yu, 2015; Yu, 2015).

The information covered by the firm-level production data set is rich. However, it is silent on the type of firm exports, so we are not able to distinguish processing exports

[1] For example, some firms have negative exports and even a negative number of employees.

[2] For more detail about the data screening, see Yu (2015).

and ordinary exports. We hence appeal to the product-level trade data set provided by the general customs. The disaggregated transaction-level monthly trade data set contains a huge number of observations. It includes 118,333,831 observations during the sample period from 2000 to 2006. There were more than 286,000 firms engaged in international trade during this period. For each transaction, the data set compiles three types of information: (i) basic trade information, which includes value (measured in US current dollars), trade status (export or import), quantity, trade unit and value per unit; (ii) trade mode and pattern, such as destination country for exports, origin country for imports, routing countries (i.e. whether the product is shipped through an intermediate country/regime), customs regime (e.g. processing trade or ordinary trade), transport mode (i.e. by sea, truck, air or post) and customs port (i.e. where the product departs or arrives); and (iii) firm-level information, in particular, seven variables are included: firm name, identification number set by customs, city of firm location, telephone number, postal code, name of manager/CEO and firm ownership type (e.g. foreign affiliate, private or SOE).

To understand whether a firm engages in processing trade, we need to merge firm production-level data and transaction-level trade data. However, the matching is particularly challenging, since the trade and production data share no common identification (Wang & Yu, 2012). Therefore, we take a detour by using the firm name (in Chinese), telephone number and postal code as identification variables.[3] Briefly, the merged data cover roughly 30% of the exporters and account for 53% of the total export value reported in the original production data. Compared with the original trade data, the merged data show a similar proportion of ordinary importers and processing importers, as in Yu (2015). Thus, a caveat here is that our estimation results only apply to large trading firms due to our data limitation.

Finally, tariff data can be accessed directly from the WTO. China's tariff data are available at the Harmonized System (HS) 6-digit level for 2000–2006. For our estimation purposes, we first aggregate tariffs to the Chinese industry classification (CIC) 2-digit level. Given that every firm corresponds to a particular industry, we are able to find the associated industry-level output tariffs for all firms.

Table 2 presents the summary statistics for some key variables both in the full sample and in the merged sample used in the estimations. We also report the mean and standard deviations for each key variable by year. It is clear that industrial output tariffs are decreasing over years. Simultaneously, survival firms are getting larger and profitable. By sharp contrast, the proportion of pure exporters is not changed much over years. This interprets why the statistics of key variables shown in Table 1 for all firms and for non-pure exporters look similar. The last column shows the summary statistics for corresponding key variables used in the full-sample data. It turns out that the means of all variables do not change much between using the full-sample data and merged-sample data. Finally, the last column of Table 2 also reports the main statistics of a new variable—pure processing indicator, which is only available from the merged-sample data set.

[3] The detailed method and technique are described in Yu (2015).

Table 2 Summary statistics of key variables (2001–2006)

	Full sample				Merged sample Avg
	Avg	2001	2003	2006	
Labour	4.92 (1.08)	5.11 (1.08)	4.98 (1.07)	4.87 (1.08)	5.38 (1.11)
Firm profit (log)	6.72 (1.93)	6.44 (1.97)	6.56 (1.89)	6.98 (1.93)	7.40 (1.92)
Industry-level output tariff	11.07 (8.15)	17.19 (9.91)	11.86 (6.74)	9.82 (5.51)	11.53 (7.51)
Pure exporter indicator	0.04 (0.19)	0.04 (0.20)	0.04 (0.19)	0.04 (0.19)	0.01 (0.10)
Pure processing indicator					0.55 (0.42)

Note Numbers in parentheses are standard deviations
Source China's National Bureau of Statistics, calculated by the authors

3 Empirics and Results

3.1 Benchmark Estimates with the Full Sample

In this section, we use the unmerged firm-level production data. Before the regression, we first compare the major information of the firms with positive R&D and no R&D in Table 3.

It is apparent that firms with positive R&D are larger, more productive and more profitable, and they export less of their product and have lower proportion of pure exporters. This is consistent with our argument that most pure exporters are processing exporters and usually invest less in R&D.

To examine the effect of input trade liberalisation on firm R&D, we consider the following empirical specification:

$$lnRnD_{it} = \beta_1 WTO_t + \beta_2 PureExporter_i + \beta_3 WTO_t \times PureExporter_i + \epsilon_{it} \tag{1}$$

Table 3 Comparison between zero R&D and positive R&D

	Productivity	Labour	Profit	Pure exporter
R&D = 0	1.16	4.82	6.63	0.04
R&D > 0	1.19	5.53	7.76	0.02
Diff	– 0.02*** (– 19.16)	– 0.71*** (– 190)	– 1.13*** (– 150)	0.02*** – 30.92

Note Robust *t*-values are in parentheses, and *** denotes 1% level of significance. The data are computed from the unmerged full-sample data where RnD_{it} denotes firm i's R&D inputs in year t. WTO_t is a dummy variable that equals one after 2001 and zero before 2001. $PureExporter_i$ is an indicator that equals one if firm i is a pure exporter and zero otherwise. With this set-up, pure exporters are treated as a control group to capture the fact that most pure exporters are processing exporters, which were not affected by further input tariff cuts after the WTO accession. If this specification is supported by the data, we shall observe that b_1 should be positive and significant, indicating that firms have more R&D investment after the WTO accession. b_2 is expected to be statistically insignificant in the sense that after matching the control group and the treatment group, pure exporters' R&D investment would not be significantly different from non-pure exporters before WTO accession. However, the key variable, the interaction term between the WTO dummy and the pure exporter indicator, must be negative and significant, suggesting that non-pure-exporting firms' R&D would significantly increase due to the WTO accession compared with its counterpart of pure exporters.

It is worthwhile stressing that the independence of irrelevant alternatives is a crucial assumption for the DID analysis. The idea is that pure exporters and non-pure exporters are different in many respects, although some variables may affect the R&D behaviour of both types of exporters. For instance, as documented by Dai et al. (2012) and Yu (2015), processing exporters are also pure exporters and processing exporters are less productive and less profitable than non-processing exporters. To avoid this potential pitfall of violating, we include control variables, such as firm Olley and Pakes's (1996) total factor productivity, firm profits and firm size (proxied by number of employees) in all estimations throughout the paper. Finally, previous works also suggest that SOEs may have less incentive to engage in R&D behaviour, since they receive an extra subsidy from the government (Hsieh & Klenow, 2009). And, because they are more productive, multinational corporations may invest more in R&D inputs (Keller & Yeaple, 2009). We thus also include a control for firm ownership type by including the SOE indicator and the foreign indicator in all the regressions.

By abstracting away year-specific fixed effects, the estimates in column (1) in Table 4 show that firms have more R&D investment after the WTO accession. More importantly, the negative and significant coefficient of the interaction term between the WTO dummy and the pure exporter indicator suggests that non-pure exporters have more R&D activity after the WTO accession. Meanwhile, the lower the industrial output tariffs, the higher the firm R&D. More productive firms invest more in R&D activity. Finally, larger firms and more profitable firms have more R&D activity. These findings are consistent with the conventional findings in the literature.

Still, there may be a concern that the increases in firm R&D were caused by other macro-economic shocks, such as appreciation of the renminbi (RMB). We thus include year-specific fixed effects in columns (2) to (4) in Table 4. All the estimation results remain robust and insensitive to those in column (1) after controlling for year-specific and firm-specific fixed effects.

Thus far, our estimation sample covers 5 years from 2001 to 2006. An interesting question is how the WTO accession affected firm R&D in the very short run. Column (3) in Table 5 presents estimation results for the sample from 2001 to 2003. All the

Table 4 Benchmark estimates

Firm R&D (log)	(1)	(2)	(3)	(4)
WTO indicator	0.284*** 6.73			
Pure exporter indicator	0.15 0.63	0.11 0.47	0.28 1.47	0.50** 2.34
WTO indicator × pure exporter indicator	– 0.564** (– 2.27)	– 0.520** (– 2.11)	– 0.696** (– 2.56)	– 0.525** (– 2.53)
Industry output tariff	– 0.009*** (– 6.92)	– 0.007*** (– 5.62)	– 0.007*** (– 4.53)	– 0.003* (– 1.88)
Firm productivity (in log)	0.636*** 15.16	0.554*** 13.23	0.464*** 7.3	0.140** 2.3
Firm size (in log)	0.442*** 42.71	0.457*** 44.32	0.454*** 27.52	0.411*** 10.28
Firm profit (in log)	0.328*** 48.06	0.312*** 45.75	0.307*** 29.5	0.131*** 10.18
SOE indicator	0.08 1.51	0.103** 2.11	0.09 1.49	0.21** 2.15
Foreign indicator	– 0.01 (– 0.50)	– 0.02 (– 0.64)	– 0.01 (– 0.28)	– 0.09 (– 0.74)
Year-specific fixed effects	No	Yes	Yes	Yes
Firm-specific fixed effects	Yes	Yes	Yes	Yes
Year covered	2001–2006	2001–2003	2001–2005	
Number of observations	43,407	43,407	11,456	31,448
R^2	0.32	0.33	0.31	0.31

Notes (i) Pure exporters served as the control group in the estimations. The simple average industry-level output tariff is computed at the CIC 4-digit level. (ii) Robust *t*-values are in parentheses. (iii) *** and ** denote 1 and 5% level of significance

previous results remain robust. Finally, in addition to RMB appreciation against the US dollar, the Multi Fibre Agreement was phased out in 2005 (Khandelwal et al., 2013). The year-specific fixed effect is a good control for RMB appreciation, but it cannot handle the industrial heterogeneity caused by the termination of the Multi Fibre Agreement. To address this concern, we hence drop 2006 from the estimates in column (4). It turns out that the key coefficient of b_3 is still negative and statistically insignificant. Thus, our results are not sensitive to the event of RMB appreciation in 2006.

In the estimates in columns (2)–(4), even after imposing firm-specific import tariffs, the pure exporters' variable is still not significant. This is because the status of pure exporters is not invariant over time. Firms can switch from pure exporters to non-pure exporters, or vice versa. However, a firm might be pure exporters in one year and not in another year; though this transition is not frequent (the probability of transition from pure exporters to non-pure exporters is 25%, and the reverse direction is only 1.5%), it may still cause problems in the classification of different groups, so

Table 5 Estimates with control group: initial pure exporter

Firm R&D (log)	(1)	(2)	(3)
WTO indicator	0.246*** 8.93	0.25*** 8.77	0.282*** 6.14
Pure exporter indicator	0.24 1.36		
WTO indicator × pure exporter indicator	− 0.50** (− 2.74)	− 0.603** (− 3.08)	− 0.691** (− 3.35)
Industry output tariff	− 1.183*** (− 10.37)	− 1.838*** (− 7.47)	− 2.244*** (− 5.60)
Firm productivity (in log)	0.581*** 17.66	0.313*** 6.45	0.407*** 4.69
Firm size (in log)	0.466*** 57.34	0.584*** 18.42	0.639*** 12.55
Firm profit (in log)	0.345*** 64.36	0.197*** 19.57	0.204*** 12.6
SOE indicator	0.013 0.35	− 0.091 (− 1.10)	− 0.006 (− 0.05)
Foreign indicator	− 0.071*** (− 3.31)	0.053 0.56	0.116 0.86
Year-specific fixed effects	No	No	No
Firm-specific fixed effects	No	Yes	Yes
Number of observations	43,524	43,524	16,851
R^2	0.34	0.32	0.37

Notes (i) In column (1)–(3), pure exporters in the initial year served as the control group in the estimations so that there is no variation of the control group across years. (ii) Column (3) drops the firms who are non-exporters in the initial year. The simple average industry-level output tariff is computed at the CIC 4-digit level. (iii) Robust *t*-values are in parentheses. (iv) *** and ** denote 1 and 5% level of significance

we instead use the firms who are pure exporters in the initial year as control group in Table 5.[4] In column (3), we take a further step to drop those non-exporting firms in the initial years, because they were not affected by the tariff before WTO accession. It turns out that the number of observation drops a lot, but our previous main findings still hold well.

Still, our estimates thus far may suffer from some possible drawbacks as pure exporting firms (i.e. our control group) are not necessarily processing exporters, as some pure exporters may still only engage in ordinary trade although they sell their whole products abroad. To address such a concern, we use the merged data between firm-level production data and product-level custom data.

[4] We thank a referee for the suggestion.

3.2 Estimates with the Merged Sample

Thus far, all the estimations have used the full-sample, firm-level production data, which reports each firm's export status but not processing status. To understand whether a firm engages in processing trade, we need to merge the firm-level production data set and customs data set. With the merged data set, we are ready to examine the effect of input trade liberalisation on firm R&D using processing exporters as the control group. More importantly, it is well documented that some firms engage in processing trade and ordinary trade (Yu, 2015). Strictly speaking, such hybrid firms are not qualified to serve as the control group in our DID estimations, as their ordinary imports are also affected by further input trade liberalisation due to the WTO accession. We hence exclude hybrid firms from the control group and only keep pure processing firms to serve as the control group in the estimations.

However, as mentioned above, if pure processing firms and non-pure processing firms had significantly different levels of R&D before the WTO accession, the DID approach would be contaminated, since it could be that the R&D difference after the WTO accession indeed was not caused by trade liberalisation. To check this out, we first examine the mean of firm R&D for the two groups. As shown in the first module of Table 6, the log R&D difference between non-pure processing firms and pure processing firms before the WTO accession is statistically insignificant. Still, to make sure that pure processing firms are comparable to non-pure processing firms, we perform propensity score matching between pure processing firms and non-pure processing firms before the WTO accession. We use firm productivity, firm size (proxied by number of employees), firm capital, firm profit and firm ownership type as covariates. The lower module of Table 7 reports the results of the balance tests, in which the bias of all the chosen covariates is statistically insignificant and the overall bias of the specification is 3.2% with a fairly high p-value (0.28), suggesting that our chosen covariates work well. The low t-value confirms that, overall, the difference in the level of R&D for the two groups is not statistically significant before the WTO accession. Thus, it is safe to use the DID estimates with the merged sample.

The estimates reported in Table 7 use the merged data to explore the effect of WTO accession on firm R&D. To make the results with the new data set comparable to those in Table 4, the estimations in column (1) of Table 7 still use pure exporters as the control group. The negative and significant coefficient of the pure exporter indicator suggests that pure exporters have less R&D investment compared with non-pure exporters. The interaction between the WTO dummy and the pure exporter indicator also has a negative and significant term, indicating that non-pure exporters have more R&D investment after the WTO accession. These results are consistent with their counterparts in column (1) of Table 4.

The rest of Table 7 replaces the pure exporter indicator with the pure processing indicator, as firms' processing information is available in the merged data set. Column (2) yields similar results as those in column (1). We thus include firm-specific fixed effects and year-specific fixed effects in column (3). Accordingly, the WTO indicator and the pure processing indicator are absorbed away from the estimations. The

Table 6 Firm R&D before WTO accession: using merged sample

R&D (log)	Treatment: non-pure processing	Control: pure processing	Difference	*t*-value
Unmatched	12.39	12.53	− 0.14	− 1.25
Matched (ATT)	12.39	12.24	0.14	0.73

Balance tests

Merged	Firm productivity (in log)	SOE	FIE	Size (in log)	Capital (in log)	Profit (in log)
Treatment	1.159	0.109	0.287	6.143	10.551	7.997
Control	1.148	0.099	0.286	6.19	10.56	8.129
Bias (%)	4.8	3.8	0.3	− 3.6	− 0.5	− 6.2
t-value	1.41	0.66	0.06	− 0.73	− 0.10	− 1.30

Notes (i) ATT, average treatment for the treated. (ii) Robust *t*-values are in parentheses

interaction of the WTO indicator and the pure processing indicator is negative and significant, once again, suggesting that ordinary firms and hybrid firms have more R&D investment after the WTO accession. Finally, to rule out the possibility that non-pure processing firms have more R&D investment after the WTO accession because of other driving forces, such as output trade liberalisation and larger foreign market size, the estimates in columns (4) and (5) control for several other variables, as mentioned above. In particular, estimates in column (5) include importing countries' GDP weighted by their bilateral trade volume as an additional variable to capture the increase in access to foreign markets due to the trade liberalisation imposed by China's trading partners (Liu & Meissner, 2015). And it still yields results very close to those in column (3).

3.3 Placebo Tests

There may still be a concern about possible serial correlation, as the data sample is for 6 years (2001–2006). Bertrand et al. (2004) point out that some unobservable macroeconomic factors would generate a time serial problem in the error term, which could in turn lead to an upward bias in our key estimated coefficients. To address this potential challenge, following Bertrand et al. (2004), we conduct following placebo tests by first dividing our whole sample into two periods (i.e. before and after WTO accession), and take the mean average of each variable in the two periods to perform the first-difference estimations. Table 8 presents the new estimation results using this approach. The results are once again qualitatively identical and quantitatively close to their counterparts in Table 7.

Thus far, we have seen rich evidence that non-pure processing exporters have invested more in R&D after China's accession to the WTO than pure processing firms have. However, as mentioned above, non-pure processing exporters include

Table 7 Impact of WTO accession on firm R&D using merged data

Firm R&D (in log)	(1)	(2)	(3)	(4)	(5)
WTO indicator	0.437*** (7.74)	0.446*** (7.94)		0.349*** (5.50)	
Pure exporter indicator	– 0.685*** (– 3.65)				
Pure processing indicator		– 0.898*** (– 5.04)			
WTO indicator × pure exporter indicator	– 0.361* (– 1.79)				
WTO indicator × pure processing indicator		– 0.585*** (– 3.07)	– 0.708*** (– 3.40)	– 0.799*** (– 2.77)	– 0.533* (– 1.69)
Industry output tariff				(0.00) (– 0.64)	(0.01) (– 1.20)
Firm productivity (in log)				0.163* (1.65)	0.410*** (3.45)
Firm size (in log)				0.381*** (5.83)	0.539*** (6.60)
Firm profit (in log)				0.131*** (6.19)	0.239*** (9.26)
SOE indicator				0.373* (1.73)	0.31 (1.03)
Foreign indicator				(0.19) (– 0.88)	(0.25) (– 0.78)
Weighted world GDP (log)					0.072*** (3.68)
Year-specific fixed effect	No	No	Yes	No	Yes
Firm-specific fixed effect	No	No	Yes	Yes	Yes
Number of observations	18,208	18,208	18,208	12,285	8626
R^2	0.01	0.02	0.1	0.13	0.07

Notes (i) Robust *t*-values are in parentheses. (ii) *** and ** denote 1 and 5% level of significance

two types of firms: ordinary exporters and hybrid exporters. In addition to ordinary imports, hybrid firms also engage in processing imports, which are not affected by further cuts in import tariffs. Hence, there may be a concern that the effect of input trade liberalisation on ordinary exporters' R&D investment is underestimated in our previous exercises.

To address this potential pitfall, we drop hybrid firms from the sample. Accordingly, columns (1) and (2) of Table 9 use ordinary exporters as the new treatment group, whereas pure processing exporters still serve as the control group. The sample in Table 9 hence is about 40 per cent smaller compared with the sample in Table 8.

Table 8 Further estimates with two periods only

Firm R&D (in log)	(1)	(2)	(3)	(4)
WTO indicator	0.191*** (3.30)			
Pure processing indicator	– 0.898*** (– 5.04)			
WTO indicator × pure processing indicator	– 0.425**** (– 2.17)	– 0.850*** (– 3.80)	– 1.147*** (– 3.22)	– 0.971*** (– 2.63)
Industry output tariff			– 0.025*** (– 3.65)	(0.01) (– 0.57)
Firm productivity (log)			(0.01) (– 0.04)	(0.06) (– 0.28)
Firm size (log)			0.833*** (5.41)	0.19 (0.98)
Firm profit (log)			0.222*** (4.39)	0.170*** (2.93)
SOE indicator			0.27 (0.61)	0.59 (1.22)
Foreign indicator			0.73 (0.99)	1.41 (1.64)
Weighted world GDP (log)				(0.01) (– 0.19)
Year-specific fixed effects	No	Yes	No	Yes
Firm-specific fixed effects	No	Yes	Yes	Yes
Number of observations	11,678	11,678	7190	7190
R^2	0.01	0.11	0.14	0.2

Notes (i) Robust *t*-values are in parentheses. (ii) *** and ** denote 1 and 5% level of significance

Still, we see robust evidence that ordinary exporters have more R&D investment after the WTO accession than pure processing exporters do.

Furthermore, the sample with positive R&D accounts for only 20% of the whole sample in the firm-level data set. This generates a large number of missing values when taking the log in our estimations. To handle the 'missing' R&D issue, we replace observations with missing R&D values with zero. In this way, we are able to perform Tobit estimation in columns (3) and (4) of Table 9, in which non-pure exporters are still used as the treatment group. The numbers of observations in columns (3) and (4) increase about ninefold compared with those in columns (1) and (2). Nevertheless, our key findings still hold firmly: non-pure processing firms invest more in R&D after the WTO accession. However, treating missing R&D as zero may cause unknown bias and enlarge the magnitude of the coefficient. Inspired by Santos Silva and Tenreyro (2006), we then use Poisson pseudo-maximum likelihood (PPML) regression to deal with zero and missing R&D in column (5).[5] The interaction term coefficient is still significantly negative though the magnitude decreases a little.

[5] We thank a referee for such suggestions.

Table 9 Estimates with ordinary firms only in control group

Firm R&D (in log)	Treatment group: ordinary firms		Tobit estimates with zero R&D		PPML
	(1)	(2)	(3)	(4)	(5)
WTO indicator	0.278 (1.56)	0.327* (1.89)	− 0.227 (− 0.53)	− 0.664 (− 1.27)	1.002*** [0.001]
Pure processing indicator	0.095 (0.55)	0.133 (0.78)	3.001*** (5.28)	5.704*** (8.28)	− 0.716*** [0.001]
WTO indicator × pure processing indicator	− 0.314** (− 1.69)	− 0.374** (− 2.07)	− 2.307*** (− 3.90)	− 1.724** (− 2.43)	− 0.059*** [0.001]
Industry output tariff				− 0.097*** (− 8.15)	− 0.016*** [0.000]
Firm productivity (log)		1.602*** (25.26)		4.410*** (14.81)	1.000*** [0.000]
Firm size (log)				5.415*** (60.42)	
SOE indicator	0.293*** (3.25)	0.322*** (3.66)	10.623*** (18.47)	4.701*** (7.54)	− 0.644*** [0.001]
Foreign indicator	− 0.357*** (− 8.48)	− 0.455*** (− 11.03)	− 8.400*** (− 42.98)	− 6.124*** (− 28.89)	− 0.182*** [0.000]
Year-specific fixed effects	Yes	Yes	Yes	Yes	Yes
Firm-specific fixed effects	Yes	Yes	No	No	No
Treatment group	Non-processing firms	Non-pure processing firms	Non-pure processing firms		
Number of observations	12,684	12,676	137,957	106,025	13,795

Notes (i) Robust t-values are in parentheses in columns (1)–(4), whereas robust standard errors are in the squared brackets (iii) Columns (3) and (4) regress on log R&D by Tobit estimations in which we replace the regress and for firms with missing R&D expenses with zero

(iii) Column (5) regresses on firm R&D by Poisson pseudo-maximum likelihood estimation and keeps only the observations with positive R&D, so the sample drops significantly. (iv) *** and **denote 1 and 5% level of significance.

Still, it is possible that large firms have more R&D investment. Accordingly, firms with more R&D expenses are not necessarily more innovative. This tells us that it is reasonable to control for firm size directly. In addition to including the number of employees (as a proxy for firm size) in the regressions, we replace firm log R&D with firm R&D intensity, defined as a firm's R&D expenses over its sales, in the estimates in Table 10. We start off our regressions using full-sample, firm-level data in which the only information available is pure exporting status. The results are consistent with their counterparts in Table 4. Finally, we use the merged data set, which provides information on firms' pure processing status. After controlling for several other variables, the interaction term between the WTO indicator and the pure processing indicator is negative and significant at the conventional statistical level, confirming that input trade liberalisation leads to firm R&D growth after China's accession to the WTO.

3.4 Robustness Checks[6]

We use the WTO indicator to distinguish firm's different response to input trade liberalisation before and after China's WTO accession. A caveat here is the WTO indicator mainly captures the impact of WTO accession which includes not only input trade liberalisation but also some other forces such as the increased FDI inflow. To address such a concern, in our estimates, we have already included both year-specific effects to wash out time-variant factors such as RMB appreciation and firm-specific effects to control for firm-variant factors. However, for the sake of completeness, we perform further robustness checks by replacing our original treat variable, the WTO indicator, with imported input tariff in Table 11. Following Topalova and Khandelwal (2011) and Yu (2015), we construct an industry-level input tariff, IIT, which is measured at 4-digit Chinese industry level as below:

$$IIT_{ft} = \sum_n \left(\frac{input_{nf}^{2002}}{\sum_n input_{nf}^{2002}} \right) \bullet \tau_{nt}$$

where $input_{nf}{}^{2002}$ is the total input value of industry n used by industry f in 2002, whereas $s_n t$ is the import tariff of product n in year t. Data on industrial inputs are from China's input– output table (2002). Inspired by Topalova and Khandelwal (2011), the input weight for each industry is fixed at the initial period to avoid possible endogeneity between input tariffs and imported input volume.

Table 11 reports our estimation results. Column (1) shows that a decrease in industry input tariff leads to an increase in firm R&D, which is consistent with previous finding. Estimates in column (2) control for the industry output tariff

[6] We thank a referee for such suggestions.

Table 10 Impact on R&D intensity

Sample	Full sample			Merged sample	
R&D intensity	(1)	(2)	(3)	(4)	(5)
WTO indicator	0.004 (0.47)		0.079^{***} (11.63)	− 0.006 (− 0.13)	
Pure exporter indicator	− 0.018 (− 0.61)	0.008 (0.26)	0.046 (1.53)		
WTO indicator × pure exporter indicator	-0.054^{*} (− 1.71)	-0.078^{**} (− 2.48)	-0.052^{*} (− 1.73)		
Pure processing indicator				0.175^{**} (2.55)	0.176^{**} (2.56)
WTO indicator × pure processing indicator				-0.135^{*} (− 1.88)	-0.136^{*} (− 1.90)
Industry output tariff	-0.001^{***} (− 5.20)	-0.001^{***} (− 3.91)	0.000 (0.56)	-0.005^{***} (− 5.92)	-0.005^{***} (− 5.94)
Firm profit (log)	0.035^{***} (34.24)	0.031^{***} (30.15)	− 0.001 (− 0.61)		
Firm size (log)	0.033^{***} (18.02)	0.039^{***} (20.63)	0.030^{***} (5.42)		
Firm productivity (log)				0.130^{***} (6.05)	0.130^{***} (6.04)
SOE indicator	0.151^{***} (14.67)	0.141^{***} (13.65)	-0.042^{*} (− 1.69)	0.318^{***} (5.93)	0.317^{***} (5.91)
Foreign indicator	-0.052^{***} (− 11.75)	-0.082^{***} (− 18.18)	− 0.010 (− 0.47)	-0.127^{***} (− 9.52)	-0.127^{***} (− 9.46)
Year-specific fixed effect	Yes	Yes	Yes	No	Yes
Firm-specific fixed effects	No	No	Yes	Yes	Yes
Industry-specific fixed effects	No	Yes	No	No	No
Number of observations	323,933	323,933	323,933	79,342	79,342
R^2	0.01	0.01	0.001	0.01	0.01

Notes (i) Robust *t*-values are in parentheses. (ii) *** and ** denote 1 and 5% level of significance

Table 11 Intermediate input tariff and firm R&D

Firm R&D (in log)	(1)	(2)	(3)	(4)
Industry input tariffs	− 0.116*** (− 32.60)	− 0.029*** (− 3.76)	− 0.032*** (− 3.82)	− 0.023** (− 2.48)
Industry output tariffs		0.001 0.83	0.001 0.43	− 0.001 (− 0.63)
Firm productivity (in log)			0.132** 2.57	0.128** 2.01
Firm size (in log)			0.445*** 12.99	0.433*** 9.99
Firm profit (in log)			0.134*** 12.28	0.127*** 9.2
SOE indicator			0.1 1.16	0.198* 1.84
Foreign indicator			0.04 0.4	− 0.03 (− 0.19)
Year-specific fixed effect	Yes	Yes	Yes	Yes
Firm-specific fixed effects	Yes	Yes	Yes	Yes
Years covered	2001–2006	2001–2005		
Number of observations	57,111	42,587	37,303	27,260
R^2	0.02	0.08	0.02	0.06

Notes (i) Robust *t*-values are in parentheses. (ii) *** and ** denote 1 and 5% level of significance

whereas those in column (3) add more firm characteristics such as firm productivity and firm size. Our last estimates in column (4) drop observations in 2006 to rule out the possible impact of the termination of the Multi Fibre Agreement (MFA). In all estimates, we see that input tariff reductions boost firm R&D expenses.

4 Concluding Remarks

This paper considered how trade liberalisation on imported intermediate inputs affects firm innovation. The analysis took advantage of the fact that processing imports in China are duty free. Further trade liberalisation after WTO accession should not have an impact on processing imports. We thus used processing firms as a control group to employ difference-in-difference estimations. Our extensive empirical search found that non-processing firms have more R&D after China's accession to the WTO, suggesting that input trade liberalisation has boosted firm innovation since China acceded to the WTO.

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Input Trade Liberalization and Import Switching: Evidence from Chinese Firms

Wei Tian and Miaojie Yu

1 Introduction

Since entering the World Trade Organization (WTO) early this century, China has experienced remarkable trade opening. The country's simple average tariff dropped from 15.3% in 2001 to 7.5% in 2017. China's trade liberalization brought huge changes in foreign and domestic markets, including the rising quality and value added imbedded in exports and imports. China's exports have increased rapidly, as noted by many studies in the literature. Increasing imports, which take off later than exports, will be the next benefit of China's opening-up strategy. China is the second largest importing country, and its annual imports increased by more than four times between 2000 and 2016. The Chinese government has launched several policies and activities to promote imports, especially consumption goods, including holding the first China International Import Exposition and further reducing the simple average tariff to 7.5% in late 2018.[1]

Chinese firms have adjusted their strategies in response to the more liberalized circumstances. The firms are more active in importing and exporting, invest more in research and development (R&D), and are changing their importing and exporting decisions. For example, Liu and Qiu (2016) argue that input trade liberalization

W. Tian
School of International Trade and Economics, University of International Business and Economics (UIBE), Beijing, China

M. Yu (✉)
National School of Development, China Center for Economic Research, Peking University, Beijing, China
e-mail: mjyu@ccer.pku.edu.cn

[1] According to the executive meeting of the State Council on September 26, 2018, chaired by Premier Li Keqiang of the State Council.

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hampers firm R&D in China. Tian and Yu (2016, 2017) find that Chinese firms have increased export intensity (i.e., the ratio of exports to domestic sales) as a response to input liberalization.

Among the various changes, the change in import sources is rarely studied, although it may have an important impact on the map of international trade. Chinese firms that used to import a large pro- portion of inputs from developing countries are switching to imports from developed countries. This is happening not only because of the decline in processing trade in China, but also to meet the needs of firm innovation and product upgrading. Many studies have documented that input tariff reduction encourages import scope and import quality and lowers import prices, which further drives innovation and leads to productivity and welfare gains, but the link behind this process is complicated and controversial. In this paper, we shed some light on the first step of firms' reaction to reduced input tariffs, that is, how firms adjust their import sources and quality.

The paper shows that firms have engaged in import source switching and the importance of import quality a Fan et al. (2015). We use a matched data set of comprehensive transaction-level trade and firm production data to generate a firm-level input tariff index, following Yu (2015). We further distinguish the tariff imposed on developing country import sources. We find that, instead of promoting imports from developing countries, the reduction in the tariff on developing country sources has enhanced the shift of import sources toward developed countries. This finding suggests a strong cost-saving effect of input trade liberalization. We further investigate the heterogeneous impacts on firms with different levels of productivity, and show that less productive firms are more largely influenced to switch import sources than more productive firms. This impact is also true for firms in high-technology industries and engaged in intensive innovation. To figure out the driving force of the switching, we examine the impacts on different types of importers and find that most switching has happened to new importers. This suggests that, as tariffs are reduced, more domestic firms are stimulated to start importing high-quality inputs from developed countries to replace domestic inputs.

An important alternative explanation for source switching might be the decline of processing trade in China since 2005. As Brandt and Morrow (2017) argue, to some extent, this decline can be attributed to the reduced input tariff, which decreases the opportunity cost of engaging in ordinary trade. This effect is unlikely to be important here, given that the sample ends in 2006, the starting year of the decline in import-processing trade. We also compare capital-intensive and labor-intensive industries, and processing firms and capital goods-intensive importers to exclude the effect of the decline in import-processing trade. We use the difference in the tariff as an instrumental variable to control for endogeneity in the first-difference regressions, following Trefler (2004). The switching happens not only in the intensive margin, but also in import scope. We show that input tariff reduction leads to greater import scope from developed countries, and this finding is robust to different measures of import variety and different types of firms.

To verify the mechanism of quality upgrading, we first generate a quality measure, following Khandelwal (2010), which handles the impact on market price of idiosyncratic demand shock. We take a further step to measure the quality function separately for ordinary firms and processing firms. The impact shows that firm profit and relative import quality from developed country origins increase as the input tariff decreases, suggesting that firms import higher quality goods from developed countries, outpacing imports from developing countries.

This paper is linked to the emerging literatures on imported intermediate inputs, innovation, and trade liberalization. The literature documents that imported intermediate inputs have a strong impact on various dimensions of firm performance, including productivity (Amiti & Konings, 2007; Choi & Hahn, 2013; Kasahara & Rodrigue, 2008; Topalova & Khandelwal, 2011; Yu, 2015), exports (Bas & Strauss-Kahn, 2014; Kasahara & Lapham, 2013; Navas, Serti, & Tomasi, 2013), product scope (Goldberg et al., 2010), quality (Fan et al., 2015), and outcomes in downstream markets, like pricing and exchange rate pass-through (Bernini & Tomasi, 2015). Changes in these dimensions have had enormous effects in improving productivity. For example, a wide range of studies find that input trade liberalization is the strongest factor promoting productivity growth. Amiti and Konings (2007) and Topalova and Khandelwal (2011) show that, compared with output liberalization, input trade liberalization contributes two to 10 times more to productivity growth. Kasahara and Rodrigue (2008) find productivity gain for Chilean firms that import intermediate goods. Yu (2015) confirms this finding, using Chinese data and considering processing trade. Input liberalization boosts firm productivity through several channels, including enhancing input quality, augmenting competition, and increasing input varieties.

These findings have stimulated research on the mechanisms through which imported intermediate inputs boost productivity. A large volume of research finds that productivity and welfare gains can be explained by the increase in firm innovation, quality upgrading, and invention of new products, which are encouraged by increasing imported intermediate imports, especially new imported varieties (Arkolakis, Demidova, Klenow, & Rodriguez-Clare, 2008; Broda & Weinstein, 2006; Feenstra, 1994; Klenow & Rodriguez-Clare, 1997). Such mechanism may also act dynamically in the long run, through further expansion of domestic input scope led by more imported varieties. For example, Halpern, Koren, and Szeidl (2011) find that increased variety of intermediates generates productivity gain among Hungarian firms. Goldberg et al. (2009), Goldberg et al. (2010) find that firms that are exposed to stronger input tariff reductions are more likely to introduce new products and invest in R&D because of the newly available imported inputs, and 31% of firms' product expansion could be attributed to the decline in input tariffs.

New imported inputs may promote innovation and productivity in several ways. The conventional argument is that production technology responds to variety, such that increasing input varieties reduces cost (Gopinath & Neiman, 2014; Kasahara & Lapham, 2013). Based on this assumption, Feenstra (1994) develops a measure of the welfare gain from more input varieties. Using data on 20 countries over 20 years, Broda and Weinstein (2004, 2006) show that the increase in imported varieties caused by input trade liberalization reduces import prices, which in turn generates welfare gain. Other literature highlights the spillover effect of the advanced technology and higher quality embedded in new imported inputs. Coe and Helpman (1995) and Keller (2002) verify the spillover effect empirically by using country-level data. Seker, Rodriguez-Delgado, and Mehmet (2015) illustrate the spillover effect theoretically. Our paper enriches understanding of the input quality channel, by demonstrating the resource changes and quality improvement that result from imported intermediate inputs. We find that firms switch from importing inputs from developing countries to importing inputs from developed countries as input tariffs are reduced. The effect is most pronounced for new importers, suggesting a higher probability of spillover from the increase in high-quality imported inputs.

Studies on how input cost reduction affects firm imports have drawn less attention than the research on output and exports, but studies on input cost reduction provide more direct evidence on how firms adjust and the effects on innovation and productivity. The change in import source is also the beginning of changes in all follow-up firm behaviors, and how firms react in imports is critical for understanding the impact of trade. Bas and Strauss-Kahn (2015) find a robust and significant increase in import and export prices among Chinese firms that experienced input tariff reduction, and the results are significant for firms sourcing imports from and selling output to developed countries. From the perspective of how import origin changes, our paper highlights the increasing use of high-quality inputs imported from developed countries as a major approach of firms that exploit input tariff reduction to upgrade quality. Furthermore, we suggest that trade distribution might be reshaped as a consequence.

The paper also fits into the literature on quality upgrading and firm innovation in China. Liu and Qiu (2016) argue that input trade liberalization hampers firm R&D in China, while Tian and Yu (2017) find the opposite effect. Lim, Trefler, and Yu (2018) examine firm innovation in China and find that, overall, Chinese firms intensify their innovation once they are exposed to stronger competition and face larger market size. Feng et al. (2016) demonstrate that product upgrading in imported inputs helped Chinese firms to increase their presence in export markets. They estimate the benefit of increased use of imported inputs on firm exports, and find that firms benefit most when the intermediate inputs are purchased from higher-income countries, facilitating exports to the presumably more demanding developed markets. In contrast to these papers, our work studies the resulting changes in China's import structure, which is important for the country's all-around opening-up strategy since 2017.

The findings of this paper are also important for understanding the changes in global trade flows associated with liberalization. As the second largest importing country, China's opening-up not only affects China's trade, but also the distribution of trade flows across regions in the world. If trade liberalization in China boosts more trade between China and developed countries disproportionally, more unparalleled changes between developed and developing countries—such as in labor markets and welfare—can be expected to happen as a consequence.

The rest of the paper is organized as follows. Section 2 discusses the details of the data and data sources. Section 3 presents the empirical findings. Section 4 concludes.

2 Data and Measurement

The data used in the paper are a combination of two disaggregated data sets: the annual survey of manufacturing firms in China and customs transaction-trade data. The two data sets provide rich in- formation on firm production and trade. We take the data from 2000 to 2006, the period when Chinese input tariffs dropped most significantly. This section presents a brief introduction to the data.

2.1 Chinese Firm-Level Production Data

The annual survey of manufacturing firms is carried out and maintained by China's National Bureau of Statistics. The survey includes all state-owned enterprises and non-state-owned enterprises whose annual sales exceed RMB 5 million (U.S.$830,000). The data cover complete information from three major accounting statements (i.e., balance sheet, profit and loss account, and cash flow statement), including firm output, profit, R&D, and inputs of labor, capital, intermediate inputs, and so on.

We started by applying stringent filters to clean the data, especially to exclude noisy and misleading data from the samples as a result of misreporting by some firms. We followed the criteria in Feenstra et al. (2014) to omit outliers. First, we dropped observations where key financial variables were missing (such as total assets, net value of fixed assets, sales, and gross value of the firm's output productivity). Second, firms with fewer than eight workers were removed, since those firms fall below the legal regime, as mentioned in Brandt et al. (2012).

Next, we screened the data according to the basic rules of the Generally Accepted Accounting Principles. Observations were excluded if any of the following were found: (1) liquid assets were greater than total assets, (2) total fixed assets were greater than total assets, (3) the net value of fixed assets was greater than total assets, (4) the firm's identification number was missing, or (5) the date when the firm was established was invalid (e.g., the opening month was later than December or earlier than January). The data were reduced by about 50% for each year to guarantee quality under the strict cleaning.

We exclude trading companies from the sample in all estimations to ensure the preciseness of the estimations. In particular, firms named with any Chinese characters for a trading company and importing and exporting companies are excluded.

2.2 Chinese Production-Level Trade Data

The transaction-trade data are extremely disaggregated, at the Harmonized System (HS) eight-digit product level, obtained from China's General Administration of

Customs. The data set records rich in- formation on each export or import transaction for all trading firms, including trading price, quantity, value, and trade mode, which distinguishes processing trade from ordinary trade. From these data, we know the import value of each product from each original country, which we further use to construct the firm average input tariff.

We merged the manufacturing firm data and customs data. We used the firms' name–year, zip code, and the last seven digits of the telephone number to merge the two data sets. The merged data skew toward large firms, as the matched sample has more exports, more sales, and more employees. The details of the approach are introduced in Yu and Tian (2012) and Yu (2015).

2.3 Measurement of Firm-Level Tariffs

Using the trade data, we measure the average intermediate input tariff faced by a single firm, as in Yu (2015). The firm-specific input tariff index is based only on nonprocessing imports (O), given that processing imports enjoy free duty in China, as follows:

$$FIT_{it} = \sum_{k \in O} \frac{m_{ik,initial\_year}}{\sum_{k \in M} initial\_year} \tau_{kt}$$

where $m_{ik,initial\_year}$ is firm i's imports of product k in the first year the firm appears in the sample. M is the set of the firm's total import varieties. The import weight for each product in the index is fixed at the firm's initial year in the sample to avoid endogeneity, following Topalova and Khandelwal (2011). Because imports might be reduced to zero by prohibitive tariffs, using import weights measured in current period firm tariffs would generate a downward bias.

To capture precisely the impact of input trade liberalization on imports from developing countries, we decompose imports from developing countries and construct the import tariff based on developing country sources using a similar approach. The weight in the following index is the import share of each import from developing countries.

$$FIT_{it}^{poor} = \sum_{k \in O} \frac{m_{ik,initial\_year}^{poor}}{\sum_{k \in M} m_{ik,initial\_year}^{poor}} \tau_{kt}$$

To fit with the related empirical literature, we also consider two dimensions of trade liberalization other than input tariff reduction, following Goldberg et al. (2010) and Topalova and Khandelwal (2011): (i) home (i.e., China) tariff cuts on final products, such as textiles and garments, namely output tariffs; and (ii) tariff cuts in the foreign destination country (i.e., the United States), namely, external tariffs. The first dimension increases competition in the home market, and the second dimension enlarges markets. The output and external tariffs are generated at the two-digit

Chinese Industry Classification (CIC) industry level. We average the tariffs of the HS six-digit products within each CIC two-digit industry code according to Amiti and Konings (2007).

We begin by showing some stylized facts on input tariffs and the pattern of imports. Figure 1 shows the correlation between the import share from developing countries and the input tariff. A positive correlation implies that input tariff reduction is associated with lower import scope share and value share from developing countries, which is consistent with our finding that imports are switched to developed countries as input trade liberalization occurs. In Figure 2, we demonstrate the time trend of imports from developing and developed countries. Imports from both sources increased rapidly after China entered the WTO; however, as trade opens up, imports from developed countries are always greater than those from developing countries, and the gap is increasing as well.

Table 1 presents the summary of statistics for the major variables used in the empirical analysis. On average, firms import 28% of the imported inputs from developing countries and firms import greater product scope from developed countries than from developing countries.

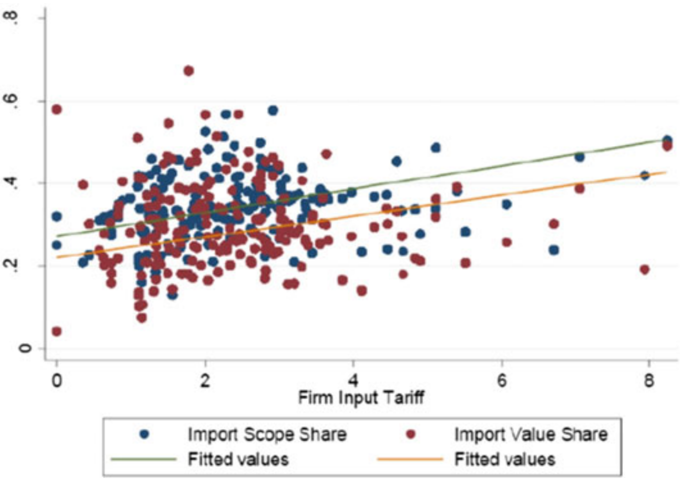

Fig. 1 Firm input tariff, import scope, and import value. *Note* Firm input tariffs are measured in percentage (horizontal axis). [Colour figure can be viewed at wileyonlinelibrary.com]

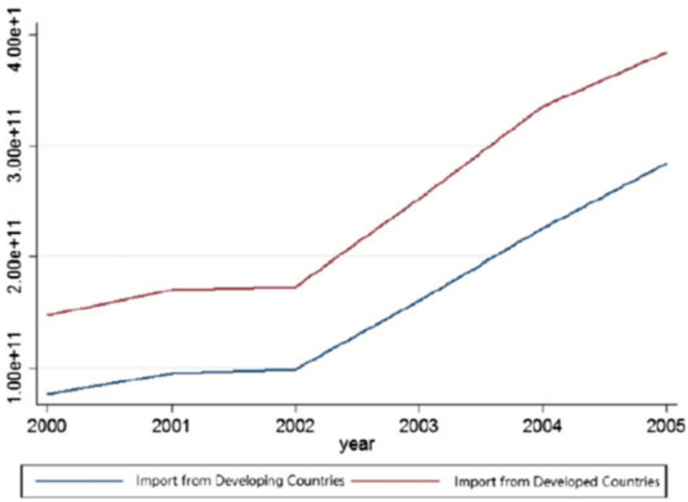

Fig. 2 Imports from developed and developing countries. *Note* Numbers in vertical axis are in dollar. [Colour figure can be viewed at wileyonlinelibrary.com]

Table 1 Summary statistics

Variable	Mean	Std. Dev
Log firm labor	5.456	1.167
Firm TFP (Olley–Pakes)	1.122	0.382
Foreign indicator	0.569	0.495
SOE indicator	0.021	0.142
Log firm import	12.018	2.954
Import share from developing countries	0.281	0.378
Firm product–country import scope	17.664	44.532
Firm product–country import scope from developed countries	15.343	35.507
Firm product–country import scope from developing countries	8.372	21.024
Home input tariff (firm level)	3.24	5.922
Home input tariff from developing countries	1.379	3.724
Home output tariffs (industry level)	0.117	0.056
Foreign tariffs (industry level)	0.096	0.048

3 Empirical Findings

Before we start the firm-level estimation, we first use the transaction-level customs-trade data to take a preliminary look. In Table 2, we regress import value on the product-level input tariff. We control for firm total factor productivity (TFP), using Olley and Pakes' (1996) approach, following Yu (2015), where we take into account firm export status and trade mode in the estimated productivity function. We use system generalized method of moments (GMM) and its normalization as an alternative measurement of TFP in the robustness checks later in the paper. In column (1) of Table 2, after controlling for industry-level output tariffs and tariffs charged by foreign countries, we show that a lower input tariff is associated with a higher import value. In columns (2) and (3), we separate the samples into two groups: imports from developed countries and developing countries, respectively. The results show that input tariff reduction favors imports from developed countries more than those from developing countries, suggesting that the import share from developed countries may be enhanced. In columns (4) and (5), we control for firm fixed effects, and the results are similar.

To explore firm behavior, we use firm-level data to examine how input tariff cuts affect import sourcing from developing and developed countries. We are interested in the resulting effect on the import share from developed countries. We also separate the tariff on developing country sources from the conventional average tariff, to compare the impacts of boosting imports from developed countries and developing countries. The following equation expresses our benchmark empirical specification, where $impshare^{rich}$ is the import share from developed countries of firm i in year t, $FIT_{it}{}^{poor}$ is the average import tariff of firm i in year t for imports from developing countries (constructed earlier), φ_{it} is the productivity of firm i in year t, X_{jt} is the industry-level output tariff and external tariff of firm i in industry j and year t, ω_i and η_t are firm-level and year-level fixed effects, respectively, and μ_{it} is the firm-level idiosyncratic shock.

$$impshare_{it}^{rich} = \beta_0 + \beta_1 FIT_{it}^{poor} + \beta_2 FIT_{it}^{poor} \times \varphi_{it} + \beta_3 \varphi_{it} + \\ \theta X_{jt} + \omega_i + \eta_t + \mu_{it}$$

We report the results of the benchmark regressions in Table 3. In column (1), the import share from developed countries increases as the import tariff on developing country imports decreases. This suggests a switch of imports from developing countries to imports from developed countries, led by input tariff reduction on developing countries. In columns (2) and (3), we introduce firm productivity to control for its impact on firm imports. In column (2), we use the system GMM method to estimate TFP, and in column (3), we normalize the TFP to range from 0 to 1 to make it comparable across industries. The impact is still significant and robust. In column (4), we add the interaction term of input tariff and TFP, and we find the impact of tariff

Table 2 Preliminary estimation

Regressand	(1)	(2)	(3)	(4)	(5)
Import value (HS6D Level)	All	From developed countries	From developed countries	From developed countries	From developed countries
Home input tariff (Product level)	− 0.036*** (−135.82)	− 0.037*** (−119.77)	− 0.033*** (−64.31)	− 0.031*** (−98.99)	− 0.025*** (−47.57)
Home output tariffs (Industry level)	− 1.483*** (−33.15)	− 1.487*** (−27.98)	− 1.181*** (−13.87)	1.274*** (12.60)	0.076 (0.4)
Foreign tariffs (Industry level)	0.837*** (14.89)	0.519*** (7.77)	1.554*** (14.72)	− 0.135 (−1.43)	− 0.411** (−2.46)
Firm TFP (Olley–Pakes)	0.376*** (85.89)	0.369*** (74.89)	0.405*** (42.05)	0.002 (0.24)	0.019 (0.81)
Foreign indicator	− 0.479*** (−96.57)	− 0.437*** (−70.75)	− 0.541*** (−63.98)	0.051 (1.58)	0.139 ** (2.10)
SOE indicator	− 0.143*** (−8.42)	− 0.031 (−1.4)	− 0.276*** (−10.47)	− 0.145** (−2.03)	− 0.067 (−0.66)
Log firm labor	0.187*** (181.64)	0.201*** (166.48)	0.147*** (71.41)	0.248*** (29.33)	0.066 *** (3.4)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	Yes	Yes
R^2	0.0619	0.0603	0.0641	0.0174	0.0136
Observations	3,747,538	2,741,321	1,006,217	2,741,321	1,006,217

Note Numbers in parentheses are robust t values. *, **, *** Denote significance at the 10%, 5%, and 1% levels, respectively reduction is more pronounced for firms with lower productivity. The reason might be that firms with higher productivity were less financially constrained by the high level of input tariffs before the tariff reduction. In columns (5) and (6), we replace TFP measurement with a dummy indicating high TFP firms if their TFP measure is greater than the industry mean. We redo the regressions in columns (3) and (4), and the results are unchanged.

In Table 4, we investigate the mechanism behind the results. First, we check whether the impact exists for firms in all industries owing to cost saving, or whether the tariff cut only enables firms in high-skill industries to innovate and upgrade production. We examine the impact on skill-intensive firms in the first three columns in the table. In column (2), we use samples with positive R&D, and in column (3), we look at firms with a positive number of patents. The results show that the impact is similar for skill-intensive firms to the overall firms shown in column (1), indicating that upgrading exists universally.

Next, we regress by firm import status to find the strongest driving party. In columns (4) to (6), we regress for new importers, always importers, and importers who exit in the next year. The results show that the impact on new importers is more pronounced than on the other two types of firms. This finding provides a hint that input tariff reduction encourages more firms to start importing from developed countries than developing countries. This result is consistent with previous findings that highlight the effect on adjustment at the extensive margin under trade liberalization (Bernard et al., 2007).

However, the results could also be driven by the decline of processing trade. Brandt and Morrow (2017) argue that China's processing trade has declined since 2005, because input tariff reduction reduces the opportunity cost of doing ordinary trade. To nullify this channel, we separate the samples into labor-intensive and capital-intensive industries, given that processing trade is more concentrated in labor-intensive industries. The results in Table 5, columns (1) and (2), are significant, and the economic magnitudes are close. Furthermore, we check the effect on processing firms and capital goods importers separately in columns (3) and (4), where we still find a consistent and robust result, as in previous studies. All the findings suggest that the processing trade is not a challenge to our interpretation.

Next, we study the impact of input tariff reduction on firm imports from the extensive margin, namely, import scope. Product variety is defined at the product–country level, and the estimation results are shown in Table 6. In the first two columns, we regress, respectively, the import scope from poor countries on input tariffs by using negative binomial estimation to deal with the count data issue. We find that when input tariffs decrease, import scope from poor countries is squeezed out. This verifies our argument that input trade liberalization fosters firms to switch importing from developing countries to developed countries, from the extensive margin.

To show the negative nexus between firm tariffs on poor countries' inputs and firm's import share from rich countries more directly, in column (3) we regress the import share from rich countries on input tariffs, and in column 4 we use the Tobit method instead of ordinary least squares to correct the bias from sample truncation, and we also find a robust result. Moreover, most of the Chinese imports are from Asian

Table 3 Benchmark regressions

Regressand: Rich import share	(1)	(2)	(3)	(4)	(5)	(6)
TFP measure	System TFP		Relative TFP		High TFP indicator	
Firm tariffs on poor inputs	-0.013^{***} (−24.98)	-0.013^{***} (−24.98)	-0.011^{***} (−15.19)	-0.018^{***} (−7.13)	-0.011^{***} (−15.18)	-0.013^{***} (−11.87)
Firm tariffs on poor inputs × Firm TFP				0.024^{***} (2.82)		0.003^{**} (2.23)
Industry output tariff	− 0.053 (−0.84)	− 0.055 (−0.86)	− 0.130 (−1.51)	− 0.130 (−1.50)	− 0.129 (−1.50)	− 0.131 (−1.52)
Industry external tariff	− 0.059 (−0.95)	− 0.058 (−0.95)	− 0.054 (−0.56)	− 0.053 (−0.55)	− 0.055 (−0.57)	− 0.054 (−0.57)
Firm TFP		-0.014^{*} (−1.73)	− 0.044 (−0.60)	− 0.076 (−1.03)	− 0.002 (−0.34)	− 0.007 (−1.02)
Observations	37,661	37,534	29,275	29,275	29,379	29,379
R^2	0.05	0.05	0.05	0.05	0.05	0.05
Number of party_id	23,194	23,132	22,338	22,338	22,405	22,405
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Note Numbers in parentheses are robust t-values. *, **, *** Denote significance at the 10%, 5%, and 1% levels, respectively

Table 4 More specifications: by firm type

	(1)	(2)	(3)	(4)	(5)	(6)
					Type of importers	
Regressand: Rich import share	All	Positive R&D	Positive patent	New	Always	Exiters
Firm tariffs on poor inputs	− 0.013*** (−24.98)	− 0.011*** (−5.84)	− 0.011*** (−4.87)	− 0.018*** (−9.96)	− 0.009*** (−12.58)	
Firm tariffs on poor inputs (one lag)						− 0.016 (−1.43)
Industry output tariff	− 0.055 (−0.86)	− 0.097 (−0.36)	0.178 (0.56)	0.052 (0.21)	0.015 (0.18)	− 1.235 (−0.72)
Industry external tariff	− 0.058 (−0.95)	− 0.071 (−0.31)	− 0.510* (−1.66)	0.305 (1.00)	− 0.195*** (−2.66)	− 2.385 (−1.40)
Firm TFP	− 0.014* (−1.73)	0.008 (0.23)	0.058 (1.14)	− 0.004 (−0.13)	− 0.019* (−1.78)	0.128 (0.59)
Observations	37,534	4357	2567	18,935	18,599	1648
R^2	0.05	0.06	0.07	0.09	0.03	0.31
Number of party_id	23,132	3331	1933	17,499	11,286	1580
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Note Numbers in parentheses are robust *t*-values. *, **, ***Denote significance at the 10%, 5%, and 1% levels, respectively

Table 5 More specifications: by sector

	(1)	(2)	(3)	(4)
	Intensive sector			
Regressand: Rich import share	Labor	Capital	Processing	Capital goods
Firm tariffs on poor inputs	-0.011^{***} (−13.85)	-0.014^{***} (−20.95)	-0.013^{***} (−18.49)	-0.013^{***} (−8.05)
Industry output tariff	− 0.145 (−1.14)	− 0.035 (−0.45)	− 0.008 (−0.09)	− 0.171 (−0.82)
Industry external tariff	− 0.162 (−1.22)	− 0.050 (−0.70)	− 0.020 (−0.23)	− 0.302 (−1.02)
Firm TFP	− 0.005 (−0.35)	-0.019^{*} (−1.80)	− 0.011 (−0.91)	-0.083^{**} (−2.32)
Observations	11,325	26,209	26,449	3358
R^2	0.06	0.05	0.05	0.06
Number of firms	7002	16,223	18,136	2155
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Note Numbers in parentheses are robust t-values. *, **, *** Denote significance at the 10%, 5%, and 1% levels, respectively

Table 6 Estimation on import scope

	(1)	(3)	(4)	(6)	(7)
Regressand: Firm import scope (product–country)	Poor only	Poor only	Import scope share	From rich	Import scope share from East Asian Rich to East Asian Rich & ASEAN
Method	OLS	OLS	OLS	Tobit	OLS
Firm tariffs on poor inputs	0.010^{**} (2.26)	0.014^{***} (4.16)	-0.005^{***} (−4.87)	-0.003^{***} (−5.27)	-0.002^{***} (−2.71)
Industry output tariff	-2.227^{***} (−5.78)	− 0.057 (−0.19)	0.313^{***} (3.26)	0.144^{***} (2.77)	− 0.079 (−1.21)
Industry external tariff	− 0.010 (−0.02)	0.274 (1.05)	− 034 (−0.27)	0.014 (0.24)	− 0.049 (−0.85)
Other controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No	Yes
Observations	12,902	6,315	11,693	11,693	8,251

Note Numbers in parentheses are robust t-values. *, **, *** Denotes significance at the 10%, 5%, and 1% levels, respectively countries, among which Association of Southeast Asian Nations (ASEAN) countries are the most important import-processing sources. ASEAN free trade agreement tariffs have dropped significantly, and trade was largely boosted. So, to exclude the impact through the decline in processing trade, we regress the import scope share from rich Asian countries in addition to that from ASEAN countries. Similar to our previous finding, we find that input tariff reduction for poorer countries promotes firms to import more from rich Asian countries relative to ASEAN countries.

Since the firm average input tariff is constructed by using the import weight of each input variety, the weight might be correlated to the import share from richer countries owing to time serial correlation of unobservable shock, although we fix the weight at the initial year in all the regressions. To handle the possible endogeneity problem, we use the one-year lag of tariffs as the instrument for the first difference in the tariff, following Trefler (2004). The results are shown in Table 7. In column (1), we show that the more the input tariff is reduced, the more the import share from rich countries increases. In column (2), we control for firm TFP as well, where TFP is measured using the system GMM method, and the result does not change. In columns (3) and (4), we use normalized TFP, and in column (4), we add an interaction term for poor countries' input tariff and firm TFP, to test the heterogeneous effect. We find that a greater reduction in the input tariff leads to a greater increase in the share of imports from richer countries, and the effect is more pronounced for less productive firms. In the last two columns, we replace the TFP measure with a dummy for high-productivity firms, generated as in Table 3, and redo columns (3) and (4) and obtain robust results.

Next, we investigate the mechanism of innovation. Import quality from developed countries, compared with that from developing countries, should be disproportionally boosted by lower input tariffs, if the scenario is true that firms exploit input tariff reductions to innovate and upgrade quality. To test this, we first follow Khandelwal (2010) to construct a measure of import quality as follows:

$$\log s_{cht} = \lambda_{1,ch} + \lambda_{2,t} + a_1 \log p_{cht} + a_2 \log ns_{cht} + \lambda_{3,cht}$$

$s_{cht} = q_{cht}/market_{it}$ is the import share of product h in industry i from country c in year t. $market_{it} = \sum_{ch\in i} q_{cht}/impen_{it}$ is the market size, where *impenit* refers to industry i's import penetration. $ns_{cht} = q_{cht}/\sum_{ch\in i} q_{cht}$ is the net share of product h from country c in total imports of product h. The estimated residual is considered as the product–country–year import quality, as follows:

$$\widehat{\lambda_{cht}} = \widehat{\lambda_{1,ch}} + \widehat{\lambda_{2,ch}} + \widehat{\lambda_{3,ch}}$$

We estimated import quality for each CIC two-digit industry, separating for processing and ordinary imports, respectively.

Table 7 IV Estimates with firm heterogeneity

Regressand: ΔRich import share	(1)	(2)	(3)	(4)	(5)	(6)
TFP measures	System TFP		Relative system TFP		High TFP indicator	
ΔFirm tariffs on poor inputs	− 0.012*** (−10.10)	− 0.012*** (−10.10)	− 0.013*** (−4.45)	− 0.021** (−2.21)	− 0.012*** (−4.41)	− 0.013*** (−3.48)
ΔIndustry output tariffs	0.192 (1.44)	0.188 (1.40)	− 0.363 (−1.21)	− 0.350 (−1.17)	− 0.372 (−1.25)	− 0.373 (−1.25)
ΔIndustry external tariffs	− 0.078 (−1.13)	− 0.079 (−1.15)	− 0.042 (−0.29)	− 0.034 (−0.23)	− 0.043 (−0.30)	− 0.043 (−0.31)
ΔFirm TFP		− 0.012 (−1.24)	− 0.079 (−0.59)	− 0.123 (−0.88)	0.012 (0.99)	0.011 (0.80)
ΔFirm tariffs on poor inputs × Firm TFP				0.029 (0.96)		0.001 (0.14)
Observations	10,520	10,461	2139	2139	2151	2151
R^2	0.04	0.04	0.06	0.06	0.06	0.06
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Note Numbers in parentheses are robust t values. *, **, *** Denotes significance at the 10%, 5%, and 1% levels, respectively

Next, we examine the input tariff reduction and import quality in Table 8. In column (1), we find that reduced input tariffs generate greater returns on assets, implying that input tariff reduction saves cost and generates higher profit. We also control for other tariffs, including output tariffs and industry-level external tariffs charged by other countries. In columns (2) and (3), we regress firm input quality on input tariff and poor countries' input tariff, respectively, and the results show that import quality is improved as the input tariff decreases. In column (4), we further examine the impact on the quality ratio of imports from developed countries over developing countries. In column (5), we add the return on assets (ROA) and its interaction with tariffs, to control for the impact of firm productivity and profit. The results show that poor countries' input tariff reduction boosts the ratio of relative import quality from developed countries to developing countries. We also find that the impact is the same for firms with different ROAs, suggesting that there might be other channels to improve import quality other than profit.

4 Conclusions

In this paper, we used comprehensive firm-level production and trade data of Chinese manufacturing firms to examine how input tariff reduction changes firm import behavior. We find that importing firms switch sources from developing countries to developed countries as the input tariff is reduced. This impact is prevalent among different types of firms, including processing firms and ordinary firms, and firms in labor-intensive and capital-intensive industries, but among the different importers, new importers benefit the most from tariff reduction.

We also show that the impact exists at the intensive margin and the extensive margin, that is, import value and scope shift toward developed countries as the input tariff decreases. We further explored the mechanism behind this result, which, consistent with the findings of the previous literature, can be attributed to the innovation and quality upgrading encouraged by lower input cost. Specifically, we find that there is a larger boost in import quality from developed countries compared with that from developing countries. And after taking care of the endogeneity problem and several robustness checks, we show that the findings are significant and robust.

This paper enriches the study of input liberalization and firm innovation and provides direct evidence of the change in import pattern. The results remind us that the distribution of the world trade flow may be affected by China's opening-up as well, in the sense that more trade within developing countries may be replaced with trade between developing and developed countries.

Table 8 Channels of input trade liberalization

	(1)	(2)	(3)	(4)	(5)
Regressand	ROA	Import quality		Developed import quality	Ratio to developing
Firm input tariff	-0.048^{***} (−3.42)	-0.835^{***} (−2.80)			
Firm tariffs on poor inputs			-0.009^{**} (−2.06)	-0.051^{***} (−3.31)	-0.058^{**} (−1.97)
Firm return on assets (ROA)			− 0.451 (−1.28)		− 2.806 (−1.02)
Firm tariffs on poor inputs × Firm ROA			0.051 (0.76)		0.159 (0.36)
Industry output tariffs	0.036^{***} (2.82)	-0.558^{**} (− 2.06)	-0.631^{*} (− 1.73)	0.484 (0.30)	1.315 (0.59)
Industry external tariffs	0.007 (0.59)	1.225^{***} (4.66)	0.818^{**} (2.23)	− 1.911 (− 1.25)	− 2.599 (− 1.20)
Firm TFP				− 0.182 (− 0.78)	− 0.122 (− 0.41)
Observations	21,984	36,644	22,551	11,200	6746
$R2$	0.01	0.06	0.07	0.01	0.01
Number of firms	14,663	22,926	14,843	7481	4708
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Note Numbers in parentheses are robust *t*-values. *, **, *** Denotes significance at the 10%, 5%, and 1% levels, respectively

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Trade Liberalisation and Chinese Firm's Exports: Sourcing from Indonesia

Lili Yan Ing, Wei Tian, and Miaojie Yu

1 Introduction

How much can a country expand its exports? It could either export more in terms of the quantity of goods (intensive margins), more in terms of the variety of goods (extensive margins) or move to a higher quality of goods (Hummels & Klenow, 2005). The conventional trade theorem predicts that a country will export goods that use its abundant factor intensively. In the North–South trade framework, this implies that developed countries will export capital-intensive goods, while developing countries will export labour-intensive goods. However, as tariffs decline, trade grows not only between countries with different levels of intensity of factors of production, but also between countries with similar levels. Furthermore, as suggested by Bernard et al. (2003), the increase of North–South trade generates more trade between developing countries as countries in different developing stages engage in different stages of global value chains.

Previous research introduced how trade liberalisation, mostly in terms of tariff rates reductions, increases exports and domestic economy. An important related research question is how sourcing from other economies, especially developing countries (refer to 'the South'), affects exports of a large trading country (Feng et al., 2016). Today, China is the largest exporter and the second largest importing country in the world. Sourcing from other economies, particularly from the South, is crucial not only for China's exports, but also the Chinese economy.

L. Y. Ing
Economic Research Institute for ASEAN and East Asia (ERIA), University of Indonesia, Depok, Indonesia

W. Tian
School of Economics, Peking University, Peking, China

M. Yu (✉)
National School of Development, Peking University, Peking, China
e-mail: mjyu@ccer.pku.edu.cn

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Indonesia, as the largest countries in South-east Asia, grouped as the Association of South and East Asian Nation (ASEAN) in terms of economic size, plays an increasing role of shaping China's imports from the South. Today, Indonesia is one of the China's most important sourcing South countries in East Asia. Motivated by such stylised facts, we hence choose Indonesia as a representative the South to investigate the impacts of import source on China's exports.

ASEAN indeed has surpassed the United States and the European Unions to become China's largest trading partners since 2019. Since the ASEAN-China Free Trade Area launched in 2010, tariff rates have been reduced resulting in increases in trade significantly. Taking the two largest developing countries in the ASEAN-China trade bloc, according to National Bureau of Statistics of China, China and Indonesia, as an example, exports from China to Indonesia increased 13-fold, from US $2.8 billion in 2000 to around US $45.0 billion in 2019, and exports from Indonesia to China increased 16 times from 2000 to 19, rising from US $1.7 billion to around US $33.5 billion, over the same period. To fully capture the impacts of trade liberalisation and fit with related empirical literature, we consider the following three dimensions of trade liberalisation: (a) home (i.e., China) tariff rate cuts in final products, such as textiles and garments; (b) tariff rate cuts of a foreign destination country (e.g., the United States); and (c) China's tariff rate cuts on its intermediate inputs imported from Indonesia (e.g., cotton). The first two types of tariffs are bilateral trade liberalisation on final goods. The last type is trade liberalisation on intermediate inputs, as noted in Goldberg et al. (2010) and Topalova and Khandelwal (2011).

The main findings of this paper are threefold. First, Chinese manufacturing firms with a significant import share from Indonesia perform better in terms of productivity, export value, number of employees and sales, and they are more likely to engage in processing exports. Second, all aspects of trade liberalisation foster firm export value, and the impact is stronger for firms with more import from Indonesia. Last, we investigate how trade liberalisation affects export and import scopes differently for firms with a different extent of imports from Indonesia. The empirical study shows that trade liberalisation (tariff rate reductions) on inputs increases both import and export scopes. The impacts on import scopes are more pronounced for firms with higher import shares from Indonesia.

Our paper contributes to the literature in two ways. First, we find that tariff reductions on inputs increase exports through tougher import competition. The main value added of our work is that the magnitude is *uneven* across firms with different import intensity. Firms with higher import shares from Indonesia tend to have increased exports. Second, we find that South–South trade liberalisation, proxied by China's tariff rate reductions on inputs sourcing from Indonesia, increases both import and export scopes. The results suggest that trade liberalisation can change import and export structures in developing countries.

The existing literature on this issue generally works on a multi-product firm framework. It is assessed that firms will reduce product scopes in response to trade liberalisation (Arkolakis & Muendler, 2011; Baldwin & Gu, 2009; Bernard et al., 2011; Dhingra, 2013; Eckel & Neary, 2010; Feenstra & Ma, 2008). Qiu and Zhou (2013) even argue that firms may increase product scopes in response to increased product-specific fixed costs. Furthermore, Mayer et al. (2014) assert that under one-sided trade liberalisation, firms will reduce product scopes, and thus, production will be concentrated in a core competitive product. Recently, Qiu and Yu (2020) show that home market liberalisation increases domestic competition and consequently leads to firm product scope reductions. On the one hand, foreign market liberalisation increases foreign market competition; on the other hand, lower tariff rates will enable exporters more profitable. The net effects depend on firm managerial efficiencies.

Empirically, Dhingra (2013) uses Thailand data to show that the one-side tariff cuts from 2003 to 06, firms in general exported less and increased product varieties, while exporting firms decreased product scopes. Iacovone and Javorcik (2010) also found that Mexican firms decided to have product churning in response to more liberalised foreign markets. Likewise, Goldberg et al. (2010) assess that Indian firms introduced more product varieties when tariff rates reduced between 1989 and 2003. By using Chinese data, Qiu and Yu (2020) show that, parallel to productive efficiency, which is usually measured by total factor productivity (TFP), managerial efficiency is an important factor in determining the extent to which firms adjust their export product scopes. Trade liberalisation at multilateral levels, however, does not necessarily increase product scopes. Study results by Baldwin and Gu (2009), Bernard et al. (2011), and Berthou and Fontagne (2013) on the impacts of multilateral trade liberalisation on product scopes, are inconclusive.

Different from the literature, our paper pays more attention on the impacts of trade liberalisation between South and North (i.e., China and high-income countries) trade, and between South and South (China and ASEAN countries) trade. Specifically, we study the three types of tariff rate reductions related to Chinese firms and how they change China's trade with Indonesia. We use the generated firm-level input tariffs to measure the tariff rates between China and the South, and the constructed industry-level output tariff rate and foreign tariff rate reductions as a measurement of trade liberalisation between China and the North.

The rest of the paper is organised as follows. Section 2 introduces the details of data and data sources. Section 3 presents econometric specifications and reports empirical findings. Section 4 concludes.

2 Data and Measurement

This paper uses three disaggregated data sets: Chinese firm-level production data are from Annual Survey Manufacturing data, China's trade data are from Customs data at the HS 8-digit level, and tariff rate data are from the HS 8-digit level tariff data. Our data set is constructed by merging these three data sets with China's customs data (China's imports from Indonesia by product).

2.1 Chinese Firm-Level Production Data

The sample is derived from a rich firm-level panel data set that covers 162,885 firms in 2000 and 301,961 firms in 2006. The data are collected and maintained by China's National Bureau of Statistics in an Annual Survey of Manufacturing Enterprises that provide important economic variables, including three major accounting statements (i.e., balance sheets, profit and loss accounts, and cash flow statements). In brief, the data set covers two types of manufacturing firms—all state-owned enterprises (SOEs) and non-SOEs whose annual sales exceed CNY5 million (equivalent to US $714,000). The data set also includes more than 100 financial variables listed in the main accounting statements of these firms.

Although the data set contains rich information, some samples are still noisy and therefore could be misleading, largely because of some firms' misreporting. Following Feenstra et al. (2014), we clean the sample and omit outliers by using the following criteria: first, observations with missing key financial variables (such as total assets, net value of fixed assets, sales and gross value of the firm's output productivity) are excluded; and second, we drop firms with fewer than eight workers since they fall under a different legal regime, as mentioned in Brandt et al. (2012).

We remove observations according to the basic rules of the generally accepted accounting principles if any of the following are true: (a) liquid assets are greater than total assets, (b) total fixed assets are greater than total assets, (c) the net value of fixed assets is greater than total assets, (d) the firm's identification number is missing, or (e) an invalid established time exists (e.g., the opening month is later than December or earlier than January). After applying such stringent filters to guarantee the quality of the production data, the filtered firm data are reduced by about 50% for each year.

To ensure the preciseness of the estimates, we exclude some trading companies from the sample in all estimates. In particular, we exclude firms with names including any Chinese characters for their trading company or importing and exporting company from the sample.

2.2 Chinese Trade Data

The Chinese trade data we use are at the most disaggregated product-level trade transaction obtained from China's General Administration of Customs. The data provide information on each firm's product list, including trading price, quantity and value at the HS 8-digit level. The most important feature of the data is they include not only import and export data, but also the breakdown of the data into several specific types of processing trade, such as processing with assembly and processing with inputs. At the most disaggregated HS 8-digit level, ~ 35% of the 18,599,507 transaction-level observations are ordinary trade, and 65% refer to processing trade. Similar proportions are obtained when measuring by trade volume: around 43% of trade volume comprises ordinary trade. Processing with inputs accounts for around

30%, whereas processing with assembly only is around 10%. The remaining 17% represents other types of processing trade, aside from assembly and processing with inputs.

Last, to estimate firms' TFP, we merge Manufacturing Firm and Customs data. The detailed approach has been introduced in Tian and Yu (2012). In particular, we use the Chinese firm's name–year, zip code and the last 7-digit of the telephone number to merge the two data sets. As discussed in Yu (2015), our merged data skew towards larger trading firms as the matched sample has more exports, more sales and even larger number of employees.

2.3 Measurement of Firm-Level Tariffs

The measurement of average intermediate input tariffs faced by a single firm is constructed in Yu (2015). Since processing imports are duty-free in China, we construct a firm-specific input tariff index based on its non-processing imports (O), as follows:

$$FIT_{it} = kO \in \sum \frac{m^k_{i,initial\_year}}{\sum_{k \in M} m^k_{i,initial\_year}} \tau^k_t,$$

where $m^k_{i,initial\_year}$ is firm i's imports of product k in the first year the firm appears in the sample. M is the set of the firm's total imports. The set of processing imports does not appear because processing imports are duty-free. Since imports are negatively affected by tariffs, the imports of products with prohibitive tariffs would be zero; thus, if the import weight is measured in the current period, the measure of firm's tariff rates would generate a downward bias. Following Topalova and Khandelwal (2011), we use the import weight for each product at the firm's first year in the sample, which is time-invariant weights to avoid such endogeneity.

We measure the output tariffs and tariffs charged by third countries (so called foreign tariffs) at 2-digit Chinese industry classification (CIC) level, according to Amiti and Konings (2007), by averaging the tariffs of HS 6-digit industries within each 2-digit CIC industry code. Particularly, to measure the output tariffs, we use the CIC 2-digit level to concord with HS 6-digit tariff level (i.e., the most disaggregated level of tariff rates). The reason of using CIC 2-digit level tariff rates, rather than HS tariff rates, is to match and identify with firm-level data. Namely, for each particular firm, we are able to find its corresponding CIC 2-digit industry and then assign the matched tariffs.[1] Last, to make the comparisons consistent, we measure the foreign tariff rates using CIC system to be consistent with output tariff rates.

[1] By contrast, a measure output tariffs using the HS system is not ideal since some firms may not export/import, and accordingly, we cannot capture the related firm's "competition effects" embodied in the output tariffs. We appreciate a referee for pointing this out.

China is the largest developing country in terms of output and contributes the largest share to the world trade, so to study the impacts of trade liberalisation between the South and the North, we choose trade liberalisation between China and the rest of the world as a sample. We use the generated firm-level input tariff rates to measure the tariff rates between China and the South, and the constructed industry-level output tariff rates and foreign tariff rate reductions to measure trade liberalisation between China and the North. This is because trade between China and other developing countries are mostly intermediate inputs or raw materials, whereas trade between China and developed countries are largely final goods. This proxy will not generate much bias to our study, although we do not distinguish whether the partner is a developed or developing country, and both country groups are important trading partners of China.[2] First, as most of China's trading partners are members of the World Trade Organization, the same level of tariff rates applied to all WTO member countries (most favoured nation, MFN). Second, the weight used in the industry-output tariff rates and foreign tariff rates is constructed according to the domestic input–output table that is irrelevant to the trading partner.

3 Empirical Findings

Before examining the nexus between trade liberalisation and Chinese firm's exports, we will show the importance of Indonesia for China's trade. Table 1 shows performance of overall exporters and exporters with import shares from Indonesia (i.e., imports from Indonesia as a proportion of their total imports). By comparing all Chinese exporting firms, those exporting firms with a significant import share from Indonesia tend to perform better in terms of export value, number of employees and sales. In particular, of the total 70,369 Chinese exporting firms during 2000–06, 1387 exporting firms had more than a 5% import share from Indonesia and 995 firms had more than a 10% import share from Indonesia. Although firms with significant imports from Indonesia perform better than those without, this does not imply that the larger the import share from Indonesia, the better the firm's performance will be. For example, Chinese firms with more than 10% import share from Indonesia apparently export less to other countries than those with more than a 5% import share, suggesting that firm performance has no simple linear relationships with its import shares from Indonesia.

Table 2 presents the summary statistics of key variables used in the estimates. We report a simple average of CIC 2-digit industry-level output import tariff rates and external tariff rates imposed by China's trading partners. The external tariff rates tend to be lower than China's output tariff rates, as China's major trading partners are developed countries that tend to have lower import tariff rates partly due to the World Trade Organization's discipline and partly due to their commitments in

[2] According to *China International Trade Report* (2015) issued by the Minister of Commerce, trade between China and Developed Countries is around 60% of the total China's trade with the world.

Table 1 Overall exporters and exporters with import shares from Indonesia

Variable	All exporting firms		> 5% import share from Indonesia		> 10% import share from Indonesia	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Log exports	9.664	1.694	10.515	1.683	10.466	1.72
Log number of employees	5.456	1.167	5.876	1.249	5.853	1.283
Log sales	10.802	1.337	11.504	1.564	11.465	1.584
Number of firms	70,369			1387	995	

Note Chinese exporters reported in this table are large-sized exporting firms, obtained by matching Chinese firm-level data and customs data from 2000 to 06
Source Authors' calculations

regional trade agreements. We measure China's input tariff rates at the firm level to capture the feature of zero import tariff rates of processing imports. It is important to stress that China's firm-level input tariff rates are much lower than output tariff rates (see Yu, 2015 for a detailed discussion). To this end, we also construct the dummy of processing indicator and find that around 27% of firms are processing importers. We also report firm's export and import scopes by product (at the HS 8-digit level) reported in China's Customs data. On average, Chinese firms' exports around 7 products to, and imports more than 21 products from, the rest of the world.

Table 2 Statistics summary of key variables

Variable	All exporters		> 5% import shares from Indonesia		> 10% import shares from Indonesia	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Exports	9.664	1.694	10.515	1.683	10.466	1.72
Home output tariffs (industry-level)	11.71	0.056	11.8	0.058	11.74	0.057
Foreign industry tariffs	9.6	0.048	10.13	0.05	10.02	0.049
Home input tariffs (firm-level)	2.554	4.255	1.536	3.135	1.561	3.256
Firm TFP (Olley–Pakes)	1.072	0.668	1.196	0.863	1.202	0.862
Foreign indicator	0.569	0.495	0.774	0.419	0.763	0.426
SOE indicator	0.021	0.142	0.013	0.113	0.013	0.114
Log labour	5.456	1.167	5.876	1.249	5.853	1.283
Processing indicator	0.271	0.445	0.513	0.5	0.49	0.5
Export scope	7.421	10.99	8.64	11.127	8.254	10.855
Import scope	20.595	37.301	26.358	41.646	23.819	39.358

Source Authors' calculations

Table 2 also shows that firm's productivity increases from 1.07 for all Chinese exporters to 1.19 for Chinese exporters with more than a 5% import share from Indonesia and 1.20 for those with more than a 10% import share from Indonesia, suggesting that the higher import shares from Indonesia, the higher firm's productivity will be. It is important to emphasise that the share of 'processing' (indicated by processing indicator) is higher for firms with higher import shares from Indonesia than that of the average exporting firms. The firms with more than a 5% import share from Indonesia have 50% more processing activities, compared to 27% of the average of all Chinese exporting firms.

3.1 Trade Liberalisation and Firm's Exports

In this section, we examine the impacts of trade liberalisation on domestic firm's export intensive margin. We estimate three types of liberalisation—home input tariff reductions, home output tariff reductions and foreign output tariff reductions—on firm's export value.

Table 3 presents the estimation results of the impacts of trade liberalisation on domestic firms' exports, Chinese firms' exports. Columns (1) and (2) include Chinese exporters with more than a 10% import share from Indonesia, whereas Columns (3) and (4) include those firms with more than a 5% import share. Columns (5) and (6) include firms with positive, but less than a 5% import share from Indonesia. The last two columns include firms with zero imports from Indonesia, but positive China's imports from other sourcing countries.

We consider the following empirical specification:

$$\begin{aligned}\log \exp_{ijt} = \beta_0 + \beta_1 TFP_{ijt} + \beta_2 OT_{jt} + \beta_3 IT_{ijt} \\ + \beta_4 ET_{jt} + \theta X_{it} + \delta_i + \delta_t + \varepsilon_{it}\end{aligned}$$

where $\log \exp_{ijt}$ is log export of firm i in industry j, TFP_{ijt} is total factor productivity, OT_{jt} is China's output tariff rate of industry j, IT_{ijt} is China's input import tariff rate faced by firm i, and ET_{jt} is foreign country tariff rates of industry j at year t. X_{it} is a vector of control variables, including firm's size, ownership type (state-owned enterprises (SOE), multinational firm and other variables) and trade mode (processing or ordinary trade). Firm-specific fixed-effects $\eth_i$ capture all time-invariant factors, such as firm location; and year-specific fixed-effects $\eth_t$ govern all time-variant factors, such as RMB depreciation or appreciation.

First, the coefficients of firm productivity are positive and significant in all estimates, indicating that firms with high productivity tend to export more. More importantly, the magnitude of firm's TFP increases with import shares from Indonesia, suggesting that the impacts of TFP on firm's exports *seem to* be more pronounced for firms with more imports from large developing countries, like Indonesia. The economic rationale is clear: as Chinese firms' import more intermediate inputs or

Table 3 Trade liberalisation on firm's exports, by import share

Log firm exports	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Import shares from Indonesia	> 10%		> 5%		< 5%		< 5% (zero imports from Indonesia included)	
Home output tariffs (industry-level)	− 3.199** (− 2.33)	− 3.657*** (− 2.72)	− 2.616** (− 2.27)	− 3.105** (− 2.72)	− 2.979*** (− 3.15)	− 2.979*** (− 3.15)	− 1.288*** (− 4.98)	− 1.418*** (− 5.50)
Foreign tariffs (industry-level)	− 2.239* (− 1.67)	− 2.440* (− 1.86)	− 2.672** (− 2.39)	− 2.816** (− 2.55)	− 3.601*** (− 4.27)	− 3.600*** (− 4.27)	0.199 (0.81)	0.024 (0.10)
Home input tariffs (firm-level)	− 0.036** (− 2.08)	0.021 (1.01)	− 0.040** (− 2.65)	0.014 (0.77)	− 0.082*** (− 5.89)	− 0.028 (− 0.50)	− 0.042*** (− 15.59)	− 0.008** (− 2.10)
Home input tariffs × import intensity		− 0.165*** (− 4.94)		− 0.130*** (− 4.66)		− 0.057 (− 1.00)		− 0.064*** (− 13.70)
Firm TFP (Olley–Pakes)	0.122 (1.62)	0.180** (2.42)	0.064 (0.98)	0.100 (1.54)	0.024 (0.45)	0.025 (0.47)	0.050*** (2.82)	0.063*** (3.55)
Foreign indicator	0.045 (0.33)	0.154 (1.14)	0.211* (1.78)	0.255** (2.17)	0.364*** (3.34)	0.372** (3.41)	0.227*** (9.89)	0.258*** (11.23)
SOE indicator	0.883 (− 1.15)	0.852 (1.13)	0.96 (1.45)	0.961 (1.48)	0.213 (0.46)	0.228 (0.49)	− 0.851*** (− 9.30)	− 0.821*** (− 9.01)
Log firm labour	0.913*** (19.29)	0.907*** (19.60)	0.895*** (21.39)	0.896*** (21.72)	0.928*** (31.86)	0.928*** (31.83)	0.783*** (86.19)	0.783*** (86.64)
Processing indicator	0.368*** (2.78)	0.272** (2.07)	0.287** (2.57)	0.222** (2.00)	− 0.118 (− 1.45)	− 0.115 (− 1.41)	− 0.012 (− 0.49)	− 0.006 (− 0.23)
R^2	0.46	0.49	0.43	0.45	0.49	0.49	0.29	0.3
Observations	743	743	1008	1008	1630	1630	29,699	29,699

Notes Numbers in parentheses are robust t-value, with *, **, *** denoting the level of significance at 10%, 5%, 1%. Firm-specific fixed effects and year-specific fixed effects are included in all regressions

Source Authors' calculations

raw materials from Indonesia, they are more likely to engage in processing trade (as confirmed in Table 2) and, hence, export more. With more available imported intermediate goods, firms are able to optimise the use of the combination of domestic inputs and imported inputs, as suggested by Halpern et al. (2015).

Second, trade liberalisation significantly boost exports. This holds for all aspects of trade liberalisation, including output tariff and input tariff rate reductions as well as foreign tariff rate reductions. Input trade liberalisation enable domestic firms to save costs in intermediate inputs and thus earn more profit. Likewise, lower trading partners' tariff rates enable firms to gain easier access to foreign markets and thus can export more. By contrast, the role of output trade liberalisation is different: output tariff reductions suggest tough import competition effects from international markets, and thus, only efficient firms who will able to survive in the markets. As efficient firms tend to be growing larger and to export more, we see negative coefficients of output tariffs.

Third, SOEs and larger firms tend to export more. Similarly, processing firms also tend to export more. Yet, it may be insufficient to claim that the differences between estimated coefficients across odd columns in Table 3 are due to the differences in import intensity from Indonesia, because many other factors such as the differences in capital stock and share of foreign investment may also affect the estimation results.[3] Indeed, to make specifications with different import intensities comparable, we have adopted a common set of control variables in all regressions of Table 3. To be precise, we run new regressions by interacting input tariffs with import intensity, given Chinese input tariffs directly affect China's imports, as shown in the even columns of Table 3.

The estimated results in Table 3 Columns (2), (4) and (6) clearly show that, with the interaction of input tariffs with import intensity from Indonesia, both output tariff rate reductions and foreign tariff rate reductions increase China's exports. Such findings are exactly consistent with the corresponding regressions, ignoring the interaction terms of tariffs as shown in Columns (1), (3) and (5). More importantly, as shown in Columns (2), (4) and (6), the coefficients of firm input tariffs interacted with Indonesian import intensity are negative and statistically significant (except insignificant in Column (6)), suggesting that the magnitude of input trade liberalisation is more pronounced for firms with more import sourcing from Indonesia. This finding indeed is reinforced in the last column of Table 3, in which all importing firms sourcing from all other countries, except Indonesia, are included in the regression. The impacts of input trade liberalisation on Chinese firm's exports are more pronounced for firms with more import sourcing.

[3] We thank a referee for pointing this out.

3.2 Trade Liberalisation and Export Scope

In this section, we estimate trade liberalisation on domestic firm's export extensive margin. In particular, we focus on the change in export and import scopes. Referring to Qiu and Yu (2020), we define a firm's export scope as the total number of product lines at the HS 8-digit level exported by a Chinese manufacturing firm.[4]

The empirical specification is as follows:

$$es_{ijt} = \beta_0 + \beta_1 TFP_{ijt} + \beta_2 OT_{jt} + \beta_3 IT_{jt} + \beta_4 ET_{jt} + \theta X_{it} + \delta_i + \delta_t + \varepsilon_{it}$$

where es_{ijt} is an export product scope of firm i in industry j in year t.

Table 4 presents the count-data estimates of the impacts of trade liberalisation on domestic firm's export scopes. Columns (1)–(3) include a sample of Chinese exporters with more than a 10% import share from Indonesia and Columns (4)–(6) cover firms with more than a 5% import share from Indonesia.

We start from Poisson estimates, in which 'the mean of export scopes' is presumed to equal its variance. The Poisson estimates in Table 4 Column (1) suggest that both domestic output tariff and foreign tariff rate reductions decrease firm's export scopes. In addition, reductions in firm-level input tariff will decrease firm's export scopes. Such findings are consistent with the findings of Qiu and Yu (2020) that cover the whole sample of Chinese exporters. The economic rationale of the positive coefficient of domestic output tariff reductions is straightforward. Lower output tariffs lead to tougher import competition, which in turn makes firms focus on their competitive products. At first glance, however, the positive coefficient of foreign output tariffs is counter-intuitive. This is because the trade-off between positive and negative shocks raised by a trading partner's tariff reductions (as discussed carefully in Lim et al., 2019). On the one hand, foreign markets induce exporting firms to expand their product lines, as generally they offer higher prices (resulting in higher profits). On the other hand, foreign markets are also much more competitive than domestic markets, due to entrance and logistics costs, so firms will also have an incentive to reduce their product scopes to avoid internal cannibalisation. As presented in Qiu and Yu (2020), once the negative competition impacts dominate the positive ones, export scopes fall.

With careful assessment, the assumption that 'the mean of the export scopes' equals its variance seems too strong. Instead, we adopt negative binomial estimates in Table 4 Column (2) for Chinese exporters with more than a 10% import share from Indonesia and those in Column (5) with more than a 5% import share from Indonesia. The negative binomial estimates are more credible here, as they allow the sample to exhibit a pattern of over-dispersion. We keep in mind that there may be a concern that a number of key macroeconomic indicators may fluctuate, such as Yuan appreciation during the sample period, particularly after 2005, can affect firms' export scopes. In addition, other unspecified factors, such as firms' managerial efficiency,

[4] Detailed calculations of firm-product year-level export and import scopes can also be found in Ing et al. (2018).

Table 4 Count-data estimates of trade liberalisation on firm's export scope

Regression: export scope	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Econometric method	Poisson	Negative binomial		Poisson	Negative binomial		Poisson	Negative binomial	
Import share from Indonesia	> 10%			> 5%			< 5%		
Home output tariffs	0.724*** (4.75)	1.100** (2.57)	0.942** (2.36)	1.102*** (9.05)	1.347*** (3.79)	0.871*** (2.71)	1.363*** (13.09)	1.050*** (3.81)	0.473** (2.10)
Foreign tariffs (industry-level)	5.078*** (21.68)	4.189*** (6.97)	1.709*** (3.05)	4.472*** (23.17)	3.848*** (7.60)	1.782*** (3.78)	1.041*** (8.40)	1.433*** (3.56)	1.589*** (4.53)
Home input tariffs (firm-level)	– 0.006 (– 1.64)	– 0.007 (– 0.85)	0.004 (0.45)	– 0.016*** (– 4.87)	– 0.013* (– 1.90)	– 0.001 (– 0.13)	– 0.006*** (– 2.80)	– 0.011 (– 1.63)	– 0.033*** (– 4.06)
Firm TFP (Olley–Pakes)	0.353 + 0** (14.31)	0.425*** (5.53)	0.226*** (2.96)	0.324*** (15.37)	0.397*** (6.02)	0.233*** (3.84)	0.485*** (37.78)	0.623*** (11.54)	0.191*** (4.42)
Foreign indicator	– 0.200*** (– 7.73)	– 0.114 (– 1.55)	– 0.047 (– 0.56)	– 0.128*** (– 5.78)	– 0.067 (– 1.05)	– 0.036 (– 0.49)	– 0.493*** (– 33.16)	– 0.548*** (– 8.46)	– 0.006 (– 0.09)
SOE indicator	0.093 (1.20)	– 0.043 (– 0.17)	0.138 (0.42)	– 0.071 (– 1.02)	– 0.138 (– 0.64)	– 0.046 (– 0.16)	– 0.709*** (– 9.86)	– 0.779*** (– 3.47)	– 0.023 (– 0.10)
Log firm labour	0.187*** (20.87)	0.187*** (8.06)	0.202*** (7.11)	0.222*** (28.75)	0.222*** (10.92)	0.201 *** (8.02)	0.223*** (51.21)	0.259*** (16.66)	0.251*** (14.33)
Processing indicator	– 0.259*** (– 10.82)	– 0.27*** (– 4.50)	– 0.12*** (– 2.63)	– 0.14*** (– 7.40)	– 0.17*** (– 3.41)	– 0.10*** (– 2.65)	– 0.197*** (– 16.29)	– 0.184*** (– 430)	– 0.124*** (– 3.91)
Year-specific fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
Firm-specific fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
Observations	948	948	948	1323	1323	1323	2123	2261	2261

Note Numbers in parentheses are robust t-value, with *, **, *** denoting the significance level at 10%, 5%, 1%
Source Authors' calculations

as introduced in Qiu and Yu (2020), may also affect firms' extensive margin. We thus control for firm-specific fixed effects and year-specific fixed effects in Columns (3) and (6). It turns out that the negative binomial estimation results in Columns (2) and (3) and (5) and (6) are qualitatively identical to their counterparts in Columns (1) and (4) with Poisson estimates. Thus, our estimates are insensitive to different empirical specifications.

In addition, the negative sign of foreign indicator suggests that multinational companies based in China have less export scopes. Such a finding is consistent with the fact that processing firms also have less export scopes, as processing firms generally are subsidiaries of multinational companies, as documented in Dai et al. (2016).

Last, we also observe that larger firms, proxied by number of employees, have relatively more export scopes than average-sized firms. Interestingly, compared to non-processing firms (i.e., ordinary firms), processing firms seem to have less export scopes. Findings in Tables 3 and 4 show that processing firms have relatively higher value of exports, and the implication is clear: processing exporters tend reduce varieties of their traded products and focus on their core competitive products.

3.3 Trade Liberalisation and Import Scope

In this section, we present the impacts of trade liberalisation on import scopes. Table 5 Columns (1) and (4) are Poisson estimates, and the rest are negative Binomial estimates. Columns (1)–(3) are estimates for Chinese exporters with more than a 10% import share from Indonesia, while Columns (4)–(6) represent firms with more than a 5% import share.

Table 5 illustrates that foreign tariff reductions will increase firms' import scopes, due to stimulated foreign demand and a larger access to foreign markets. We also find that home output tariff reduction increases firm import scopes. The implication is straightforward: with tougher import competition, firms tend to import more foreign (Indonesia's) input varieties to promote firm productivity. Strikingly enough, home input tariff reductions are found to decrease firms' import scopes. This finding is very counter-intuitive. We suspect that the results may be due to the sample restriction, as the sample in our previous estimates only covers firms with a certain percentage of import sourcing from Indonesia. We therefore include all samples sourced from Indonesia in Table 6 and allow the three types of tariff liberalisation—home input tariff reductions, home output tariff reductions and foreign output tariff reductions—to interact with import shares from Indonesia. Although the coefficients of firm's own input tariffs are still positive, as shown in Table 7. Poisson estimates of Column (1) and negative binominal estimates of Column (2), their interaction terms with import shares from Indonesia turn to be negative and statistically significant.

To fully understand the whole picture of the impacts of tariff rate reductions on Chinese firms' import scopes, it is worthwhile to also examine the impacts of imports from countries, other than Indonesia, on Chinese firms' import scopes. Therefore, we

Table 5 Count-data estimates of trade liberalisation on firm's import scope

Regression: import scope	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Econometric method	Poisson	Negative binomial		Poisson	Negative binomial		Poisson	Negative binomial	
Import share from Indonesia	> 10%			> 5%			< 5%		
Home output tariffs	– 0.073 (– 0.49)	– 1.419*** (– 13.96)	– 0.601*** (– 5.98)	– 0.977*** (– 8.10)	– 1.183*** (– 14.87)	– 1.038** (– 2.52)	– 1.526*** (– 23.04)	0.109*** (3.03)	0.109 (0.44)
Foreign tariffs (industry-level)	– 2.214*** (– 13.57)	– 1.164**** (– 7.79)	– 0.439*** (– 3.45)	– 2.415*** (– 18.30)	– 1.469*** (– 12.32)	– 0.135 (– 0.24)	– 2.638*** (– 42.63)	– 3.367*** (– 60.42)	– 2.762*** (– 7.70)
Home input tariffs (firm-level)	0.014*** (7.41)	0.023*** (12.20)	0.019*** (10.28)	0.022*** (13.92)	0.029*** (18.86)	0.046*** (3.92)	0.030*** (34.94)	0.034*** (39.51)	0.056*** (6.98)
Firm TFP (Olley–Pakes)	0.260*** (16.36)	0.271*** (17.43)	0.192*** (11.70)	0.340*** (26.06)	0.346*** (27.68)	0.540*** (7.67)	0.452*** (71.08)	0.482*** (78.44)	0.624*** (13.46)
Foreign indicator	1.221*** (54.47)	1.249*** (55.68)	1.143*** (46.68)	1.168*** (63.41)	1.224*** (65.98)	1.116*** (16.19)	0.971*** (87.49)	0.932*** (87.63)	0.802*** (14.66)
SOE indicator	– 0.846*** (– 8.66)	– 0.865*** (– 10.33)	– 0.932*** (– 7.93)	– 0.860*** (– 10.33)	– 0.810*** (– 11.50)	– 0.727*** (– 2.92)	0.481*** (12.78)	0.369*** (9.87)	0.464** (2.38)
Log firm labour	0.497*** (94.06)	0.473*** (93.53)	0.475*** (78.49)	0.468*** (107.16)	0.454*** (107.85)	0.455*** (20.67)	0.418*** (202.28)	0.419*** (214.05)	0.385*** (30.09)
Processing indicator	– 0.108*** (– 7.31)	– 0.128*** (– 8.93)	– 0.096*** (– 9.13)	– 0.074*** (– 6.18)	– 0.097*** (– 8.42)	– 0.067 (– 1.14)	– 0.232*** (– 40.84)	– 0.220*** (– 40.01)	– 0.195*** (– 5.22)
Year-specific fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-specific fixed effects	No	No	No	No	No	No	No	No	No
Observations	948	948	948	1323	1323	1323	2123	2261	2261

Note Numbers in parentheses are robust t-value, with, *, **, *** denoting the level of significance 10%, 5%, 1%

Table 6 Estimates of trade liberalisation on import and export scope

Variables	(1)	(2)	(3)	(4)	(5)
	Import scope				Export scope
	Poisson	Negative binomial	Negative binomial	Negative binomial	Negative binomial
Home output tariffs	– 0.625*** (– 6.32)	– 0.584 (– 1.04)	– 0.693*** (– 3.73)	0.100 (0.62)	– 0.291** (– 1.99)
Foreign tariffs (industry-level)	– 0.028 (– 0.25)	0.460 (0.74)	– 0.371 (– 1.47)	– 0.149 (– 1.12)	– 0.004 (– 0.03)
Home input tariffs (firm-level)	0.035*** (33.95)	0.080*** (8.90)	– 0.011*** (– 5.84)	– 0.012*** (– 6.90)	– 0.008*** (– 6.41)
Home output tariffs × import share from Indonesia	– 6.155*** (– 11.93)	– 4.477*** (– 2.95)	1.544 0.8	0.786 0.59	0.925 0.72
Foreign tariffs × import share from Indonesia	– 8.498*** (– 15.18)	– 7.745*** (– 4.83)	– 3.642* (– 1.85)	0.671 0.47	1.386 0.95
Home input tariffs × import share from Indonesia	– 0.107*** (– 14.80)	– 0.165*** (– 6.25)	0.071* – 1.96	– 0.018 (– 0.57)	– 0.024 (– 0.88)
Firm TFP (Olley–Pakes)	0.061*** (14.12)	0.094*** (3.75)	0.242*** (19.40)	0.025** (2.87)	0.020** = (2.17)
Foreign indicator	0.958*** (88.83)	0.932*** (19.85)	1.282*** (90.14)	0.331*** (8.16)	0.191*** (4.75)
SOE indicator	0.212*** (4.45)	0.325 (1.45)	– 0.073 (– 1.37)	– 0.137 (– 1.64)	– 0.030 (– 0.47)
Log firm labour	0.404*** (174.20)	0.387*** (28.28)	0.388*** (75.21)	0.110*** (9.31)	0.090*** (7.34)
Processing indicator	– 0.206*** (– 33.35)	– 0.109*** (– 3.04)	0.222*** (16.28)	0.067*** (6.77)	– 0.045*** (– 4.83)
Observations	2638	2638	32,337	19,103	19,103
Industry-specific fixed effects	Yes	Yes	Yes	No	No
Firm-specific fixed effects	No	No	No	Yes	Yes
Year-specific fixed effects	Yes	Yes	Yes	Yes	Yes
Zero imports from Indonesia included	No	No	Yes	Yes	Yes

Note Numbers in parentheses are robust *t*-value, with *, **, *** denoting the level of significance at 10%, 5%, 1%
Source Authors' calculations

Table 7 Estimates of trade liberalization on firm productivity

Import shares from Indonesia regress and firm TFP (system-GMM)	> 10%		> 5%	
	(1)	(2)	(3)	(4)
Home output tariffs (industry-level)	− 1.177*** (− 4.76)	− 0.666** (− 2.08)	− 1.343*** (− 6.46)	− 0.925*** (− 3.42)
Foreign tariffs (industry-level)	− 0.770*** (− 2.70)	− 1.089*** (− 3.17)	− 0.768*** (− 3.24)	− 1.034*** (− 3.57)
Home input tariffs (firm-level)	0.237 (0.71)	0.412 (0.95)	0.249 (0.83)	0.329 (0.84)
Foreign indicator	0.138 (0.70)	0.357** (2.22)	0.064 (0.43)	0.209 (1.63)
SOE indicator	− 0.002 (− 0.05)	0.028 (0.76)	0.016 (0.60)	0.038 (1.20)
Log firm labour	0.067*** (6.92)	0.067*** (5.61)	0.069*** (8.27)	0.063*** (5.94)
Processing indicator	− 0.092*** (− 3.61)	− 0.087*** (− 2.62)	− 0.085*** (− 3.89)	− 0.084*** (− 2.98)
Year-specific fixed effects	No	Yes	No	Yes
Firm-specific fixed effects	No	Yes	No	Yes
R^2	0.15	0.21	0.15	0.19
Observations	828	828	1156	1156

Note Numbers in parentheses are robust t-value, with *, **, *** denoting the level of significance at 10%, 5%, 1%
Source Authors' calculations

include all Chinese importing firms in Column (3).[5] The results show both own term and interacted terms of home input tariffs are negative. By adding more parsimonious firm-specific fixed effects in Column (4), the coefficient of own input tariffs is still negative, whereas its coefficient interacted with import shares is positive. Since the import shares from Indonesia are only around 2%, the entire effects of input trade liberalisation on firms' imports turn out to be negative. Just for a comparison, Table 6 Column (5) includes the impacts of trade liberalisation on firms' export scopes. The results are consistent with the abovementioned findings.

The estimation results presented in Tables 5 and 6 jointly suggest that trade liberalisation affects trade differently in terms of extensive margins. Input trade liberalisation will increase firms' import scopes for firms with a significant sourcing shares from Indonesia. Such a finding is more pronounced when import shares from Indonesia increase. In addition, input trade liberalisation also indirectly increases firms' export scopes, largely due to the prevalence of processing trade in China.

[5] The number of total firms in Column (3) is of course significantly much higher compared to those in Columns (1) and (2).

3.4 More Robustness Checks

Thus far we use the augmented Olley–Pakes TFP to measure firm productivity. Although such measured TFP has many advantages compared to other alternative measures of productivity, we acknowledge that it has two main disadvantages. First, the Olley–Pakes TFP assumes that firms adjust capital inputs, when facing an exogenous shock. However, this may not happen in China, as China is a labour-abundant country, and hence, firms find it easier to adjust labour than capital. Second, the Olley–Pakes TFP does not allow output to have any serial correlations, which are likely to occur. For these reasons, the system-general method of moments (GMM) TFP measure seems an ideal complementary measure, as it has enough flexibility to allow for possible serial autocorrelations. We hence use the system-GMM TFP to check whether our results will remain robust even when using other measures of TFP. Table 7 shows these comparisons.

Following Yu (2015), we now discuss whether trade liberalisation boosts productivity of Chinese exporting firms with a significant import share from Indonesia. Once again, we consider firms with 10% and 5% import shares from Indonesia, respectively. As in other studies, we find that both output trade liberalisation and external trade liberalisation boost firm productivity. However, we do not find that input trade liberalisation raises firm productivity. The impacts of home input trade liberalisation on firm productivity are insignificant. Such findings are robust, even when we control for year-specific fixed effects and firm-specific fixed effects in Column (2) of Table 7 for firms with a 10% import share from Indonesia and in Column (4) for those firms with a 5% corresponding import share.

This raises a concern over the previous estimates of the effects of trade liberalisation on firm productivity. One may worry that our estimates above may contain an estimation bias. To address this concern, following Feenstra et al. (2014), we distinguish between Ex-Ante TFP and Ex-Post TFP measures.

The conventional measures of TFP, including our above measures—both Olley–Pakes and system-GMM—are a Solow residual that includes both unspecified factors and production productivity. In this way, the measured TFP correlates with the error terms. To avoid such a shortcoming and to be closer with the spirit of Melitz (2003) that emphasises more on Ex-Ante random draw of firm productivity, we trail Feenstra et al. (2014) and Qiu and Yu (2020) to construct an Ex-Ante TFP.

Table 8 reports the estimation results using the Ex-Ante TFP measure. Column (1) is firms' export volume, Columns (2) and (3) are export scopes, and Column (4) is import scope. Estimates in Column (1) show that all types of trade liberalisation boost firms' exports, which make good economic senses. Meanwhile, all estimates on export and import scopes are consistent with estimates with Ex-Post firm productivity presented in Tables 5 and 6. Thus, our main findings are robust, even when using different measures of TFP.

Table 8 Estimates of trade liberalisation with Ex-Ante firm productivity

Regress and import shares from Indonesia	Log exports	Export scope		Import scope
	> 5%	> 5%	> 10%	> 5%
	(1)	(2)	(3)	(4)
Home output tariffs (industry-level)	– 0.708	0.682*	0.826*	– 1.218***
	(– 0.78)	1.89	1.95	(– 2.86)
Foreign tariffs (industry-level)	– 1.936**	2.806***	4.164***	0.734
	(– 2.36)	5.3	6.97	1.16
Home input tariffs (firm-level)	– 0.059***	– 0.002	– 0.005	0.063***
	(– 3.24)	(– 0.23)	(– 0.64)	– 5.36
Firm TFP (Olley–Pakes)	– 0.064	0.749***	0.666***	0.025
	(– 0.49)	9.16	6.89	0.27
Foreign indicator	0.280***	– 0.035	– 0.115	1.134***
	2.82	(– 0.57)	(– 1.58)	16.22
SOE indicator	0.304	0.052	0.061	– 0.512**
	0.83	0.26	0.25	(– 2.04)
Log firm labour	0.893***	0.247***	0.236***	0.471***
	28.39	12.65	10.05	20.61
Processing indicator	0.258***	– 0.171***	– 0.281******	– 0.056
	3.26	(– 3.38)	(– 4.60)	(– 0.95)
Year-specific fixed effects	No	Yes	Yes	Yes
Firm-specific fixed effects	No	Yes	Yes	Yes
Observations	1192	1324	949	1324

Note Numbers in parentheses are robust t-value, with *, **, *** denoting the level of significance at 10%, 5%, 1%
Source Authors' calculations

3.5 Dealing with Possible Endogeneity

One last possible concern is that firm-level output tariffs and foreign tariffs are highly correlated with firm exports. It is not clear whether the impacts of tariff liberalisation on the export volume, because the causality can be reversed. This concern may be more relevant for countries with strong special interest groups (Grossman & Helpman, 1994). However, the endogeneity caused by this reverse causality will not cause any serious bias in our estimations, given that we use the industry-level output and foreign output tariffs in our paper. A single firm's exports cannot economically significantly affect the average industry-level tariff rates that the firm locates. Also, labour unions or other special interest groups in China are impotent to affect China's tariff and trade policies. Still, for the sake of avoiding this possible endogeneity, we adopt a measure of firm-level previous year (output and foreign) tariffs as robustness checks.

Table 9 picks up this task, examining the impacts of tariff reductions on firm exports by using a one-year period lag of home firm-level tariffs and foreign output tariffs. The impacts of trade liberalisation on firm export scopes (i.e., intensive margins) shown in Table 9 Columns (1)–(3) with the coefficients of home firm-level tariff and foreign output tariffs are, overall, still negatively significant. In particular, the coefficients of home firm-level output tariffs are insensitive to the use of one-period lag output tariffs. We also see similar findings of the one-period lag external tariffs, though its coefficient in Column (1) with Indonesia's import shares higher than 10% is statistically insignificant. In conclusion, the coefficients of input tariffs are still negative and statistically significant in all cases.

Table 9 Lagged impacts of tariff reductions on exports

Import shares from Indonesia	Exports			
	> 10%	> 5%	< 5%	< 5% (zero imports from Indonesia included)
	(1)	(2)	(3)	(4)
Home industrial output tariffs (1-period lag)	– 4.086*	– 2.23	– 6.734***	– 1.260***
	(– 1.74)	(– 1.11)	(– 3.33)	(– 3.55)
Foreign industrial output tariffs (1-period lag)	– 0.88	– 3.664*	– 2.443	0.091
	(– 0.36)	(– 1.84)	(– 1.40)	0.26
Home firm-level input tariffs (1-period lag)	– 0.133***	– 0.144***	– 0.061**	– 0.025***
	(– 3.09)	(– 3.69)	(– 2.05)	(– 7.00)
Firm TFP (Olley–Pakes)	0.327***	0.297***	0.145	0.054*
	(2.67)	(2.95)	(1.23)	(1.95)
Foreign indicator	0.306 (1.25)	0.260 (1.25)	0.536** (2.06)	0.186*** (5.73)
SOE indicator	1.142 (1.04)	1.251 (1.17)	0.681 (0.74)	– 1.005*** (– 9.04)
Log firm labour	0.774*** (10.87)	0.819*** (13.74)	1.031*** (16.68)	0.733*** (53.30)
Processing indicator	0.189 (0.86)	0.466** (2.47)	– 0.049 (– 0.28)	0.066* (1.79)
Observations	202	280	356	11,260
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.58	0.6	0.57	0.29

Note Numbers in parentheses are robust *t*-value, with *, **, *** denoting the level of significance at 10%, 5%, 1%
Source Authors' calculations

4 Conclusions

In this paper, we examine how trade liberalisation affects the performance of Chinese manufacturing firms via sourcing from the South. In particular, we use both Chinese firm-level production and transaction-level trade data to examine the impacts of three types of tariff reductions—input tariff reductions, output tariff reductions and foreign output tariff reductions—on firm export, firm productivity, and firm export and import scopes for firms with significant import shares from Indonesia, the largest South country in the ASEAN bloc.

Our findings assert that trade liberalisation, particularly, home input tariff and foreign output tariff rate reductions, significantly raises home firm exports. The impacts are, overall, more pronounced for firms with higher import shares from Indonesia. Chinese firms with a higher import shares from Indonesia perform better in productivity, export and sales, and they are more likely to engage in processing exports. In addition, input trade liberalisation boosts not only firm's import scopes but also firm's export scopes for firms, with a significant sourcing shares from Indonesia. Such a finding is more pronounced as firm's import shares from Indonesia increase.

Last, our findings also have rich policy implications: first, if deeper integration between South and South can increase trade flows, governments in the developing countries should provide more trade facilitation to enable deeper and wider coverage of trade integration; second and equally important, we find that trade liberalisation from the sourcing countries can boost firm productivity and raise firms' exports. Thus, it would be a prudent strategy for countries to encourage sourcing from other developing and competitive countries by cut their home input tariffs, phase out unjustified non-tariff barriers and improve transparency of non-tariff measures.

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Measured Skill Premia and Input Trade Liberalization: Evidence from Chinese Firms

Bo Chen, Miaojie Yu, and Zhihao Yu

1 Introduction

Tariffs have declined dramatically worldwide as a result of many rounds of trade negotiations under the General Agreement on Tariffs and Trade (GATT)/World Trade Organization (WTO) (Bagwell & Staiger, 1999). The labor markets in each country have been impacted by the trade liberalization in final-goods and intermediate input sectors. The question of how trade liberalization affects wage inequality between skilled and unskilled workers, especially for developing countries, has once again become one of the research focuses in the international trade literature.

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B. Chen
School of Economics, Huazhong University of Science and Technology, 1037 Luoyu Rd., Wuhan, Hubei 430074, China

M. Yu (✉)
China Center for Economic Research (CCER), National School of Development, Peking University, Beijing 100871, China
e-mail: mjyu@nsd.pku.edu.cn

Z. Yu
Department of Economics, Carleton University, 1125 Colonel By Drive, Ottawa, ON K1S 5B6, Canada
e-mail: zhihao.yu@carleton.ca

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Most of the early studies in the literature follow the HeckscherOhlin model to test whether trade liberalization benefits the abundant factors. According to the Stopler-Samuelson theorem, trade liberalization would mitigate wage inequality between skilled and unskilled labor in the developing countries. However, this theoretical assertion has received little empirical support because most studies find increased skill premium in both developed and developing countries.[1] For example, Feenstra and Hanson (1996, 1999) find that, in the presence of vertical integration and international outsourcing, freer trade could actually increase skill premium in both developed and developing countries·[2]

Recent studies in the literature use firm-level data to investigate the impact of globalization on wage inequality but they mainly focus on the impact of export-side trade liberalization (e.g. Bustos, 2011; Frías et al., 2012; Helpman et al., 2017; Verhoogen, 2008). For example, using Brazilian data, Helpman et al. (2017) find that much of the overall wage inequality occurs within sector-occupations, which is mainly driven by wage dispersion between, rather than within, firms. However, the impact of input trade liberalization on firm-level wage inequality is equally important and may also have distinct differences in how the employers might share the surplus with various input factors because of their different bargaining power. In particular, imported intermediate inputs have been found to be crucial for boosting firm productivity in both developed and developing countries such as the United States (Hanson et al., 2005), Indonesia (Amiti & Konings, 2007), India (Goldberg et al., 2010; Topalova & Khandelwal, 2011), and China (Yu, 2015).

The purpose of the present paper is to investigate the impact of input trade liberalization on wage inequality in China and intend to make the following two contributions to the literature. First, investigations on the impact of input trade liberalization on wage inequality in developing countries usually rely on industry-level wage data, household survey data, and the Gini coefficient as a proxy for income inequality (e.g., Beyer et al., 1999).[3] For example, using urban industrial survey data, Han et al. (2012) found that widening wage inequality in China was strongly associated with

[1] Previous works have contributed to an intense discussion on the validity of factor price equalization (FPE) in explaining wage inequality in developed countries. See Johnson and Stafford (1993), Leamer (1993, 1996), and Lawrence and Slaughter (1993), among many others.

[2] Technology is identified as the major factor driving wage inequality; international trade is nevertheless also believed to play an important role. See more details in Feenstra and Hanson (1996, 1999).

[3] An outstanding exception is Akerman et al. (2013), who find that trade liberalization not only enhances the dispersion of revenues across heterogeneous firms, but also widens wage inequality across workers and firms. This paper is also in line with Groizard et al. (2014) who explore the endogenous nexus between trade liberalization and job flow in California and Rodriguez-Lopez and Yu (2017) who examine the relationship between all-around trade liberalization and firm-level employment in China. Furusawa and Konishi (2014) propose a model to interpret why international trade can increase wage inequality between top income earners and others, and thus cause job polarization.

China's accession to the WTO in 2001.[4] In the present paper, we use Chinese firm-level production and customs' trade data to investigate the impact of tariff reductions for imported inputs on firm-level skill premium in China. To our knowledge, this is the first paper to investigate how import trade liberalization affects firm-level skill premium for manufacturing firms in China, the largest developing country in the world. The study could enrich our understanding of the sources of China's growing income inequality from the wage differentials at the firm levels.[5]

Second, a major challenge to investigate firm-level wage inequality between skilled and unskilled labor in China, as in most developing countries, is lack of data for direct firm-level wages for skilled and unskilled workers. To overcome this major obstacle, the current paper has developed a method of constructing firm-level skill premium from a firm's average wage and share of skilled labor. Together with a Mincer (1974)-type regression, we are able to estimate the impact of input trade liberalization on firm-level skill premium in China. This method can be applied to other research facing similar data limitations.

Using firm-level production and transaction-level trade data from China, we find that, when controlling for product-market tariffs in a firm's industry, the reduced input tariffs in a firm's industry are associated with a higher skill premium at firms with more skilled workforces. This effect is more pronounced at ordinary (nonprocessing) firms. Compared with processing importers, ordinary importers respond more forcefully to input trade liberalization in their wage schedule. Our main finding that input trade liberalization increases firm-level skill premium in China is robust for all three regions (east, central and west) in China, as well as for different measures of wage inequality, different empirical specifications and data spans. By contrast, output trade liberalization, which is measured by product-market tariffs reduction, show opposite signs of the effect of import tariffs on the skill premium at firms with more skill-intensive production. However, the product-market tariff effects are not robustly significant across specifications.

Inspired by the literature on "fair wages" (e.g. Egger & Kreickemeier, 2012), we also provide an interpretation for our main finding that input trade liberalization leads to an increase in firm skill premium. If skilled workers have greater bargaining power with their employers than unskilled workers, incomes of the skilled workers shall be more closely linked to firms' economic profits but the incomes of unskilled workers shall be more in line with those of other firms in the same industry. Thus, a fall in input tariffs increases the firm's value-added, which in turn raises the firm's skill premium because the skilled labor commands a larger proportion of the incremental surplus than the unskilled labor. We also provide some evidence for our conjecture.

In addition to the literature discussed earlier, our paper is also closely related to the studies on how import trade liberalization affects skill compositions and

[4] Autor et al. (2013) show that China' s exports to the American market have significantly contributed to the aggregate decline in the U.S. manufacturing employment and caused the sharp increases in U.S. social benefit claims.

[5] Khan and Riskin (1998) found that wage inequality contributed to half of the income inequality in China in 1995.

factor returns. For example, using data from multinational companies, Biscourp and Kramarz (2007) examine the impact of offshoring on plant-level skill composition in France. Similarly, Becker et al. (2013) investigate the impact of offshoring on firm-level task composition and wages in Germany. Amiti and Davis (2011) is another influential study that investigates the impact of output and input tariff reductions on wages. In particular, they find that a reduction in-input tariffs raises wages at import-using firms relative to those using only domestic intermediate inputs. However, these studies do not focus on firm wage inequality, or skill premium.

The rest of the paper is organized as follows. Section 2 describes the data and introduces the econometric methods to measure firm skill premium and the empirical specifications of Mincer regression. Section 3 presents the main empirical evidence, offers robustness checks and discussion on the possible mechanism. Section 4 concludes.

2 Data, Measures, and Empirics

2.1 Data

To investigate the impact of input trade liberalization on firms' skill premium, our analysis uses the following three disaggregated panel data sets: firm-level production data compiled by China's National Bureau of Statistics (NBS), production-level trade data maintained by China's General Administration of Customs, and China's import tariff (ad valorem) data at the HS 6-digit level, maintained by the World Integrated Trade Solution (WITS) database of the World Bank.

China's NBS conducts an annual survey of industrial firms (ASIF) with two types of manufacturing firms: all state-owned enterprises (SOEs) and non-SOEs whose annual sales exceed RMB 5 million (or equivalently \$725,000). The sample used in this paper has ~ 230,000 manufacturing firms per year, varying from 162,885 firms in 2000 to 301,961 firms in 2006. On average, the sample accounts for more than 95% of China's total annual output in the manufacturing sectors.[6] The data set covers more than 100 accounting variables and contains all of the information from the main accounting sheets, which includes balance sheets, loss and profit sheets and cash flow statements.

Given its rich information, the firm-level production data set is widely used in research by, among others, Cai and Liu (2009), Brandt et al. (2012), and Feenstra et al. (2014). However, the data set has two limitations for our research purpose. The first one is common: some unqualified firms are wrongly included in the data set, largely because of mis-reporting or false recording. Thus, following Feenstra et al. (2014), we keep the observations in our analysis according to the requirements

[6] In 2006, the total value added of all the firms included in the survey was RMB 9107 billion, which accounted for 99% of the value added of all firms in the manufacturing sectors (RMB 9131 billion), as reported by China' s Statistics Yearbook (2007).

of the Generally Accepted Accounting Principles (GAAP).[7] Accordingly, the total number of firms covered in the data set was reduced from 615,951 to 438,165, and approximately one-third of the firms were removed from the sample after the rigorous filter was applied. The drop in the percentage of sales is only around 25%. Thus, the drop in sales is smaller, since larger firms meet the GAAP more frequently. This suggests that larger firms that follow GAAP may generate larger rents per worker, so they have a large surplus to share and the measured effect of reduced input tariffs might be an upper bound.

The second limitation of the data is specific to the present paper. The data set does not separate wages for skilled and unskilled labor. Furthermore, the numbers (i.e. the share) of skilled and unskilled workers are only available for 2004. To overcome this problem, we conduct our baseline test on cross-firm data for 2004. Then we carry out panel data tests that include other years by multiplying the skilled labor shares in 2004 by the change in the skilled labor share (relative to 2004) at the provincial level. To ensure the precision of our estimates, we exclude the pure trade intermediaries (that do not have production activities) from the sample in all the estimates. The trade intermediaries are identified according to the same procedures as in Ahn et al. (2011).

Finally, we use customs' data to match with the firm-level production data so that we are able to identify each firm's importing and processing status. As introduced in Feenstra et al. (2014), the production-level trade data maintained by China's General Administration of Customs include a large variety of information such as each trading firm's importing (or exporting) status and processing (or non-processing) status. Such information is essential for us to conduct our empirical estimations, which will be discussed shortly.

2.2 Measures

This subsection starts by introducing the index of input trade liberalization, and then focuses on constructing firm-level measured skill premium because the data sets do not directly provide firm-level wages for skilled and unskilled labor.

2.2.1 Measures of Input Tariffs

Inspired by Amiti and Konings (2007) and Topalova and Khandelwal (2011), we construct the industry-level input tariffs, IT_j as follows:

[7] We keep observations if all of the following hold: (1) total assets exceed liquid assets; (2) total assets exceed total fixed assets; (3) the net value of fixed assets is less than that of total assets; (4) the firm's identification number exists and is unique, and (5) the established time is valid.

$$IT_j = \sum_n \left(\frac{input_{nj}^{2002}}{\sum_n input_{nj}^{2002}} \right) \tau_n \tag{1}$$

where IT_j denotes the industry-level input tariffs facing firms in industry j in 2004 and t_n is the tariff on input n in 2004. The weight in parentheses is the production cost share of input n in industry j.

We use China's Input-Output Table of 2002 to construct the weight because NBS reports the Input–Output Table every 5 years and our data are for 2004. In the spirit of Bartik (1991), we use the input-output matrix from 2002 to compute the relevant weighted industry input tariffs since the weight in 2002 reflects the initial conditions prior to China's tariff cuts in 2004.[8] The industrial input tariffs are obtained as follows. First, since there are 71 manufacturing sectors reported in China's Input–Output Table (2002) and only 28 manufacturing sectors reported in the Chinese Industrial Classification (CIC), we start by making a concordance between the Input–Output Table and the CIC sectors. Second, we match the CIC sectors with the International Standard Industrial Classification (ISIC, rev. 3).[9] Third, we make another concordance to link the ISIC and HS 6-digit trade data, where we can find the corresponding tariffs from the WITS database. Fourth, we calculate the industry-level tariffs that are aggregated to the CIC sector level.[10] Since simple-average tariffs cannot take into account the difference of the importance of imports, we consider the following weighted industrial tariffs:

$$\tau_n = \sum_{k \in n} \left(\frac{m_k}{\sum_{k \in n} m_k} \right) \tau_k \tag{2}$$

where m_k is the import values for product k in CIC 2-digit industry n in 2004. Finally, we calculate the industry-level input tariffs using Eq. (1). The industry-level output tariff for industry n in 2004 is also obtained from Eq. (2).

To see how the input tariff reductions affect firms' skill premium, we examine the evolution of China's trade liberalization throughout the sample period. Table 1 reports the mean and standard deviation for this key variable by spreading the sample from 2000 to 2006. As shown in Table 1, the average industry input tariffs were cut in half, from 15.73% in 2000 to 7.71% in 2006, and their standard deviation also dropped by about a half over the same period. The industry input tariffs were around half of their initial levels in 2000, before the WTO accession. Finally, the industry input tariffs in 2004 were also lower than the corresponding industry output tariffs, as shown in Table 2.

[8] By the same token, we use China' s Input–Output Table of 1997 to construct the initial weight of the input tariffs for the sample period of 2000–2006 in our robustness checks.

[9] Since Chinese government adjusted its CIC in 2003, we also made similar adjustments in our data.

[10] We do not report the input weight by industry to save space; these data are available upon request.

Table 1 China's industrial input tariffs

Year	2000	2001	2002	2003	2004	2005	2006	Average
Ind. input tariffs	15.73	14.35	10.52	9.21	8.21	7.84	7.71	9.14
SD	3.90	3.10	2.78	2.31	2.08	1.85	1.72	3.22

Notes This table reports the mean and standard deviation of 3-digit industry-level input tariffs

Table 2 Summary statistics of key variables (2000–2006)

Year coverage	2004 only		2000–2006	
Variables	Mean	SD	Mean	SD
Firm average wage	12.807	9.385	13.231	9.843
Firm skilled share	0.449	0.285	0.437	0.272
Industry input tariffs (%)	8.219	2.084	9.147	3.22
Industry output tariffs (%)	10.111	6.591	11.073	8.195
Measured unskilled wage	1.35	1.441	1.382	1.497
Log of firm sales	9.939	1.178	10.161	1.205
Log of firm labor	4.708	1.088	4.903	1.103
Exporter indicator	0.287	0.452	0.292	0.455
Processing indicator	0.32	0.46	–	–
Importer indicator	0.36	0.47	–	–
Log TFP (Olley-Pakes)	1.153	0.354	1.155	0.347
SOEs indicator	0.038	0.191	0.056	0.229
Foreign indicator	0.213	0.409	0.222	0.416
Wage premium	0.453	8.796	0.001	9.235
Year	2004	–	2003	1.739

Notes The import indicator is only available in the customs firm matched data set. The first two columns cover ASIF data for 2004 only, whereas the last two columns cover ASIF data for 2000–2006

2.2.2 Measures of Skill Premium

The skill premium is defined as $s_{it} = (w_{it}^s - w_{it}^u)/w_{it}^u$ for the skilled wages (w_{it}^s) and unskilled wages (w_{it}^u).[11] Given the share of firm i' s skilled workers (θ_{it}), the firm average wage ($\overline{w_{it}}$) can be written as $\overline{w_{it}} = \theta_{it} w_{it}^s + (1 - \theta_{it}) w_{it}^u$ or, relative to the unskilled wages, $\overline{w_{it}}/w_{it}^u = 1 + \theta_{it} s_{it}$. Hence, the log term of the average wage is:

$$ln\overline{w_{it}} = lnw_{it}^u + ln(1 + \theta_{it} s_{it}) \tag{3}$$

[11] Wage inequality and skilled wage premium are monotonically related although they are two different concepts. Inequality measures are typically statistics that capture dispersion or variance (see e.g. Shorrocks, 1980)—that is second-order. In contrast, skill premium reflects a relative difference in first-order moments. We thank a referee for pointing this out.

When $\theta_{it}s_{it}$ is small, we can omit the higher-order terms and have $(1 + \theta_{it}s_{it}) \approx \theta_{it}s_{it}$. Therefore,

$$ln\overline{w_{it}} \approx lnw_{it}^{u} + \theta_{it}s_{it} \tag{4}$$

The key advantage of Eq. (4) is that it gives rise to a plausible Mincertype regression for our empirical estimation. The trade-off is that, if $\theta_{it}s_{it}$ is not small enough, our Mincer-type regressions are not precise enough to interpret the economic magnitudes of the estimated coefficients. Hence, in the rest of the paper, economic interpretation should be focused on the sign, rather than the magnitude, of our estimates.[12]

Table 2 reports the summary statistics for the key variables used in our estimations. In the firm data set, information on firms' skilled labor share is available only for 2004, although firms' average wages are available for 2000–2006. Since firms' skill share is crucial in Specification (4), we use the cross-section data for 2004 to conduct the main analysis and a panel sample for 2000–2006 for robustness checks only. Since the firm-level data set provides employment information on skilled and unskilled labor only for 2004, we use a proxy for the skilled labor share for all other years. To obtain the proxy $(\widehat{\theta_{it}})$, we multiply the skilled labor share in 2004 $(\theta_{i,2004})$ by the provincial skilled labor share (η_{rt}) in all years, using 2004 as the base year: $\widehat{\theta_{it}} \equiv \eta_{rt}\theta_{i,2004}$. Table 2 reports the mean and standard deviation of the key variables for the samples for 2004 and 2000–2006.

Three variables in Table 2 relate to wage information. The first is firm average wage, which is reported from the data sets directly. The second is the measured wage premium (μ_i), which is defined as firm I's log wage relative to that of the average firm in industry j and region r (to be discussed in details in the next section). The last wage variable is the measured unskilled wage. Since the annual survey of industrial firms does not provide firm-level unskilled wages, we define the measured unskilled wage as the minimum level of firm wages in each (3-digit) industry-province pair based on the following two observations. First, as shown in Table 2, firms' average wages are significantly positively correlated with the skill share,[13] but the mean of measured unskilled wages is much lower than that of the firms' average wage (around 15%). Second, according to Anwar and Sun (2012), wages of unskilled workers in China are actually different across industries and provinces, especially after 2004. As a robustness check, however, we also use an alternative measure of the unskilled wages for our estimations. Finally, the firm-level data set for 2004 reports five education levels: graduate (and above), university, college, high school, and below middle school. As in most studies, we define skilled workers as employees with a college degree or higher.

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[12] Higher-order terms under a proper McLaurin expansion, however, would not be estimable given the sample size and measurement error. We appreciate a referee for pointing this out.

[13] A simple regression of firms' average wage on the skilled share, using the sample for 2004 and controlling for 3-digit industry fixed effects and province fixed effects, suggests a positive coefficient of the skilled share that is highly significant at the conventional statistical level (t-value = 77.25).

2.3 Mincer Empirical Specification

Let us suppose that firm i's skill premium, s_i, takes a linear form

$$s_{it} = \sum_{p=0}^{P} \gamma_p \chi_{it}^{p} + \varepsilon_{it} \tag{5}$$

where x^p denotes a vector of predictors. From Eqs. (4) and (5), we obtain the following. Mincertype empirical specification:

$$\begin{aligned}\ln \overline{w_{it}} = {} & \gamma_0 + \gamma_u \ln w_{it}^{u} + \gamma_0 \hat{\theta}_{it} + \gamma_1 \left(\hat{\theta}_{it} IT_{jt}\right) + \gamma_2 \left(\hat{\theta}_{it} IT_{jt}\right) IM_{it} \\ & + \gamma_3 \left(\hat{\theta}_{it} PT_{jt}\right) + \gamma_4 \left(\hat{\theta}_{it} PT_{jt}\right) FX_{it} + \gamma_5 \left(\hat{\theta}_{it} FX_{jt}\right) \\ & + \gamma_6 \left(\hat{\theta}_{it} IM_{jt}\right) + \gamma_7 IT_{jt} + \gamma_8 PT_{jt} + \gamma_9 IM_{it} \\ & + \gamma_{10} FX_{it} + \gamma_{11} \mu_{it} + \gamma_{12} \hat{\theta}_{it} \mu_{it} + \gamma X_{ijt} \\ & + \delta_i + \delta_{jr} + \delta_t + \varepsilon_{it}\end{aligned} \tag{6}$$

where the error term is defined as $\varepsilon_{it} \equiv \widehat{\theta_{it}} \varepsilon_{it}$. The main regressors in this Mincer regression include three sets of variables: (i) we include unskilled wage ($\ln(w_{it}^{u})$), measured skilled labor share ($\widehat{\theta}_{it}$) and its interaction with input tariffs (IT_{jt}) and output tariffs (PT_{jt})[14]; (ii) we also include import dummy (IM_{it}) (export dummy, FX_{it}) and its interaction with tariffs; (iii) We also include the own terms and their interaction terms with skill share of firm-level controls $\mathbf{X}_{ijt}$ such as firm ownership (state-owned enterprise, foreign firm, or private firm), firm size (poxied by firms' log sales), and firm productivity; finally, (iv) in addition to firm-specific fixed-effects (δ_i), interacted industry-region fixed-effects (δ_{jr}), and year-specific fixed effects (δ_t), we also include firm wage premium, defined as $\mu_{it} \equiv ln\overline{w_{it}} - \sum_{i \in I(jr)}^{N} (ln\overline{w_{it}}) / |\mathrm{Jr}|$ where |Jr| is the cardinality of the set of it i ∈ I(jr) it firms in industry-region pair jr, and its interaction with. Firms' skill share in the regression.

Among the regressors, there are five important points that are worth noting. First and foremost, among the set of predictors, the most important variable of interest is the average intermediate input tariffs in industry j (IT_j) that firm i is associated with. If the coefficient c_1 in Eq. (6) is negative and statistically significant, it suggests that input trade liberalization would increase firm skill premium. It is also reasonable to anticipate that the impact of input trade liberalization on skill premium would be stronger for ordinary (i.e., non-processing) importing firms, since processing imports have already enjoyed the special treatment of free duty (Yu, 2015) and hence would be less impacted by a further input trade liberalization. Thus, we expect that c_2, the

[14] Note that we do not restrict the coefficient of the unskilled wage *cu* to unity given that it is not the observed firm-level low-skilled wage, although our main estimation results won't change even with such a restriction.

triple interaction term among skill share, intermediate input tariffs, and the importer indicator, should be negative. By constrast, another triple interaction term among skill share, intermediate input tariffs, and the processing indicator (not shown in the Eq. (6)) is expected to be positive.

Second, we include the industry average output tariff (PT_j) and its interaction with the firm export indicator as control variables for the reasons as follows. After its accession to the WTO, China cut not only its intermediate input tariffs, but also its final output tariffs (see Yu, 2015, for a detailed discussion). It would be expected that the impact of output trade liberalization on wage inequality may be different between exporting firms and non-exporting firms. Thus, the interactions of output tariffs with firm-level exporting indicators are introduced for that purpose (see Biscourp & Kramarz, 2007; Verhoogen, 2008). Of course, skill premium in exporting (importing) firms may be affected through channels other than trade liberalization. We thus also include firms' own exporting and importing indicators in the regressions.

Third and equally important, the regression Eq. (6) requires panel data. However, we have recorded data on the share of skilled labor only for year 2004, and a proxy for the share of skilled labor for other years: $\widehat{\theta_{it}} \equiv \eta_{rt}\theta_{i,2004}$, which is the skilled labor share in 2004 ($\theta_{i,2004}$) multiplied by the provincial skilled labor share (η_{rt}) in all other years by using 2004 as the base year. The limitation of using the above panel-data estimation is that the within-firm variation generated by the interaction terms of $\widehat{\theta_{it}}$ are mainly from the η_{rt} portion. Thus, we will first use 2004 data and the following baseline cross-section regression for our estimation:

$$\begin{aligned}
\ln \overline{w_i} = \gamma_c &+ \gamma_u \ln w_i^u + \gamma_0 \theta_i + \gamma_1 \big(\theta_i IT_j\big) \\
&+ \gamma_2 \big(\theta_i IT_j\big) IM_i + \gamma_3 \big(\theta_i PT_j\big) \\
&+ \gamma_4 \big(\theta_i PT_j\big) FX_i + \gamma_5 (\theta_i FX_i) \\
&+ \gamma_6 (\theta_i IM_i) + \gamma_7 IT_j + \gamma_8 PT_j \\
&+ \gamma_9 IM_i + \gamma_{10} FX_i + \gamma_{11} \mu_i \\
&+ \gamma_{12} \theta_i \mu_i + \gamma X_i + \delta_{jr} + \varepsilon_i.
\end{aligned} \tag{7}$$

Fourth, μ_{it} is firm i's log wage relative to the average firm in industry j and province r. These we premia (or discounts) can come from different skill composition of firm i's workforce, or the different surplus that firm i generates. It is important to emphasize that this variable plays an important role here. It helps us properly control for between-firm skill premium (e.g. Amiti & Davis, 2011; Egger & Kreickemeier, 2009; Helpman et al., 2017). In the cross-section regression in Eq. (7), with proper region-industry fixed effects, the second component $\sum_{i \in I(jr)}^{N} (ln\overline{w_{it}})/|\mathrm{Jr}|$ of the measured between-firm wage premium (μ_{it}) should be fully absorbed into the industry fixed effects. Thus, the OLS estimator would then exhibit a coefficient of the variable μ_{it} close to unity. The interaction term $\theta_i \mu_i$ is also needed for our Mincer-regression specification.

Finally, our empirical specifications implicitly draw on theory suggested by Helpman et al. (2010). By treating multiple skill groups in the firm-level framework, the regression residuals will depend on (i) the tightness of the local labor market in a province-industry pair, (ii) the locally available skilled workers in an industry and location, (iii) firms' anticipated performance and associated wage offers, and (iv) any firm-specific shocks to the wage bargaining or screening technology (Blaum et al., 2015; Helpman et al., 2017). Thus, we add the following three sets of dummies in the regressions. First, we include province-specific fixed effects to control for province invariant but unobservable factors (such as export subsidy rates, etc.). Second, we include 2-digit industry-specific fixed effects, which control for industry-invariant factors such as industrial capital intensity. Third, we allow for a full set of interacted industry-province dummies to absorb local labor market conditions. The remaining identifying assumption is the idiosyncratic effect $\varepsilon_i \sim N(0, \sigma^2)$,which takes into account firms' anticipated performance and firm-specific shocks that do not differentially affect individual skill groups.

Some studies have investigated whether more productive firms use more skill-biased technology (e.g., Bustos, 2011; Verhoogen, 2008). It is possible that trade liberalization induces the most productive firms to adopt skill-biased technology or upgrade product quality, and hence increases the demand for skilled labor for these firms. If such a multi-collinearity problem is a big concern, our data should exhibit a strong negative correlation between input tariffs and the skill share. However, this is not the case for our sample as the simple correlation in 2004 cross-section data between industrial input tariffs and the skill share is small (− 0.11). Moreover, the simple correlation in the whole sample for 2000–2006 is even smaller in absolute value (− 0.06). The low correlations suggest that the change of firms' skill share is not sensitive to the change of trade liberalization, at least in our current sample.

3 Estimation Results

3.1 Baseline Mincer Regressions

Table 3 presents the baseline results for the cross-section empirical specification Eq. (7). Since the firm-level data set does not report firms' import status, Table 3 does not include the importer indicator. Columns (1) and (2) are a single regression in which column (1) reports the own coefficient of each regressor whereas column (2) reports its corresponding coefficient interacted with the skill share. From column (2), the coefficient of industry input tariffs interacted with firm skill share, the key variable of interest, is negative and statistically significant, suggesting that input trade liberalization tends to increase skill premium. Sheng and Yang (2016) provide evidence that foreign firms in China attract more skill-intensive production, which in turn would raise firms' skill premium. Thus, we include the interactions of skill share with the foreign indicator and with the SOE indicator in the regression.[15] The positive sign of the coefficient of the foreign indicator ascertains the finding in Sheng and Yang (2016). We also include firm size (proxied by firms' log sales) and firm total factor productivity (measured by the augmented Olley and Pakes (1996) approach, as suggested by Yu, 2015). Exporting firms may have their own channels affecting the skill premium. We thus interact the skill share with the exporting indicator in column (2). Consistent with most of the previous studies, we find that the skill premium is higher for larger firms, more productive firms, and exporting firms.

It is also reasonable to anticipate that firms of different sizes may respond differently to input tariffs. Therefore, we run another regression with results jointly shown in columns (3) and (4). Specifically, we include a triple interaction term among the skill share, input tariffs, and firms' log sales. Importantly, the skill share is an important predictor in itself, beyond size (log sales), and that the skill share prediction is slightly weaker at larger firms. Because the coefficient of the novel triple interaction term among input tariffs, skill share, and log sales has a different (i.e., positive) sign than that of the interaction term between input tariffs and skill share, we take a further step to evaluate their net effect at the sample mean. Overall, the net effect of input tariffs on firm average wages is still negative since $(-0.181 + 0.013 \times 9.94) \times 0.449 < 0$ given that the sample mean of log of firm sales is 9.94 whereas that of firm skilled share is 0.449 as seen from Table 2. Thus, the counteracting effect generated by the new triple term with log sales does not overwhelm our previous main finding.

As recognized by Cai (2010), China's labor force generally migrates from the inland (i.e., western and middle) provinces to the costal (eastern) provinces. It is reasonable to expect that firms have different wage premiums in the different regions. We thus classify all 31 provinces into three regions: east, middle, and west. In the single regression as reported in columns (3) and (4), we also take a step further to control for region-specific fixed effects and industry-specific fixed effects to take into account local market tightness (as discussed earlier). In addition, we also include a full set of interacted industryregion dummies. With such rich sets of fixed effects controlled, the coefficient of input tariffs interacted with skill share—our main interest in the estimation—still remains negative and statistically significant.

Our main empirical specification Eq. (6) also permits a regional analysis by grouping the sample for 2004 into three regions: east, central, and west. We first split the entire national sample into 31 provinces and then repeat the Mincer regression, similar to columns (3–4) of Table 3, for the east region, central region and west

[15] By the official definition reported in the China City Statistical Yearbook (2006), SOEs include firms such as domestic SOEs (code: 110), state-owned joint venture enterprises (141), and state-owned and collective joint venture enterprises (143), but exclude state-owned limited corporations (151). In contrast, foreign firms include the following firms: foreign-invested joint-stock corporations (code: 310), foreign-invested joint venture enterprises (320), fully foreign-invested firms (330), foreign-invested limited corporations (340), Hong Kong/Macao/Taiwan joint-stock corporations (210), Hong Kong/Macao/Taiwan joint venture enterprises (220), fully Hong Kong/Macao/Taiwan-invested enterprises (230), and Hong Kong/Macao/Taiwaninvested limited corporations (240).

Table 3 Mincer regression using matched data for 2004

Firm average wages	(1)	(2)	(3)	(4)	(5)
		× Skill share		× Skill share	× Skill share × processing indicator
Measured unskilled wages	0.210^{***} (8.89)		0.209^{***} (8.93)		
Skill share	0.988 (1.49)		1.175^{*} (1.76)		
Industry input tariffs	0.022 (0.83)	-0.069^{*} (− 1.91)	0.029 (1.06)	-0.088^{**} (− 2.34)	0.137^{***} (3.77)
Industry input tariffs × importer indicator		− 0.013 (− 0.40)		− 0.017 (− 0.53)	
Industry output tariffs	0.029^{***} (5.30)	− 0.012 (− 0.68)	0.027^{***} (5.05)	− 0.008 (− 0.44)	0.017 (1.22)
Industry output tariffs × exporter indicator		− 0.015 (− 0.91)		− 0.018 (− 1.12)	
SOEs	− 0.700 (− 0.84)	1.277 (1.04)	− 0.714 (− 0.85)	1.304 (1.06)	
Foreign indicator	0.613^{***} (10.43)	0.122 (0.85)	0.606^{***} (10.15)	0.162 (1.12)	
Log sales	0.079^{***} (3.13)	-0.172^{***} (− 3.35)	0.082^{***} (3.24)	-0.180^{**} (− 3.49)	

(continued)

Table 3 (continued)

Firm average wages	(1)	(2)	(3)	(4)	(5)
		× Skill share		× Skill share	× Skill share × processing indicator
TFP (Olley-Pakes)	0.041 (0.41)	0.673*** (2.85)	0.044 (0.43)	0.667*** (2.83)	
Exporter indicator	− 0.077 (− 0.62)	0.500* (1.74)	− 0.083 (− 0.66)	0.570** (1.96)	
Importer indicator	0.138** (2.21)	0.570* (1.80)	0.144** (2.29)	0.596* (1.89)	
Processing indicator			0.044 (0.73)	− 1.698*** (− 4.65)	
Wage premium	0.972** (221.45)	0.049*** (6.76)	0.972** (221.61)	0.048*** (6.62)	
Region × industry FE	Y			Y	
R^2	0.88			0.93	

Notes Robust *t*-values corrected for clustering at the firm level are in parentheses. *** and **, * represent significance at the 1 and 5%, 10% level, respectively, respectively. Columns (1) and (2) are a single regression with industry-region fixed effect in which column (2) reports the interaction with skill share for related variables. Similarly, Columns (3)–(5) are a single fixed-effects regression with region-industry fixed effects and additional controls. Numbers of observations in each regression are 18,820 region. Results are reported in columns (1–2), (3–4), and (5–6) of Table 3, respectively. In each regression, we control for the interacted province and industry fixed effects. According to the China Regional Statistical Yearbook, the eastern region includes fifteen provinces, the central includes six provinces, and the western region includes the rest of the provinces.[16] Thus, the regional regression for the eastern region has the largest number of observations, followed by the west region, and then by the central region. In the three regressions shown in Table 3, the interaction terms between industry input tariffs and skill share are all negative and highly statistically significant.[17] Thus, our main finding that reduced input tariffs in a firm's industry are associated with a higher skill premium at firms with more skilled workforces is robust for all three regions in China.

3.2 Mincer Regressions Using Matched Sample

Table 3 use the firm-level data set for 2004 to conduct the regressions. The advantage of using only this data set is that it contains all manufacturing firms. Yet, the data set does not contain information on firms' import status. To overcome this data challenge, we match the ASIF data set with the product-level customs data to perform similar Mincer-type regression in Table 3.[18]

Columns (1) and (2) in Table 3 are a single regression with industry-region fixed-effects in which column (1) reports the own coefficient of each regressor whereas column (2) reports the corresponding variables interacted with skill share. Different from estimates in Table 3, we include firms' importing status in estimates of Table 3 since this variable can better capture firm's exposures to globalization. The regression shown in columns (1) and (2) includes the own variable of firms' importing indicator and its interaction with the skill share. The coefficient of industry input tariffs interacted with the skill share is negative and statistically significant, suggesting that reduced input tariffs in a firm's industry are associated with a higher skill premium at firms with more skilled workforces. In addition, the regression includes a triple interaction term among the importer indicator, skill share, and industry input tariffs. The negative, though insignificant, triple interaction term hints that importers might respond more forcefully to input trade liberalization in their wage schedule.

Furthermore, import processing firms may behave differently from ordinary firms, as suggested by Dai et al. (2016). By definition, import processing firms are firms that import raw material or intermediate inputs and then, after local processing

[16] In particular, the eastern region includes the following 15 provinces: Heilongjiang, Jilin, Liaoning, Beijing, Tianjin, Hebei, Shandong, Jiangsu, Anhui, Zhejiang, Shanghai, Fujian, Guangdong, Guangxi, and Hainan. The middle region includes the following six provinces: Inner Mongolia, Shanxi, Henan, Hubei, Hunan, and Jiangxi. Finally, the western region includes the rest of the provinces.

[17] Yet, we also see some regional disparity from Table 3. In particular, the own terms of industry input tariffs in each region have different signs and magnitudes.

[18] The detailed matching method and procedure are introduced in Yu (2015).

or assembly, export the value-added final goods (Feenstra & Hanson, 2005). A processing indicator is defined as one (1) if a firm has any processing imports and zero (0) otherwise. As processing imports have zero import tariffs (Yu, 2015), the effect of input trade liberalization on firms' skill premium is expected to be less pronounced for an industry with many import processing firms.

We run another regression which is jointly reported in columns (3)–(5). As before, column (3) reports the own coefficients of regressors whereas column (4) shows the coefficients of their interaction with skill share. Column (5) reports the coefficient of triple interaction among input (output) tariffs, skill share, and processing indicator. Similar to our previous findings, reduced input tariffs in a firm's industry are associated with a higher skill premium at firms with more skilled workforces, because the coefficient between industry input tariffs and skill premium is negative and statistically significant. The novel finding is that the coefficient of the triple interaction term between industry input tariffs, skill share, and processing indicator is positive and statistically significant, suggesting that the effect of input trade liberalization on firms' skill premium is more pronounced for non-processing (i.e., ordinary) firms.

To see this more precisely, we can take one step further to evaluate the net effect of input trade liberalization on firm wages. As shown in the single regression of columns (3)–(5), there are three types of firms in the regression: non-importing firms, ordinary importers, and processing importers. The net effect of input tariffs on firm average wage for non-importing firms is $0.0290.088 \times 0.45 < 0$ given that the sample mean of firm's skill share is 0.45 and the own coefficient of input tariffs is 0.029 whereas that of the interaction between input tariffs and skill share is $-$ 0.088. Similarly, the net effect for ordinary importers (i.e., importer indicator equals one) is $0.029 - (0.088 + 0.017) \times 0.45 < 0$ given that the coefficient of the triple interaction term among input tariffs, skill share and import indicator is -0.017. These two results are consistent with our previous main finding that a fall in industry input tariffs is associated with a higher skill premium at firms with more skilled workforce.

By contrast, the net effect of input tariffs on firm wages for processing firms is positive since it equals $0.029 + (0.137 - 0.088 - 0.017) \times 0.45 > 0$ given that the coefficient of the triple interaction term among input tariffs, skill share and processing indicator is 0.137. The finding that the sample-mean effect for processing exporters is overturned is also intuitive. Processing imports in China enjoy a special treatment of free duty (see, e.g., Yu, 2015). Thus, further import tariff reductions on processing input encourage processing exporters to switch to ordinary exporters over time, as found by Brandt and Morrow (2017), which in turn lower the employment demand for processing exporters. Accordingly, the average wages for processing firms fall, as shown in the regression of Columns (3)–(5) of Table 3.

3.3 Estimates Using Panel Data

So far, we have used data only for 2004 to estimate the Mincer regressions, because data on firms' skill shares are only available for census year of 2004. The empirical specifications are useful for understanding cross-section firms' skill premium. To gain a better understanding on the variation of within-firm skill premium in response to input trade liberalization, in this section we make an effort to use the panel data for the period of 2000–2006.

Since data on the share of skilled labor are available only for year 2004, to compute a proxy for the skilled labor share for all other years from 2000 to 2006, we multiply the skilled labor share in 2004 by the provincial skilled labor share in all the other years using 2004 as the base year. In addition, industry input and output tariffs are now calculated using the Input–Output Table for 1997 to obtain the corresponding weights because the information in the Input–Output Table of 1997 reflects the initial conditions prior to China's trade liberalization in 2001 (Bartik, 1991).

As data on the share of skilled labor are unavailable for years other than 2004, we compute a proxy for the skilled labor share (hit) for all other years from 2000 to 2006 by multiplying the skilled labor share in 2004 with the provincial skilled labor share in all other years using 2004 as the base year. Equally important, industry input and output tariffs are now calculated using the Input–Output Table for 1997 to calculate the corresponding weights, as the weights in 1997 reflect the initial conditions prior to China's trade liberalization in 2001, as suggested by Bartik (1991).

With cross-section data in 2004, Table 3 has already demonstrated that the results for empirical specification with both own coefficients and coefficients interacted with skill share for each regressor are very close to those without own coefficients. Since the latter specification follows Mincer regressions more closely, in the panel-data analysis we only report those empirical results of estimation with the coefficients interacted with firms' skill share.

Column (1) of Table 4 reports the Mincer regression results by using the 1997 Input–Output Table and controlling year-specific fixed-effects, industry-specific fixed effects, and region-specific fixed effects, respectively. The estimation results are very close to their counterparts in the last two columns of Table 3. The coefficient of industry input tariffs interacted with firms' skill share is negative and statistically significant, indicating that input trade liberalization increases firm's skill premium over time. Similar to the estimation results shown in column (6) of Table 3, the coefficient of output tariffs interacted with the skill share is positive, for the same reason discussed earlier. Estimates in column (2) take a step further to run a more parsimonious regression by controlling the interacted industry and region fixed effects. All regressors have very similar coefficients to their counterparts in column (1).

Finally, it is possible that firms may take more time to respond to tariff reductions in their wage schedule. In our last enrichment, column (3) of Table 4 instead uses firms' past (i.e., one-year lag) export status and past performance (sing log sales or total factor productivity as a proxy). The estimation results for all the variables in column (3), with some variables in one-lag period are close to their counterparts in column (2) when all variables are in the current period. In all cases, the coefficients of industry input tariffs are found to be negative and statistically significant for all the regressions.

Table 4 Mincer regression using the 1997 IO table (2000–2006)

Variable:	Current period		One-lag
Regressand: firm average wages	(1)	(2)	(3)
Measured unskilled wages	0.203*** (22.86)	0.285*** (31.97)	0.255*** (23.78)
Skill share	0.960* (1.88)	0.935* (1.88)	– 0.670 (– 1.08)
Skill share × Industry input tariffs	– 0.454*** (– 8.10)	– 0.244*** (– 4.43)	– 0.153** (– 2.13)
Skill share × Industry output tariffs	0.015*** (3.82)	0.012*** (2.94)	0.023*** (4.54)
Skill share × Industry output tariffs × (One-lag) exporter indicator	– 0.000 (– 0.03)	0.037*** (5.40)	0.026*** (3.11)
Skill share × SOEs	0.394*** (3.79)	0.433*** (4.48)	0.712*** (5.85)
Skill share × Foreign indicator	2.329** (42.10)	1.406*** (27.00)	1.293*** (20.47)
Skill share × Log sales	– 0.188*** (– 3.79)	– 0.223*** (– 4.69)	– 0.184*** (– 3.11)
Skill share × (One-lag) Olley-Pakes TFP	1.876** (27.01)	1.198**** (18.53)	0.921*** (11.31)
Skill share × (One-lag) exporter indicator	0.643*** (6.39)	– 0.103 (– 1.09)	0.100 (0.89)
Skill share × Wage premium	1.288*** (574.20)	1.299*** (623.74)	1.372*** (552.14)
Skill share × Industry input tariffs × (One-lag) log sales	0.034*** (6.26)	0.026*** (4.90)	0.020*** (2.94)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Region × Industry fixed effects	No	Yes	Yes
Observations	507,084	507,084	345,543
R^2	0.75	0.78	0.77

Notes Robust *t*-values corrected for clustering at the firm level are in parentheses. *** and **, * represent significance at the 1 and 5%, 10% level, respectively

3.4 Endogeneity Issues

In the previous estimations, input trade liberalization was considered as exogenous. However, tariff formation could be endogenous in the sense that skill premium could have a reverse effect on tariff changes. With widening skill premium, unskilled workers could blame free trade policies and form labor unions to lobby the government for temporary trade protection (Bagwell & Staiger, 1990, 1999; Bown & Crowley, 2013). Although this happens in developed countries like the United States (Goldberg & Maggi, 1999) and in some developing countries like Turkey

(Gawande & Bandyopadhyay, 2000), it is less likely to happen in China because labor unions in China are symbolic organizations. In addition, if these types of political factors are time invariant, they should have been accounted and statistically controlled for by the fixed-effect panel estimates in Table 4 (Goldberg & Pavcnik, 2007). However, if they are time variant, the estimations of the related Mincer regressions in Table 4 would be biased.

Moreover, if the residual in Eq. (6), e_{it}, is related to the firm's measured skill share ($\widehat{\theta}_{it}$), the estimated coefficients will be biased. As a robustness check, below we use the instrumental variables (IV) approach to address the potential endogeneity issues. If the negative reverse causality is a main source of endogeneity issue, we should expect that the key estimated coefficient for the interaction term between input tariffs and skill share under the two-stage least square (2SLS) approach should be greater than its counterpart under the OLS approach.

It is challenging to find an ideal instrument for tariffs. Inspired by Trefler (2004) and Amiti and Davis (2011), we use the one-year lag of industry input tariffs as the instrument of the first difference in industrial input tariffs. The economic rationale is that lagged input tariffs are less likely to influence the time difference of input tariffs (Trefler, 2004). In particular, we consider the following first-difference Mincer regression:

$$\begin{aligned}\Delta \ln \overline{w_{it}} = {} & \gamma_c + \gamma_u \Delta \ln w_{it}^u + \gamma_0 \Delta\hat{\theta}_{it} + \gamma_1 \Delta\left(\hat{\theta}_{it} IT_{jt}\right) \\ & + \gamma_2 \Delta\left(\hat{\theta}_{it} IT_{jt}\right) IM_{it} + \gamma_3 \Delta\left(\hat{\theta}_{it} PT_{jt}\right) \\ & + \gamma_4 \Delta\left(\hat{\theta}_{it} PT_{jt}\right) FX_{it} + \gamma_5 \Delta\left(\hat{\theta}_{it} FX_{it}\right) \\ & + \gamma_6 \Delta\left(\hat{\theta}_{it} IM_{jt}\right) + \gamma_7 \Delta IT_{jt} + \gamma_8 \Delta PT_{jt} \\ & + \gamma_9 \Delta IM_{it} + \gamma_{10} \Delta FX_{it} + \gamma \Delta X_{jt} + \delta_i \\ & + \delta_{jr} + \delta_t + \varepsilon_{it}\end{aligned} \tag{8}$$

Accordingly, the regressand and all regressors in Table 5 are in the first difference. Columns (1) and (2) are a single OLS regression in which IV reports the coefficients of the own one-lag industry input tariffs and its interaction with firm skill share using the first difference in industry input tariffs and its interaction with firm skill share as the regressands. Once again, the interaction term between skill share and industry input tariffs is negative and statistically significant, which is consistent with our previous findings. Finally, to show that our 2SLS estimation results are robust to the inclusion of the own terms of the regressors, we run another single estimation by abstracting away the own coefficients of related regressors, which is jointly reported in columns (3) and (4). Similarly, the regression in columns (3) and (4) use the one-lag industry input tariffs interacted with firm skill share as the instrument whereas the first difference in industry input tariffs interacted with firm skill share is served as the regressand. Again, the coefficient of industry input tariffs, the variable of our key interests, is negative and statistically significant. Thus, the 2SLS estimation results are consistent with our previous OLS estimates.

We now perform related statistical tests to check the validity of the instrument. The bottom module in Table 5 provides the first-stage estimates for all specifications. The coefficients of the instruments are negative and highly statistically significant,

Table 5 2SLS estimates using panel data (2000–2006)

First difference in firm average wage	(1)	(2) × Skill share	(3)	(4) × Skill share
Industry input tariffs	0.210*** (6.71)	− 0.546*** (− 9.28)		− 0.145*** (− 2.93)
Measured unskilled wages	0.114*** (4.29)		0.115*** (4.34)	
Skill share	− 5.251*** (− 2.66)		− 29.285*** (− 16.15)	
Industry output tariffs	− 0.012*** (− 3.02)	0.025*** (2.92)		0.004 (0.75)
Industry output tariffs × Exporter indicator		− 0.001 (− 0.13)		− 0.001 (− 0.15)
SOEs	− 0.761* (− 1.74)	1.430* (1.96)		0.272 (0.91)
Foreign indicator	0.744** (2.42)	− 1.322** (− 2.32)		− 0.148 (− 0.49)
Log sales	1.818*** (29.15)	− 0.125 (− 1.04)		2.856*** (44.71)
TFP (Olley-Pakes)	0.579*** (6.56)	0.072 (0.45)		0.959*** (11.40)
Exporter indicator	− 0.136 (− 1.50)	0.182 (0.91)		− 0.065 (− 0.48)
Anderson canon.conr.LM satistics	43.21		86.40	
cragg-DonaMd Wald F statistic	1.4e + 05		2.3e + 05	
Year fixed effects	Y		Y	
Region × Industry FE	Y		Y	
Observations	326,211			
First-stage Reg	− 0.577*** (− 964.1)	− 0.112*** (− 472.7)		− 0.128*** (− 483.8)

Notes Robust *t*-values corrected for clustering at the firm level are in parentheses. *** and **, * represent significance at the 1 and 5%, 10% level, respectively, respectively. The regressand and all regressors are in the first difference. Columns (1) and (2) are a single OLS regression in which IV reports the coefficients of the own one-lag industry input tariffs and its interaction with firm skill share using the first difference in industry input tariffs and its interaction with firm skill share as the regressands. Similarly, columns (3) and (4) are another single regression in which IV reports the coefficients of the one-lag industry input tariffs interacted with firm skill share using the first difference in industry input tariffs interacted with firm skill share as the regressand suggesting that it is more challenging to remove tariff barriers in industries with high initial tariffs. In addition, several tests were performed to verify the quality of the instruments. First, we use the Anderson canon correlated LM w^2 statistic to check whether the excluded instruments are correlated with the endogenous regressors. As shown in the upper module in Table 5, the null hypothesis that the model is under-identified is rejected at the 1% significance level. Second, the Cragg-Donald Wald F-statistic provides strong evidence for rejecting the null hypothesis that the first stage is weakly identified at a high significance level. The tests suggest that the instrument is valid and the specifications are well justified.

3.5 *On the Possible Mechanism*[19]

The objective of this section is to discuss a possible mechanism to enrich our understanding of the main empirical finding that input trade liberalization leads to an increase in firms' skill premium and provide some evidence for our theoretical conjecture. Inspired by the literature on "fair wages" (e.g. Egger & Kreickemeier, 2012), a possible mechanism to interpret our empirical findings is that skilled workers have greater bargaining power with their employers than unskilled workers.[20] As a result, the incomes of skilled workers are more closely linked to firms' profits but the incomes of unskilled workers are more in line with those of other firms in the same industry. Thus, a fall in input tariffs increases the firm's economic profit, which in turn raises firms' skill premium because the skilled labor commands a larger proportion of the incremental surplus than the unskilled labor.[21]

To check whether such a conjecture is supported by the data, we replace the firm's average wage, the regressand in our Mincer-type regressions, with the firm's value-added per worker. Value-added per worker is one possible measure of labor productivity or, more generally, a proxy to the firm's surplus per worker. If input tariff reductions raise the firm's skill premium, we should observe that input trade liberalization also increases the firm's value-added per worker because value-added per worker can be treated as another side of the same coin of firms' skill premium. It is the core of our paper's main hypothesis that intermediate input tariffs move

[19] We thank a referee for providing great comments and suggestions on this subsection.

[20] We are aware that our findings are also consistent with both the bargaining model of Helpman et al. (2010) and the efficiency wage model of Amiti and Davis (2011). On the broad interpretation of our findings, higher value added means firms generate more surplus to share. The surplus may be skill group specific (see appendix to Helpman et al., 2010) or general. In the former case, workers of different skill might have the same bargaining power but generate more additional surplus. In the latter case, more skilled workers might command stronger bargaining power. Note, all these models do not allow for bargaining power to change with trade liberalization because they have no unions but use individual wage determination instead. This may be quite adequate for China, where labor unions are merely symbolic.

[21] We provide a theoretical framework for such a mechanism in our working paper (see Chen et al., 2016).

value-added per worker in essentially the same way as they move the average wage (per worker), which is directly testable.

Specifically, we replace log of firm average wage with log of firm value-added per worker in the empirical specification in Eq. (7). To ensure that our estimation results are not contaminated by using the time-series proxy of the firm's skill share, we focus on cross-section data in 2004 and report the estimation results in Table 5. The estimates in column (1) of Table 5 are obtained by using the ASIF customs matched data (as used in Table 3). After controlling a rich set of interacted region and industry fixed effects, the regression results show that the key coefficient of industry input tariffs interacted with skill share is negative and statistically significant, suggesting that input trade liberalization increases the firm's value-added per worker.

The advantage of using ASIF-customs matched data is to allow us to govern firms' importing status, but it is at the expense of reducing the number of observations since the matching between the two datasets (i.e., ASIF dataset and customs dataset) is imperfect (see more discussions in Yu, 2015). To see whether our findings are robust to different regression samples, column (3) runs the same regression as column (1) but instead uses the ASIF data set only. The key variable of interest, the interaction term between input tariffs and skill share, still exhibits a negative sign and statistically significant, indicating that our findings are robust by using different data sample.

Finally, we also replace the regressand of log average value-added with that of log per-worker profit and run the regressions using ASIF customs matched data in column (2) and sole ASIF data in column (4), respectively.[22] Our key finding is robust in all specifications: When controlling for product-market tariffs in a firm's industry, reduced input tariffs in a firm's industry are associated with higher surplus per worker or overall profits at firms with skill intensive production (skilled workforces).

Although our interpretation is consistent with the evidence, it does not rule out other possible channels or mechanisms. There are other possible interpretations. For instance, an additionally employed skilled worker may generate a larger surplus, all else equal, and yet might receive a smaller share than unskilled workers (after bargaining). The large incremental surplus can be more than proportionally larger than the bargaining share difference to unskilled workers. Thus, skilled workers may seem to capture a larger proportion of the incremental surplus, but really they simply generate more surplus. However, we cannot validate this argument because it requires that the data contain variables that would directly measure the bargaining weight by skill groups, or related quantities.

[22] The number of observations in columns (2) and (4) is smaller than their counterpart in columns (1) and (3), because some firms with negative profits are dropped out.

4 Concluding Remarks

China has experienced dramatic tariff reductions since its accession to the WTO in 2001. On the other hand, wage inequality between skilled and unskilled labor of Chinese manufacturing firms has also increased significantly. To our knowledge, so far there is no study using micro-level evidence to explore the link between the two because there are no firm-level data on wages for skilled and unskilled labor. In this paper, we have developed a Mincer-type econometric approach to estimate firms' skill premium based on imperfect Chinese firm level data on wage information. As in other ambitious attempts to investigate important issues with imperfect data, some compromises were made to conduct our estimations. Nevertheless, the finding that a fall in input tariffs is associated with an increase in the skill premium at firms with more skilled workforces is robust under different econometric specifications.

Such a finding is consistent with the idea that firms share the additional surplus generated by input trade liberalization mostly with skilled workers. Potential reasons for the observed increase in relative skill earnings at more skill intensive firms include technological and institutional factors: skills might be complementary with newly accessible foreign inputs on the technological side, or skilled workers might command stronger bargaining power over additional surplus generated under input trade liberalization.

Our findings also have rich policy implications. Trade liberalization can increase skill demand in China by prompting firms to use intermediate inputs that raise firms' surplus. This happens either because less expensive or newly accessible inputs are complementary to skill or because skilled workers have a stronger bargaining power in their negotiation over the newly generated surplus. In any case, input trade liberalization is an appropriate policy instrument to foster firms' surplus.

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All-Around Trade Liberalization and Firm-Level Employment: Theory and Evidence from China

Antonio Rodrigue-Lopez and Miaojie Yu

1 Introduction

China's profound trade liberalization has been associated with large employment changes throughout the world. In particular, the rise of China as the world's largest trader has been related to substantial net job destruction in developed countries (see, for example, Acemoglu et al., 2016; Autor et al., 2013; Feenstra & Sasahara, 2017; Feenstra et al., 2017; Pierce & Schott, 2016 for the impact of Chinese competition on U.S. labor markets, and Mion & Zhu, 2013 for its impact on employment in Belgium). However, the study of Chinese labor market responses to trade liberalization is a relatively unexplored topic. Using unique firm-level tariff data for trading Chinese manufacturing firms, the goal of this paper is to contribute to fill this gap by estimating the effects of trade liberalization on Chinese firm-level employment, taking into account differences across firms' types and productivities.

Since China's accession to the WTO in December 2001, Chinese firms have been subject to a process of trade liberalization encompassing several dimensions. On the one hand, trade barriers imposed by other countries on Chinese goods declined, which made it easier for Chinese firms to export. On the other hand, China also lowered trade barriers imposed on other countries' final goods—which increased competition for Chinese firms—and on other countries' inputs, which helped Chinese input-importing firms become more productive. Hence, the trade-induced real-location of labor inside and between Chinese firms is the result of three liberalization forces that are related, but may act through different mechanisms. Crucially, this paper is able to disentangle the firm-level employment effects of these three liberalization forces.

A. Rodrigue-Lopez
Department of Economics, University of California, Irvine, CA, USA

M. Yu (✉)
China Center for Economic Research, Peking University, Beijing, China
e-mail: mjyu@ccer.pku.edu.cn

Liaoning University, Liaoning, China

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To empirically disentangle the impact of each type of liberalization on Chinese firm-level employment, we use firm-level and customs data for Chinese trading firms from 2000 to 2006. A key feature of our empirical approach is that the richness of our data allows us to calculate firm-level tariff measures à la Lileeva and Trefler (2010) and Yu (2015). Hence, for each Chinese firm in each year we compute (i) its foreign tariff, which captures the degree of foreign protection the firm's goods face in all its export destinations, (ii) its final-good Chinese tariff, which captures the effective rate of protection received by the firm based on the tariff China imposes on products that are similar to the goods the firm produces, and (iii) its Chinese input tariff, which captures the firm's cost of importing inputs based on Chinese tariffs on the inputs the firm imports.

Abstracting from firm type, the first part of our empirical analysis focuses on the importance of firm heterogeneity in productivity for the responses of firm-level employment to changes in each type of tariff. We find that foreign and Chinese trade liberalization in final goods are associated with job destruction in the least productive firms, and job creation in the most productive firms. In general, final-good Chinese liberalization causes the stronger effects for both low- and high-productivity firms. These results highlight significant Melitz-type effects by which trade liberalization causes reallocation of market shares from low-productivity firms to high-productivity firms, with direct consequences on firm-level employment.

We then take a step further and separate all manufacturing trading firms into four types of firms: processing firms, nonimporting exporters, importing exporters, and importing nonexporters. We find that firm heterogeneity in productivity is also relevant for comparisons across firms of the same type, with both types of liberalization in final goods having similar effects across all types of firms: job destruction in the least productive firms and job creation in the most productive firms. In contrast, Chinese input-trade liberalization effects on firm-level employment are limited to job destruction in the least productive firms.

The current paper contributes to the literature in at least three important ways. First, we are able to examine the effects of all-around trade liberalization on China's employment. The studies mentioned above look at the effects of import competition from China on the U.S. and other labor markets, and they all find that growing imports from China reduce employment. But it is also important to understand the other side of the coin: the extent to which China's global booming exports, after its WTO accession, affect China's manufacturing employment. Second, by distinguishing firms according to their type, this paper enriches our understanding of the consequences of China's export structure—heavily based on processing exports (see Brandt & Morrow, 2017; Feenstra & Hanson, 2005; Yu, 2015)—on firm-level employment. And third, to motivate the empirical exercise, this paper develops a theoretical model that highlights the different channels through which all-around trade liberalization affects China's firm-level employment.

Our theoretical model includes trade in both final goods and tasks, combining features of the heterogenous-firm model with monopolistic competition of Melitz (2003) and the trade-in-tasks (or inputs) models of Feenstra and Hanson (1996, 1997) and Grossman and Rossi-Hansberg (2008). Notably, the model carefully considers the different types of Chinese firms, which can be classified as either pure processing firms (which import inputs duty free but cannot sell domestically) or ordinary firms (which can import inputs and can access both the domestic and export markets). The model then characterizes how each type of trade liberalization—a reduction in the foreign tariff on final goods, a reduction in the Chinese tariff on final goods, or a reduction in the Chinese tariff on inputs—affects employment in each type of firm.

Within the model, firm-level employment responses are the result of the interaction of three main mechanisms: changes in the competitive environment in China and abroad (competition effects), changes in the fraction of tasks performed inside the firms (task relocation effects), and changes in marginal costs—efficiency gains or losses—due to task relocation effects (productivity effects). In general, trade liberalization is associated with tougher competition in both markets, which is a source of job destruction. On the other hand, the task relocation and productivity effects always drive opposite responses in firm-level employment. For example, after input trade liberalization, ordinary importing firms reduce the number of tasks performed inside the firm (a source of job destruction) but they become more productive, which allows them to charge lower prices and capture larger market shares (a source of job creation). This structure provides a guide for the interpretation of the results from our empirical exercise.

In our model, Chinese liberalization in final goods exposes Chinese firms to tougher competition from foreign firms, which is a source of job destruction that can explain the predicted employment losses for all types of low-productivity firms. Meanwhile, Chinese liberalization in input trade reduces employment in low-productivity firms, and the impact is small and statistically insignificant for high-productivity ordinary firms. The negative effects are likely a consequence of competition and task relocation effects, while the small effects for high productivity firms reveal countervailing forces due to market share reallocations toward more productive firms, as well as market share expansions driven by efficiency gains. Lastly, destruction in low-productivity firms after foreign trade liberalization can be explained by competition effects, with slight job creation for high-productivity firms due to countervailing forces such as an easier domestic environment, the direct expansive effect on exporters, and possible efficiency gains.

The rest of the paper is organized as follows. Section 2 presents the model that help us understand the several channels through which different types of trade liberalization affect the different types of Chinese firms. Section 3 describes our firm-level and trade data, with particular emphasis in our firm-level tariff measures. In Sects. 4 and 5 we present our empirical results. Lastly, Sect. 6 concludes.

2 Theoretical Motivation

This section presents the model that motivates our empirical exercise. In a setting with heterogeneous firms à la Melitz, we show how changes in the trinity of trade costs (external final-good trade costs, internal final-good trade costs, and input trade costs) affect Chinese firm-level employment.

There are two countries, China, which we call Home, and the rest of the world, which we call Foreign. Home has a mass of households of size L, while Foreign's size is L∗—Foreign variable are denoted with a star (∗). Each household in each country provides one unit of labor per unit of time to either a homogeneous-good sector or a heterogeneous-good sector. The homogeneous good is produced under perfect competition and is costlessly traded; on the other hand, differentiated goods are produced under monopolistic competition and each variety is potentially tradable.

The homogeneous good is the numeraire and its production requires only labor. One unit of Home labor produces exactly one unit of the homogeneous good; hence, the wage at Home is 1. At Foreign, however, one unit of labor produces $w^* > 1$ of the homogeneous good, and hence, the wage at Foreign is w^*.

2.1 Preferences and Demand

The utility function of the representative Home household is given by

$$U = H^{1-\eta} Z^{\eta} \tag{1}$$

where H denotes the consumption of the homogeneous good, $Z = \left(\int_{\omega\in\Omega} z^c(\omega)^{\frac{\sigma-1}{\sigma}} d\omega\right)^{\frac{\sigma}{\sigma-1}}$ is the constant elasticity of substitution (CES) consumption aggregator of differentiated goods, and $\eta \in (0, 1)$. In Z, $z^c(\omega)$ denotes the consumption of variety ω, Ω is the set of differentiated goods available for purchase, and $\sigma > 1$ is the elasticity of substitution between varieties. It follows that the representative household spends a fraction η of its income on differentiated goods and the rest on the homogeneous good.

The representative Home household's demand for variety ω is then given by $z^c(\omega) = \frac{p(\omega)^{-\sigma}}{P^{1-\sigma}}\eta$, where $p(\omega)$ is the price of variety ω, and $P = \left[\int_{\omega\in\Omega} p(\omega)^{1-\sigma} d\omega\right]^{\frac{1}{1-\sigma}}$ is the price of the CES aggregator Z. Total Home labor income is L (there are L households, and the labor income of each household is 1), and thus, the total expenditure on differentiated goods is ηL. Hence, the market demand for variety ω is given by

$$z^D(\omega) = \frac{p(\omega)^{-\sigma}}{P^{1-\sigma}} \eta \mathbb{L} \tag{2}$$

With similar preferences for Foreign households, their total expenditure on differentiated goods is $\eta w^* \mathrm{L}^*$, and hence Foreign's market demand for variety ω is $z^{*D}(\omega) = \frac{p^*(\omega)^{-\sigma}}{P^{*1-\sigma}} \eta w^* \mathbb{L}^*$, where $p^*(\omega)$ is the Foreign price of variety ω, and $P^* = \left[\int_{\omega \in \Omega} p^*(\omega)^{1-\sigma} d\omega\right]^{\frac{1}{1-\sigma}}$.

2.2 Production of Differentiated Goods

Differentiated-good firms in both countries are heterogeneous in productivity. As in the Chaney (2008) version of the Melitz (2003) model, there is a constant pool of potential producers in each country, with each of them drawing its productivity φ from a cumulative distribution function $\mathrm{G}(\varphi)$. The probability density function is denoted by $\mathrm{g}(\varphi)$.

Each differentiated good is produced using a continuum of tasks in the interval [0, 1]. A fraction of these tasks is produced inside the firm using domestic labor, while the rest are obtained outside the firm from domestic or foreign input suppliers. Home firms are classified into the following three categories:

1. *Pure processing firms* ($\mathcal{P}$): They import inputs duty-free, but in exchange they must export all their output.
2. *Nonimporting firms* ($\mathcal{N}$): They obtain all their inputs domestically, sell for the domestic market, and may also export.
3. *Importing firms* ($\mathcal{J}$): They import inputs (paying input trade costs), and sell for both the domestic and export markets.

This classification, summarized in Fig. 1, captures very well the full range of Chinese firms. The assumptions that not all exporters import inputs, but that all importers export fit well our Chinese data, which yields that for ordinary firms, 39% of exporters are also importers, but that 85% of importers are also exporters. This is broadly consistent with the stylized facts described in Feng et al. (2016).

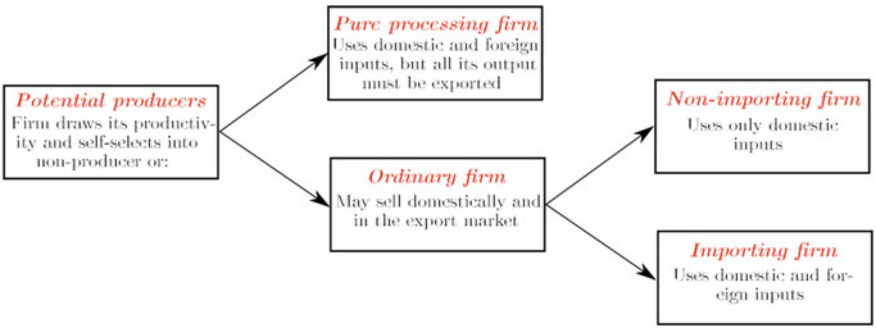

Fig. 1 The types of home firms. Colour figure can be viewed at wileyonlinelibrary.com

The production function of a Home firm with productivity φ and status $s \in \{\mathcal{P}, \mathcal{N}, \mathcal{J}\}$ is $z_s(\varphi) = \varphi Y_s$, where $Y_s = \left[\int_0^1 y_s(\alpha)^{\frac{\theta-1}{\theta}} d\alpha\right]^{\frac{\theta}{\theta-1}}$ is a CES tasks aggregator. In $Y_s, \theta \in [0, \infty)$ is the elasticity of complementarity/substitution between tasks: when $\theta \in [0, 1)$ tasks are complementary, when $\theta = 1$ we obtain the Cobb–Douglas aggregator and tasks are neither substitutes nor complements, and when $\theta > 1$ there is substitutability between tasks.

The production function for task α for a firm with status $s \in \{\mathcal{P}, \mathcal{N}, \mathcal{J}\}$ is given by

$$y_s(\alpha) = l + A_{Ms} a_M(\alpha) m \tag{3}$$

where l denotes units of Home labor, m denotes units of a composite input—which we call *materials*—procured from outside the firm, A_{Ms} is an aggregate productivity factor for materials, and $a_M(\alpha)$ is a task-specific materials' productivity factor. Given the perfect substitutability between l and m in (3), to obtain one unit of task α a Home firm with status s employs either one unit of domestic labor, or buy $1/A_{Ms}\alpha_M(\alpha)$ units of materials. Letting P_{Ms} denote the price of materials for a firm with status s, it follows that the cost of production of one unit of $y_s(\alpha)$ is the minimum between the cost of producing the task with hired labor, 1, and the cost of procuring the task with materials, $P_{Ms}/A_{Ms}\alpha_M(\alpha)$.

Following Feenstra and Hanson (1996, 1997) and Grossman and Rossi-Hansberg (2008), tasks are ordered in the unit interval so that $\alpha_M(\alpha)$ is strictly increasing: the task-specific productivity of materials is higher for higher indexed tasks, and hence, the comparative advantage of labor declines as we move from 0 to 1. Assuming also that $\alpha_M(0) < \mathrm{P}_{M\mathrm{s}}/A_{Ms}$ and $\alpha_M(1) > \mathrm{P}_{M\mathrm{s}}/A_{Ms}$ for every s, there exists a cutoff $\hat{\alpha}_{\mathrm{s}}$ such that tasks in the interval $[0, \hat{\alpha}_{\mathrm{s}})$ are produced inside the firm (with hired domestic labor), and tasks in the interval $[\hat{\alpha}_{\mathrm{s}}, 1]$ are procured using outside materials. At $\hat{\alpha}_{\mathrm{s}}$ the firm is indifferent between producing the input with labor and procuring the input with materials, i.e., $\hat{\alpha}_{\mathrm{s}}$ solves

$$a_M\left(\hat{\alpha}_s\right) = \frac{\mathrm{P}_{M\mathrm{s}}}{A_{Ms}} \tag{4}$$

Foreign is better at producing materials than Home. This is reflected in a lower price and a higher aggregate productivity for Foreign materials; that is, $p_M^* < p_M$ and $A_M^* > A_M$. Pure processing firms do not face any tariffs when importing materials and hence $P_{MP} = P_M^*$. On the other hand, ordinary importing firms incur an import tariff, $\lambda > 0$, so that for nonimporting firms $p_{MN} = p_M$. In addition, we assume that $A_{MP} = A_{MI} = A_M^*$, $A_{MN} = A_M$, and that λ is sufficiently small so that the following ordering always holds:

$$\frac{p_{MP}}{A_{MP}} < \frac{p_{MI}}{A_{MI}} < \frac{p_{M\mathcal{N}}}{A_{M\mathcal{N}}} \tag{5}$$

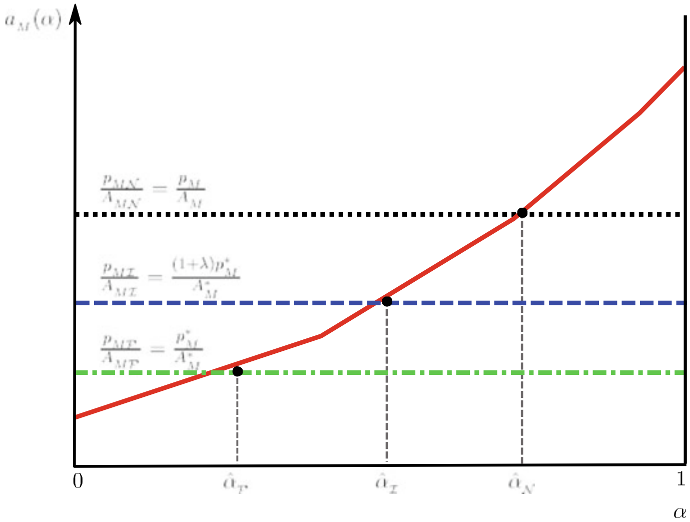

Fig. 2 Tasks performed inside the firm with home labor (by type of firm). Colour figure can be viewed at wileyonlinelibrary.com

Assumption (5) and Eq. (4) imply that $\hat{\alpha}_P < \hat{\alpha}_I < \hat{\alpha}_N$; thus, a pure processing firm performs less tasks inside the firm than the other types of firms, and a nonimporting firm performs more tasks inside the firm than any other type of firm. Figure 2 summarizes this feature of the model.

We can now rewrite the task aggregator for a firm with status s, Y_s, in terms of required labor and materials, and obtain its unit cost. The following lemma shows these results.

Lemma 1 *Let L_s and M_s denote the total amounts of labor and materials used for the production of the task aggregator Y_s. Then*

$$Y_s = \left(\hat{\alpha}_s^{\frac{1}{\theta}} L_s^{\frac{\theta-1}{\theta}} + \upsilon_s\left(\hat{\alpha}_s\right)^{\frac{1}{\theta}} M_s^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}} \tag{6}$$

where $\upsilon_s\left(\hat{\alpha}_s\right) \equiv \int_{\hat{\alpha}_s}^1 \left[A_{Ms} a_M(\alpha)\right]^{\theta-1} d\alpha$. The cost of one unit of Y_s is given by

$$c\left(\hat{\alpha}_s\right) = \left\{\hat{\alpha}_s + \int_{\hat{\alpha}_s}^{1} \left[\frac{a_M\left(\hat{\alpha}_s\right)}{a_M(\alpha)}\right]^{1-\theta} d\alpha\right\}^{\frac{1}{1-\theta}} < 1 \tag{7}$$

which is strictly increasing in $\hat{\alpha}_s$ (i.e., $c'(\hat{\alpha}_s) > 0$), and approaches 1 as $\hat{\alpha}_s \rightarrow 1$.

Therefore, the marginal cost of a Home firm with status $s \in \{\mathcal{P}, \mathcal{N}, \mathcal{J}\}$ and productivity φ is $c(\hat{\alpha}_s)/\varphi$. If the firm decides to export its finished good, its marginal *cost from selling at Foreign is* $(1+\tau)c(\hat{\alpha}_s)/\varphi$*, where* $\tau > 0$ *is the tariff imposed by Foreign on differentiated-good imports from Home.*

2.3 Pricing and Profits

Assuming market segmentation and given CES preferences, the prices that a Home firm with productivity φ and status s sets in the domestic (D) and export (X) markets are given by $p_{Ds}(\varphi) = \left(\frac{\sigma}{\sigma-1}\right)\frac{c(\hat{\alpha}_s)}{\varphi}$ and $p_{Xs}(\varphi) = \left(\frac{\sigma}{\sigma-1}\right)\frac{(1+\tau)c(\hat{\alpha}_s)}{\varphi}$, respectively. Using these pricing equations and the market demand functions, we obtain that the firm's gross profit functions—before deducting fixed costs—from selling in each market are

$$\pi_{Ds}(\varphi) = \frac{1}{\sigma}\left[\frac{P}{p_{Ds}(\varphi)}\right]^{\sigma-1}\eta\mathbb{L} \textit{ and } \pi_{Xs}(\varphi) = \frac{1}{\sigma}\left[\frac{P^*}{p_{Xs}(\varphi)}\right]^{\sigma-1}\eta w^*\mathbb{L}^* \tag{8}$$

As usual, for $r \in \{D, X\}$ and $s \in \{\mathcal{P}, \mathcal{N}, \mathcal{J}\}$, $p'_{rs}(\varphi) < 0$ and $\pi'_{rs}(\varphi) > 0$ so that more productive firms charge lower prices and obtain larger profits.

Foreign differentiated-good firms do not have incentives to purchase materials from Home; thus, the production function of a Foreign firm with productivity φ is $z^*(\varphi) = A^*\varphi Y^*$, where A^* is an aggregate productivity factor for Foreign firms (normalized to 1 for Home firms) and $Y^* = \left[\int_0^1 y^*(\alpha)^{\frac{\theta-1}{\theta}} d\alpha\right]^{\frac{\theta}{\theta-1}}$ is the CES task aggregator. The Foreign firms' task production function is analogous to (3), their cost of producing one unit of task α with Foreign labor is w^*, and their cost of producing it with materials is $\frac{p_M^*}{A_M^* a_M^*(\alpha)}$. It follows that the fraction of tasks produced inside a Foreign firm with Foreign labor, $\hat{\alpha}^*$, is the solution to

$$a_M^*(\hat{\alpha}^*) = \frac{p_M^*}{A_M^* \mathrm{w}^*} \tag{9}$$

Analogously to Lemma 1, the unit cost of Y^* is $\mathrm{c}^*(\hat{\alpha}^*)w^*$, where $\mathrm{c}^*(\hat{\alpha}^*)$ is similar to (7) but with $\hat{\alpha}^*$ and $\mathrm{a}^*\mathrm{M}(\cdot)$ instead of $\hat{\alpha}_s$ and $\mathrm{a_M}(\cdot)$. The marginal cost for a Foreign firm with productivity φ is then $\frac{c^*(\hat{\alpha}^*)w^*}{A^*\varphi}$ from selling domestically, and $\frac{(1+\tau^*)c^*(\hat{\alpha}^*)w^*}{A^*\varphi}$ from selling in the Home market, with $\tau^* > 0$ denoting the tariff imposed by Home on differentiated-good imports from Foreign. Hence, the prices set by a Foreign firm with productivity φ are $p_D^*(\varphi) = \left(\frac{\sigma}{\sigma-1}\right)\frac{c^*(\hat{\alpha}^*)w^*}{A^*\varphi}$ in the domestic market, and $p_X^*(\varphi) = \left(\frac{\sigma}{\sigma-1}\right)\frac{(1+\tau^*)c^*(\hat{\alpha}^*)w^*}{A^*\varphi}$ in the export market. The firm's gross profit functions from selling in each market are

$$\pi_D^*(\varphi) = \frac{1}{\sigma}\left[\frac{P^*}{p_D^*(\varphi)}\right]^{\sigma-1}\eta w^*\mathbb{L}^* \textit{ and } \pi_X^*(\varphi) = \frac{1}{\sigma}\left[\frac{P}{p_X^*(\varphi)}\right]^{\sigma-1}\eta\mathbb{L} \tag{10}$$

2.4 Cutoff Productivity Levels and the Masses of Firms

By Lemma 1 and $\hat{\alpha}_p < \hat{\alpha}_1 < \hat{\alpha}_{\mathcal{N}}$, it is the case that $c(\hat{\alpha}_p) < c(\hat{\alpha}_1) < c(\hat{\alpha}_{\mathcal{N}})$. Although pure processing firms face the lowest cost of the task aggregator, the trade-off is that they are not allowed to access the domestic market (and they are not exempt of Foreign tariffs). There are fixed costs of importing inputs for both processing and ordinary firms, and there are fixed costs of selling in each market. These fixed costs along with the CES demand system imply the existence of cutoff productivity levels that determine firm status s (for Home firms) and the tradability of each differentiated good in each market.

There are four cutoff productivity levels for Home firms: one for pure processing firms, $\hat{\varphi}_p$, one for nonimporting firms selling only in the domestic market, $\hat{\varphi}_D$, one for nonimporting firms selling to both the domestic and export markets, $\hat{\varphi}_X$, and one for importing-exporting firms, $\hat{\varphi}_I$. In our Chinese data, Dai et al. (2016) show that processing firms are on average the least productive of all types of firms, and importing firms (of which the vast majority, 85%, are also exporters) are on average the most productive. Accordingly, we assume parameters such that $\hat{\varphi}_p < \hat{\varphi}_D < \hat{\varphi}_X < \hat{\varphi}_I$ always holds. Then, for example, a Home firm with productivity below $\hat{\varphi}_p$ does not produce, while a firm with productivity between $\hat{\varphi}_X$ and $\hat{\varphi}_I$ is an ordinary nonimporting firm that sells to both markets. For Foreign firms there are only two cutoff productivity levels, $\hat{\varphi}_D^*$ and $\hat{\varphi}_X^*$, and we assume fixed costs and trade costs such that $\hat{\varphi}_D^* < \hat{\varphi}_x^*$ always holds.

Fixed costs are in terms of the homogeneous good. For $r \in \{D, X\}$, let f_r be the fixed cost of selling in market r for Home ordinary firms, and let f^* be the fixed cost of selling in market r for Foreign firms. The fixed cost for Home processing firms, f_p, includes both importing and exporting fixed costs. On the other hand, ordinary importing firms pay f_I in addition to f_D and f_X. Hence, based on net profits, the cutoff productivity levels satisfy the following indifference conditions:

$$\pi_{X\mathcal{P}}(\hat{\varphi}_{\mathcal{P}}) = f_{\mathcal{P}} \tag{11}$$

$$\pi_{D\mathcal{N}}(\hat{\varphi}_D) - f_D = \pi_{X\mathcal{P}}(\hat{\varphi}_D) - f_{\mathcal{P}} \tag{12}$$

$$\pi_{X\mathcal{N}}(\hat{\varphi}_X) = f_X \tag{13}$$

$$\pi_{D\mathcal{J}}(\hat{\varphi}_{\mathcal{J}}) + \pi_{X\mathcal{J}}(\hat{\varphi}_{\mathcal{J}}) - f_{\mathcal{J}} = \pi_{D\mathcal{N}}(\hat{\varphi}_{\mathcal{J}}) + \pi_{X\mathcal{N}}(\hat{\varphi}_{\mathcal{J}}) \tag{14}$$

$$\pi_D^*(\hat{\varphi}_D^*) = f_D^* \tag{15}$$

$$\pi_X^*(\hat{\varphi}_X^*) = f_X^* \tag{16}$$

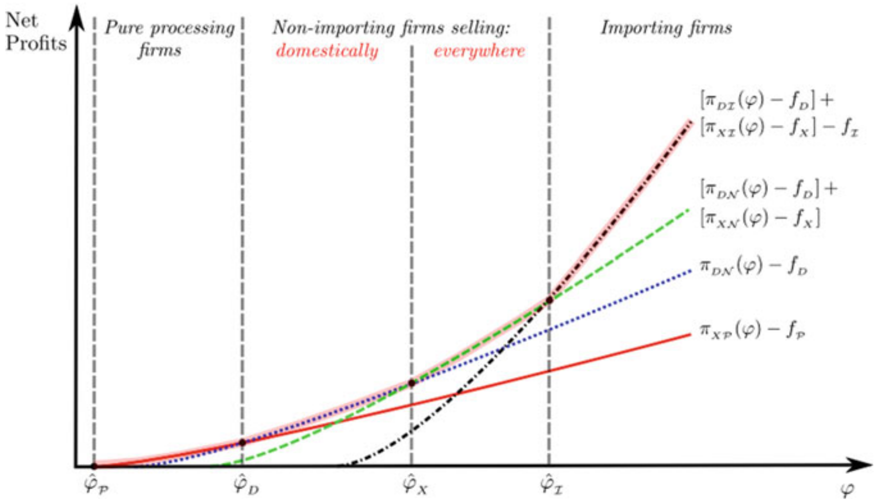

Fig. 3 Cutoff productivity levels and the partition of firms. Colour figure can be viewed at wileyonlinelibrary.com

where the profit functions are given by (8) and (10). Figure 3 shows the partition of firms for Home producers. The four marked intersections represent the indifference conditions (11)–(14). For example, a firm with productivity $\hat{\varphi}_I$—shown in condition (14)—is indifferent between being an ordinary nonimporting firm accessing both markets, and being an ordinary importing firm accessing both markets.

There is a mass of $\overline{N}$ potential producers at Home, and a mass of $\overline{N}^*$ potential producers at Foreign. For Home producers, N_p is the mass of pure processing firms (who can only sell to the export market), $N_{r,N}$ is the mass of ordinary nonimporting firms selling to market r, for $r \in \{D, X\}$, and N_I is the mass of ordinary importing firms (who always sell to both markets). With firm productivity distributed with distribution function $G(\varphi)$ and given the ordering of the cutoff productivity levels in Fig. 3, the masses of each type of Home producers are

$$N_\mathcal{P} = \left[G\left(\hat{\varphi}_D\right) - G\left(\hat{\varphi}_\mathcal{P}\right)\right]\overline{N} \tag{17}$$

$$N_{D\mathcal{N}} = \left[G\left(\hat{\varphi}_\mathcal{J}\right) - G\left(\hat{\varphi}_D\right)\right]\overline{N} \tag{18}$$

$$N_{X\mathcal{N}} = \left[G\left(\hat{\varphi}_\mathcal{J}\right) - G\left(\hat{\varphi}_X\right)\right]\overline{N} \tag{19}$$

$$N_\mathcal{J} = \left[1 - G\left(\hat{\varphi}_\mathcal{J}\right)\right]\overline{N} \tag{20}$$

Foreign potential producers have the same productivity distribution as Home potential producers, and thus the mass of Foreign producers selling in their domestic market, $N_D{}^*$, and the mass of Foreign exporters, $N_X{}^*$, are given by

$$N_D^* = \left[1 - G\left(\hat{\varphi}_D^*\right)\right]\overline{N}^* \tag{21}$$

$$N_X^* = \left[1 - G\left(\hat{\varphi}_X^*\right)\right]\overline{N}^* \tag{22}$$

With N denoting the mass of differentiated-good varieties available for purchase at Home, and N^* denoting the mass of varieties available at Foreign, it follows that

$$N = N_{D\mathcal{N}} + N_{\mathcal{J}} + N_X^* \tag{23}$$

$$N^* = N_D^* + N_{\mathcal{P}} + N_{X\mathcal{N}} + N_{\mathcal{J}} \tag{24}$$

2.5 Equilibrium and Trade Liberalization

To close the model we rely on the expressions for the CES prices indexes P and P^*:

$$P = \left[N_{D\mathcal{N}}\overline{p}_{D\mathcal{N}}^{1-\sigma} + N_{\mathcal{J}}\overline{p}_{D\mathcal{J}}^{1-\sigma} + N_X^*\overline{p}_X^{*1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{25}$$

$$P^* = \left[N_D^*\overline{p}_D^{*1-\sigma} + N_P\overline{p}_{XP}^{1-\sigma} + N_{X\mathcal{N}}^*\overline{p}_{X\mathcal{N}}^{*1-\sigma} + N_{\mathcal{J}}\overline{p}_{X\mathcal{J}}^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{26}$$

where the masses of firms are given by (17)–(22), $\overline{p}_{rs} \equiv p_{rs}\left(\overline{\varphi}_{rs}\right)$ is the average price of Home firms with status s selling in market r, $\overline{p}_r^* \equiv p_r^*\left(\overline{\varphi}_r^*\right)$ is the average price of Foreign firms selling in market r, $\overline{\varphi}_{rs} = \left[\int_{\varphi\in\Phi_{rs}} \varphi^{\sigma-1} g(\varphi|\varphi \in \Phi_{rs})d\varphi\right]^{\frac{1}{\sigma-1}}$ is the average productivity for status-s firms that sell in market r (with Φ_{rs} denoting the set of productivity values they take), and $\overline{\varphi}_r^* = \left[\int_{\hat{\varphi}_r^*}^{\infty} \varphi^{\sigma-1} g\left(\varphi|\varphi \in \left[\hat{\varphi}_r^*, \infty\right)\right)d\varphi\right]^{\frac{1}{\sigma-1}}$ is the average productivity of Foreign firms selling in market r. We can now describe the equilibrium.

Definition 1 An equilibrium in this model obtains $\hat{\alpha}_s$ for every s from (4), $\hat{\alpha}^*$ from (9), $c(\hat{\alpha}_s)$ for every s and $c^*(\hat{\alpha}^*)$ from Lemma 1, and then uses the indifference conditions (11)–(16) along with (25) and (26) to solve for P, P^*, $\hat{\varphi}_p$, $\hat{\varphi}_D$, $\hat{\varphi}_X$, $\hat{\varphi}_I$, $\hat{\varphi}_D^*$, and $\hat{\varphi}_X^*$.

Our trade liberalization parameters are τ, τ^*, and λ—recall that τ is the Foreign tariff on final goods from Home, τ^* is the Home tariff on final goods from Foreign, and λ is the Home tariff on inputs from Foreign. Therefore, in this paper we refer to a decline in τ as "Foreign trade liberalization", to a decline in τ^* as "Home trade liberalization in final goods", and to a decline in λ as "Home trade liberalization in inputs".

To understand the model's implications for the impact of each type of trade liberalization on firm-level employment, first we need to look at how equilibrium aggregate prices, cutoff productivity levels, and task cutoffs respond. We solve the model numerically using as benchmark the following parameter values: $\sigma = 3$, $A^* = 1.2$, $w^* = 1.1$, $\eta = 0.5$, $\mathbb{L} = \mathbb{L}^* = \overline{N} = \overline{N}^* = 1$, $f_p = 0.01$, $f_D = f_X = f_D^* = f_X^* = 0.02$, $f_\tau = 0.06$, $p_M = 1$, $p_M^* = 0.7$, $A_{MP} = A_{MI} = A_M^* = 0.5$, $A_{MN} = A_M = 0.3$, $\theta = 1$, $a_M(\alpha) = 2a_M^*(\alpha) = 1 + 5\alpha^2$, $\tau = \tau^* = 2$, and $\lambda = 1.6$. Based on Combes et al. (2012), who find that the distribution of firm productivity for French firms is better approximated by a lognormal distribution, we assume that $g(\varphi) = \frac{1}{\varphi\sqrt{2\pi\rho}}\exp\left(-\frac{(\ln\varphi-\mu)^2}{2\rho}\right)$ with $\mu = -0.02$ and $\rho = 0.35$. These parameters yield an interior solution with $\hat{\alpha}_p < \hat{\alpha}_1 < \hat{\alpha}_{\mathcal{N}}$ and $\hat{\varphi}_p < \hat{\varphi}_D < \hat{\varphi}_X < \hat{\varphi}_I$. For our numerical comparative statics, we assume that τ and τ^* decline to 1.6 and that λ declines to 1.4. Table 11 in the Appendix shows the equilibrium values of our endogenous variables in the benchmark case along with their changes after a reduction in each type of tariff. Table 1 summarizes these numerical comparative static results.

For the cutoff task levels, it is evident from Fig. 2 that changes in τ and τ^* do not affect $\hat{\alpha}_s$ for every $s \in \{P, N, I\}$. Note also that the input tariff, λ, does not affect $\hat{\alpha}_p$ and $\hat{\alpha}_N$, but it does affect $\hat{a}_I$. In particular, Home trade liberalization in inputs ($\downarrow \lambda$) makes materials' imports cheaper and reduces the fraction of tasks performed with Home labor in ordinary importing Home firms $\left(i.e., \frac{d\hat{\alpha}_I}{d\lambda} > 0\right)$; this can be seen in Fig. 2 with a decline in the $\frac{(1+\lambda)P_M^*}{A_M^*}$ horizontal line. As trade liberalization (no matter the type) does not affect $\hat{\alpha}_p$ and $\hat{\alpha}_N$, Table 1 only includes $\hat{a}_I$.

The responses of aggregate prices summarize the changes in the competitive environment in each market. For example, a decline in P indicates a tougher competitive environment at Home—from (2), note that a decline in P implies that the demand for each differentiated-good variety shifts to the left. Therefore, the second and third columns of Table 1 show that Home trade liberalization in either final goods or inputs—a decline in τ^* or λ—causes tougher competitive environments in both countries (P and P^* decline), while Foreign trade liberalization—a decline in τ—toughens the competitive environment at Foreign but softens it at Home (P^* declines but P increases).

Pure processing firms play a crucial role in the decline in P^* after Home liberalization in final goods ($\downarrow \tau^*$), and in the increase in P after Foreign trade liberalization ($\downarrow \tau$). In the first case, the reduction in τ^* makes Foreign firms more competitive at

Table 1 Responses of prices and cutoff levels to tariff reductions

	$\widehat{\alpha_{\mathcal{J}}}$	P	P*	$\widehat{\varphi_P}$	$\widehat{\varphi_D}$	$\widehat{\varphi_X}$	$\widehat{\varphi_{\mathcal{J}}}$	$\widehat{\varphi_D^*}$	$\widehat{\varphi_X^*}$
$\downarrow \tau$	–	↑	↓	↓	↑	↓	↓	↑	↓
$\downarrow \tau^*$	–	↓	↓	↑	↑	↑	↑	↑	↓
$\downarrow \lambda$	↓	↓	↓	↑|	↑	↑	↓	↑	↑

Home, which drives some Home firms to switch from ordinary to pure processing status to avoid the competition from Foreign firms inside Home ($\hat{\varphi}_D$ increases). This effect is strong enough to increase the number of firms selling in Foreign, which drives up competition and lowers the aggregate price, P^*. In the second case, the decline in τ encourages Home firms to export, with some of them deciding to change their status from ordinary nonimporting firms to pure processing firms ($\hat{\varphi}_D$ increases), which negatively affects the number of varieties sold at Home—recall that pure processing firms are not allowed to sell in the Home market. These firms are then replaced in the Home market by less productive Foreign firms, which yields the increase in the aggregate price P.

Regarding cutoff levels for Home firms, Foreign trade liberalization ($\downarrow \tau$) makes it easier for Home firms to export, which is translated to lower $\hat{\varphi}_P$, $\hat{\varphi}_X$, and $\hat{\varphi}_I$. As mentioned before, increases as some Home nonimporting firms selling only domestically decide to become pure processing firms. Home trade liberalization in final goods ($\downarrow \tau^*$) exposes all Home firms to tougher competition from Foreign firms in both markets, which leads to an increase in all the cutoff levels for Home firms. Lastly, Home trade liberalization in inputs ($\downarrow \lambda$) drives a decline in $\hat{\varphi}_I$, as profit opportunities for ordinary importing firms increase; given that the marginal costs of new importing firms decline, it becomes harder for other types of Home firms to compete and $\hat{\varphi}_P$, $\hat{\varphi}_D$, and $\hat{\varphi}_X$ rise.

2.6 Trade Liberalization and Firm-Level Employment

We can now obtain the amount of labor employed by each type of Home firm. As described above, a Home firm with status s uses domestic labor to produce the tasks in the interval $0, \hat{\alpha}_s)$, while tasks in the interval $\left[\hat{a}_s, 1\right]$ are procured using material inputs from outside the firm. The following lemma shows the firm-level demand for Home labor from selling in each market.

Lemma 2 *For a producing Home firm whose productivity φ sorts it into status $S \in \{P, N, I\}$, its demands for domestic labor to produce for each market are given by*

$$L_{Ds}(\varphi) = \frac{\Upsilon \varphi^{\sigma-1} \hat{\alpha}_s P^{\sigma-1} \mathbb{L}}{c\left(\hat{\alpha}_s\right)^{\sigma-O}} \tag{27}$$

$$L_{Xs}(\varphi) = \frac{\Upsilon \varphi^{\sigma-1} \hat{\alpha}_s P^{*\sigma-1} w^* \mathbb{L}^*}{c\left(\hat{\alpha}_s\right)^{\sigma-O} (1+\tau)^{\sigma-1}} \tag{28}$$

where $\gamma \equiv \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} \eta$ is a constant. The two exceptions to (27)–(28) are (1) $L_{DP}(\varphi) = 0$ because pure processing firms are not allowed to sell domestically, and (2) $L_{XN}(\varphi) = 0$ if $\varphi \in \hat{\varphi}_D, \hat{\varphi}_X$ because these nonimporting firms do not export.

Given the results in Table 1, Eqs. (27) and (28) indicate that trade liberalization affects firm-level employment at Home through the following channels: (i) by affecting each country's competitive environment (as reflected by changes in P and P^*), (ii) in the case of foreign trade liberalization ($\downarrow \tau$), by directly expanding employment in exporting firms, which become instantly more competitive in the Foreign market, (iii) in the case of input trade liberalization ($\downarrow \lambda$), by reducing the fraction of tasks performed inside the firm by ordinary importing firms $\left(\downarrow \hat{a}_I\right)$, with the consequent reduction on these firms' unit cost of the task aggregator $\left(c\left(\hat{\alpha}_I\right)\right)$.

In addition, Table 1 shows that all types of trade liberalization affect the cutoff productivity levels, and hence, some firms change their status $s \in \{P, N, I\}$ and market destinations $r \in \{D, X\}$, which also alters their employment (e.g., an initially ordinary nonimporting and nonexporting firm that becomes a pure processing firm after trade liberalization—due to the increase in $\hat{\varphi}_D$—changes its employment from $L_{DN}(\varphi)$ to $L_{XP}(\varphi)$). In the following sections we describe the model's implications regarding the employment effects of each type of trade liberalization for each type of firm. In the end of this section, Table 2 summarizes the results.

Table 2 Trading firms' employment responses to trade liberalization

		Home trade liberalization	
	Foreign trade liberalization (I)	In final goods (Il r″)	In inputs (l 3)
Pure processing firms (P)	Same as next column, plus creation from direct effect on exporters and creation from new P firms	Destruction from tougher competition at Foreign. For N → P switchers, destruction from task relocation, creation from efficiency gains, and destruction or creation from market size effect	
Ordinary nonimporting firms (N) that export	Destruction from tougher competition at Foreign, creation from easier competition at Home, creation from direct effect. And creation from new exporters	Destruction from tougher competition—other channels for both markets. I → N switchers creation from task relocation, destruction from efficiency losses	Destruction from tougher competition in in both markets
Ordinary importing firms (I)	Destruction from tougher competition at Foreign, creation from easier competition at Home, creation from direct effect, other channels for N → I switchers: destruction from task relocation, creation from efficiency gains	Destruction from tougher competition in both markets	Destruction from tougher competition in both markets, destruction from task relocation, creation from efficiency gains, same channels for N → I switchers

2.6.1 Pure Processing Firms (*P*)

The employment of a pure processing firm with productivity φ is $L_{XP}(\varphi) = \frac{\gamma\varphi^{\sigma-1}\hat{a}_P P^{*\sigma-1} w^* L^*}{c(\hat{a}_P)^{\sigma-\theta}(1+\tau)^{\sigma-1}}$. We describe first the case of firms that have status *P* before and after a trade cost shock, and then we study the case of firms that switch their status to *P* after the shock. For firms that keep status *P*, note first from Table 1 that all types of trade liberalization cause a decline in P^* (the competitive environment becomes tougher at Foreign). This is a source of job destruction in $L_{XP}(\varphi)$, and the only active channel in these firms after Home trade liberalization in final goods ($\downarrow \tau^*$) or in inputs ($\downarrow \lambda$). With Foreign trade liberalization ($\downarrow \tau$), however, there is a direct countervailing force of job creation in $L_{XP}(\varphi)$ as Home exporters become more competitive abroad.

Table 1 shows that all types of trade liberalization increase the cutoff productivity level that separates pure processing firms and ordinary nonimporting firms, $\hat{\varphi}_D$, so that some firms switch from status *N* to status *P*. Let $\hat{\varphi}'_D$ denote the post-liberalization cutoff. Hence, for a Home firm with productivity $\varphi \in \hat{\varphi}_D, \hat{\varphi}'_D$, its domestic employment switches from $L_{DN}(\varphi)$ to $L_{XP}(\varphi)$. From (27) and (28), the ratio between the firm's post-liberalization and pre-liberalization employment is given by

$$\frac{L_{XP}(\varphi)}{L_{D\mathcal{N}}(\varphi)} = \left(\frac{\hat{a}_P}{\hat{a}_{\mathcal{N}}}\right)\left[\frac{c(\hat{a}_{\mathcal{N}})}{c(\hat{a}_P)}\right]^{\sigma-\theta}\left[\frac{P^{*\sigma-1}w^*\mathbb{L}^*}{(1+\tau)^{\sigma-1}P^{\sigma-1}\mathbb{L}}\right]$$

This firm's increase or decrease in employment depends on three channels. First, there is a reduction in the fraction of tasks performed inside the firm (recall that $\hat{\alpha}_P < \hat{\alpha}_N$), which is a source of job destruction. Second, there is a reduction in the firm's cost of the task aggregator, $c(\hat{\alpha}_P) < c(\hat{\alpha}_N)$, which yields efficiency gains and is a source of job creation as long as $\sigma > \theta$ (i.e., as long as the substitutability across varieties is higher than the substitutability across tasks). And third, as the firm switches between markets, the effect of trade liberalization on the firm's employment also depends on the size of the Foreign market (adjusted by the export cost) relative to the size of the Home market.

In the case of Foreign trade liberalization ($\downarrow \tau$) there is also a decline in $\hat{\varphi}_P$. Thus, some previously inactive firms become pure processing producers. For these firms their employment jumps from 0 to $L_{XP}(\varphi)$.

2.6.2 Ordinary Nonimporting Firms (*N*)

Ordinary nonimporting firms may sell only domestically or also export. We describe first the employment changes in nonexporting firms, and then we discuss the impact on exporting firms.

Home trade liberalization in final goods ($\downarrow \tau^*$) or in inputs ($\downarrow \lambda$) cause a tougher competitive environment at Home (*P* declines), while the opposite happens for

Foreign trade liberalization (a decline in τ increases P). Therefore, from (27) it follows that each continuing nonexporting firm reduces its employment after Home trade liberalization (in final goods or in inputs), but expands its employment after Foreign trade liberalization. Either type of Home trade liberalization also makes exporting harder for ordinary nonimporting firms, and thus, some previously exporting firms become nonexporters ($\hat{\varphi}_X$ rises), which also causes these firms' to reduce their employment.

The total demand for domestic labor of an ordinary nonimporting firm that also exports is given by $L_{DN}(\varphi) + L_{XN}(\varphi)$. Such a firm faces tougher competitive environments in both markets after either type of Home trade liberalization (P and P^* fall after a decline in either τ^* or λ), which implies job destruction. On the other hand, this type of firm is more likely to create jobs after Foreign trade liberalization ($\downarrow \tau$). In that case, there is an increase in $L_{DN}(\varphi)$ because the competitive environment becomes easier at Home (P rises), and in spite of a tougher competitive environment at Foreign (P^* falls), an expansion in $L_{XN}(\varphi)$ is also possible due to the direct countervailing impact of a lower τ. In addition, Foreign trade liberalization causes a decline in $\hat{\varphi}_X$, which drives an expansion in employment in the new exporting firms.

Home trade liberalization in final goods causes a reduction in profits for all Home firms, as they become subject to stronger competition from Foreign firms. As a consequence, some ordinary importing firms are no longer able to cover the fixed cost of importing inputs and switch their status to nonimporting (N)—note from Table 1 that $\hat{\varphi}_I$ rises after a decline in τ^*. Hence, those firms with productivities between the old and new $\hat{\varphi}_I$ change their employment from $L_{DI}(\varphi) + L_{XI}(\varphi)$ to $L_{DN}(\varphi) + L_{XN}(\varphi)$, so that

$$\frac{L_{D\mathcal{N}}(\varphi) + L_{X\mathcal{N}}(\varphi)}{L_{D\mathcal{J}}(\varphi) + L_{X\mathcal{J}}(\varphi)} = \left(\frac{\hat{a}_{\mathcal{N}}}{\hat{a}_{\mathcal{J}}}\right)\left[\frac{c(\hat{a}_{\mathcal{J}})}{c(\hat{a}_{\mathcal{N}})}\right]^{\sigma-\theta}\left[\frac{(1+\tau)^{\sigma-1}P^{\sigma-1}\mathbb{L} + P^{*\prime\sigma-1}w^*\mathbb{L}^*}{(1+\tau)^{\sigma-1}P^{\sigma-1}\mathbb{L} + P^{*\sigma-1}w^*\mathbb{L}^*}\right]$$

where P' and $P^{*\prime}$ are the post-liberalization aggregate prices. This expression shows one source of job creation and three sources of job destruction for these firms. First, the share of tasks performed inside these firms rises from $\hat{\alpha}_I$ to $\hat{a}_I$, which is a source of job creation. Second, these firms' cost of the task aggregator rises from $c(\hat{\alpha}_I)$ to $c(\hat{\alpha}_N)$, which increases their marginal costs and prices, and thus makes them less competitive with respect to the other types of firms; this is a source of job destruction as long as $\sigma > \theta$. Lastly, tougher competitive environments at Home and Foreign ($P' < P$ and $P^{*\prime} < P^*$) are sources of job destruction.

2.6.3 Ordinary Importing Firms (*I*)

In this model, ordinary importing firms are the most productive of the three types and they sell in both markets. After trade liberalization in final goods ($\downarrow \tau$ or $\downarrow \tau^*$), the response of firm-level employment in a continuing ordinary importer is similar to the response of a continuing nonimporting exporters: job destruction after a decline in τ^*

due to tougher competition in both markets, but possible job creation after a decline in τ due to Home firms become instantly more competitive at Foreign and a weaker competitive environment at Home (a job destruction force is also present when τ declines, however, as the increase in Home exporters cause a tougher competitive environment at Foreign).

Table 1 shows that trade liberalization in inputs ($\downarrow \lambda$) causes a decline in $\hat{\alpha}_I$ (so that the fraction of imported inputs rises) and hence $c(\hat{\alpha}_I)$ falls. From (27) and (28), note that these changes generate two opposing effects on importing firms' employment: job destruction due to the lower fraction of tasks performed inside these firms $(\downarrow \hat{a}_I)$, and job creation due to the fall in these firms' marginal costs—driven by the decline in the unit cost of the task aggregator, $c(\hat{\alpha}_I)$—which allows them to charge lower prices and capture larger market shares. In turn, the increase in importing firms' efficiency toughens the competitive environment in both countries (P and P^* fall after a decline in λ), which causes further job destruction. In the end, these firms will create jobs after a decline in λ only if efficiency gains are sufficiently strong.

From Table 1, note that $\hat{\varphi}_I$ falls after a decline in τ or λ. Therefore, after Foreign trade liberalization or Home input trade liberalization some firms switch status from nonimporting to importing, changing their employment from $L_{DN}(\varphi) + L_{XN}(\varphi)$ to $L_{DI}(\varphi) + L_{XI}(\varphi)$. These firms reduce the number of tasks performed inside the firm $(\hat{\alpha}_I < \hat{\alpha}_N)$, which destroys jobs, but they also have efficiency gains that lead to job creation (as long as $\sigma > \theta$) because their cost of the task aggregator falls, $c(\hat{\alpha}_I) < c(\hat{\alpha}_N)$. Home input trade liberalization toughens competition in both countries, causing further job destruction in these firms. Foreign trade liberalization also toughens competition in the Foreign market, but also promotes job creation in these firms through its direct positive impact on all Home exporters and the softening of competition at Home.

2.6.4 Summary

As a guide for the interpretation of the results of the empirical exercise below, Table 2 presents a summary of the model's implications for the employment responses of trading firms to each type of trade liberalization. The table excludes ordinary nonimporting firms that do not export because our data only includes trading firms.

3 Data and Measures

This section describes the data and the construction of our tariff measures. The key advantage of our empirical approach is that we are able to exploit firm-level differences in exposure to each type of trade liberalization by constructing firm-level tariffs.

3.1 Data

We study the effects of each type of trade liberalization on Chinese firm-level employment from 2000 to 2006—a period that includes the pinnacle of the so-called "China shock" on international labor markets—using three highly disaggregated yearly panel data sets: firm-level production data, tariff data, and product-level trade data. These datasets will allow us to compute firm productivity, firm-level tariffs, as well as other important firm-level control variables.

The firm-level production data comes from China's National Bureau of Statistics (NBS) annual survey on manufacturing firms, which includes all state-owned enterprises (SOEs) and non-SOEs whose annual sales exceed RMB 5 million (or equivalently $725,000). On average, the sample accounts for more than 95% of China's total annual output in the manufacturing sector.[7] As seen from Fig. 5 in the Appendix, the output of firms in the manufacturing sector accounts for around 40.4% of China's GDP in 2000 and around 43.4% of China's GDP in 2006. Besides firm-level employment, this dataset covers more than 100 accounting variables and contains all of the information from the main accounting sheets, which includes balance sheets, loss and profit sheets, and cash flow statements.

However, as documented by Brandt et al. (2012) and other studies, the firm-level production dataset has obvious errors and omissions. Therefore, we clean the dataset following the procedures of Cai and Liu (2009) and Feenstra et al. (2014). In particular, manufacturing firms are kept in our sample only if they meet the requirements of the Generally Accepted Accounting Principles (GAAP).[8] After this rigorous filter is applied, approximately one-third of the total number of firms and one-quarter of firm sales are dropped.

Data on both China's exports and imports are accessed from China's General Administration of Customs. The trade data is compiled at the HS eight-digit product level and includes information of each product's quantity, value (in U.S. dollars), type of trade (i.e., processing or nonprocessing), and even export destination (or import source). The tariff data comes from the World Integrated Trade Solution (WITS) database of the World Bank, and consists of ad valorem duties imposed by China and its trading partners at the six-digit level Harmonized System (HS).

The construction of firm-level tariffs requires matching firm-level production data and product-level trade data. Following Yu (2015), we use the firms' zip code, telephone numbers, and Chinese names, which in the end allow us to match 76,823 common trading firms, including both exporters and importers. Admittedly, the merged dataset loses many observations due to the well-known shortcoming of missing common matching identifiers in the two datasets. As discussed in Yu (2015), the merged sample is skewed towards large firms—as reflected by the higher averages in firm-level employment and exports—and therefore, the results in this paper are valid for large Chinese trading firms. The merged dataset accounts for around 40% of the manufacturing firms reported in the NBS manufacturing survey and contains about half of the export value reported in the customs dataset.

3.2 Firm-Level Tariff Measures

Even if a firm belongs to a narrowly-defined industry, it could produce multiple products and, thus, its employment could be affected by multiple tariff lines. Inspired by Lileeva and Trefler (2010), who highlight the potential aggregation bias from using industry-level tariffs, we construct firm-specific tariffs to better capture the impact of each type of trade liberalization on Chinese firm-level employment. For each Chinese firm (indexed by i) at time t, we calculate the foreign tariff against its final goods (τ_{it}), the Chinese tariff against competing final goods $\left(\tau_{it}^{*}\right)$, and the Chinese tariff on inputs the firm imports (λ_{it}).

Firms not only export multiple products, but also export them to multiple countries, with different subsets of products for different countries. The foreign tariff for Chinese firm i at time t, τ_{it}, captures the degree of foreign protection faced by the firm's products. Based on tariffs on the firm's goods in all its export destinations, τ_{it} is given by

$$\tau_{it} = \sum_{j\in J_i}\left[\frac{X_O^{ij}}{\sum_{j\in J_i} X_O^{ij}}\sum_{k\in K_i}\left[\frac{X_O^{ijk}}{\sum_{j\in J_i} X_O^{ij}}\right]\mathcal{T}_t^{jk}\right] \tag{29}$$

where T_t^{jk} is good j's ad valorem tariff imposed by country k in year t, X_0^{ijk} is the value of firm i's exports of good j to country k in the first year the product appears in the sample, $X_0^{ij} = \sum_{k\in K_{it}} X_0^{ijk}$, K_i is the set of export destinations of firm i, and J_i is the set of goods produced by firm i. Following Topalova and Khandelwal (2011), we fix exports for each good at the initial period to avoid possible reverse causality in firm's exports with respect to foreign tariffs. The ratio X_0^{ijk}/X_0^{ij} governs the share of firm i's good j exported to country k in the first year the firm appears in the sample; thus, it captures the relative importance of T_t^{jk} in affecting firm i's exports of good j.

Chinese tariffs on final goods shield Chinese firms from foreign competition in the domestic market. Our measure for the Chinese tariff on final goods for firm i at time t, τ_{it}^{*}, captures the effective rate of protection received by the firm based on the tariffs China imposes on products that are similar to the goods the firm produces (see Qiu & Yu, 2020). A tariff line has a more pronounced impact if the firm has a larger share of the corresponding good in its total domestic sales. Hence, τ_{it}^{*} should be calculated as the average of all relevant tariffs weighted by the share of each good's domestic sales. Our firm-level production dataset, however, reports information on a firm's total domestic sales but not on each product's domestic sales. Following Yu (2015), we adopt a less satisfactory measure for τ_{it}^{*} it that approximates the share of a good on a firm's domestic sales with the good's share on the firm's exports so that

$$\tau_{it}^{*} = \sum_{j\in J_i}\left(\frac{X_O^{ij}}{\sum_{j\in J_i} X_O^{ij}}\right)\mathcal{T}_t^{*j} \tag{30}$$

where T_t^{*j} is China's ad valorem tariff on product j in year t.

Our measure for the input tariff faced by an ordinary Chinese firm i at time t, λ_{it}, captures the firm's cost of importing inputs as a result of Chinese tariffs on the products imported by the firm. As discussed here and in other works (see, e.g., Feenstra & Hanson, 2005), processing imports are duty-free in China and that is the reason why pure processing firms face no input tariffs. An ordinary Chinese firm, however, may engage in both processing imports and nonprocessing imports. Therefore, λ_{it} is constructed as

$$\lambda_{it} = \sum_{j \in J_i^O} \left(\frac{M_O^{ij}}{\sum_{j \in J_i^M} M_O^{ij}} \right) \mathcal{T}_t^{*j} \tag{31}$$

where M_0^{ij} is firm i's imports of product j in the first year the firm appears in the sample, J_i^M is the set of firm i's imported products, and $J_i^O \subset J_i^M$ is the set of firm i's ordinary (nonprocessing) imported products. Note that (31) takes into account the zero tariff on the firm's processing imports. As with τ_{it} and τ_{it}^*, we use time-invariant weights to avoid an endogeneity problem due to the negative relationship between imports and tariffs.

Table 12 in the Appendix shows the mean and standard deviation per year of our firm-level tariffs in (29), (30), and (31). Average Chinese tariffs on final goods fall the most during the period (from 15.47 to 7.46%), while the reductions in average foreign tariffs and Chinese input tariffs are rather small. Nevertheless, the standard deviations indicate large cross-sectional variation throughout the period. Note that firm-level input tariffs are small (about 2% on average for the entire period), which is a consequence of the large share of (duty-free) processing imports in ordinary firms (see Yu, 2015). Important for the precise estimation of the impact of each type of tariff reduction on firm-level employment, the pairwise simple correlations among foreign tariffs, Chinese final-good tariffs, and Chinese input tariffs are extremely low: the correlation is 0.01 between foreign tariffs and both Chinese final-good and input tariffs, and is 0.012 between Chinese final-good tariffs and input tariffs.

4 Liberalization and Chinese Firm-Level Employment

This section presents our empirical analysis for the effects of foreign tariffs (τ), Chinese final-good tariffs, and Chinese input tariffs (λ) on firm-level employment. We start with specifications that ignore firm type to focus on the importance of firm heterogeneity in productivity, and later we consider specifications that capture differences across the different types of firms.

4.1 The Relevance of Heterogeneity in Productivity

Let E_{it} denote the employment of firm i at time t. Ignoring firm type, the econometric specification for the linearized firm-level labor demand is

$$E_{it} = \beta_{\tau}\tau_{it} + \gamma_{\tau}\Phi_{it}\tau_{it} + \beta_{\tau^*}\tau_{it}^* + \gamma_{\tau^*}\Phi_{it}\tau_{it}^* \\ + \beta_{\lambda}\lambda_{it} + \gamma_{\lambda}\Phi_{it}\lambda_{it} + \psi_i + \upsilon_t + \kappa\Psi_{it} + \varepsilon_{it} \quad (32)$$

where $E_{it} = \ln E_{it}$, τ_{it}, τ_{it}^* and λ_{it} are the firm-level tariffs described above, ψ_i is a firm fixed effect, υ_t denotes a time fixed effect, Ψ_{it} is a vector of firm-level characteristics, and ε_{it} is the error term. The variable Φ_{it} is a measure of the productivity of firm i at time t, which interacted with firm-level tariffs allows us to capture heterogeneous impacts on firm-level employment. The coefficients of interest are $\{\beta_{\tau}, \gamma_t\}$, $\{\beta_{\tau^*}, \gamma_{\tau^*}\}$, $\{\beta_{\lambda}, \gamma_{\lambda}\}$, with each pair characterizing the response of firm-level employment to a change in each type of tariff. For example, the semi-elasticity of employment with respect to foreign tariffs for firm i at time t is given by $\beta_{\tau} + \gamma_{\tau}\Phi_{it}$, so that for a one percentage point increase in the firm's foreign tariff (e.g., from 6 to 7%), the firm's employment changes by $\beta_{\tau} + \gamma_{\lambda}\Phi_{it}$ percent.

Firm productivity is typically measured by total factor productivity (TFP). The most popular methods to compute TFP are the semi-parametric approaches of Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015). Table 3 reports the estimation of (32) under different productivity measures. Column 1 starts with the value-added labor productivity and column 2 uses the standard OLS TFP measure. We then use the augmented Olley and Pakes (1996) TFP in column 3, the Levinsohn and Petrin (2003) TFP in column 4, and the Ackerberg et al. (2015) TFP in column 5. Gandhi et al. (2020) point out that labor—as one of the most important inputs—may also be correlated with unobserved productivity shocks, and that the standard semi-parametric approaches may not yield enough variation to correctly identify the labor coefficient in the TFP estimation. This concern is especially relevant for labor-abundant countries such as China. Taking this into account, we also measure productivity for Chinese firms using the system-GMM approach of Blundell and Bond (1998), which better captures the dynamic effects of all inputs including labor, capital and materials (Yu, 2015). Thus, column 6 shows the estimation results using the system-GMM TFP, and column 7 shows the results using a within-industry normalized version of the system-GMM TFP.

All our specifications in Table 3 include firm-level fixed effects and time fixed effects. As firm size, ownership type, and export status may influence firm-level employment, our specifications include as controls firm-level log sales (as a proxy for firm size), a state-owned-enterprise (SOE) indicator, a foreign-owned status indicator, and an export-status indicator. Given that firms may substitute between capital and labor during episodes of trade liberalization, we also include log capital per worker as control. To preserve space we do not report the estimated coefficients for these controls in any of our tables; however, and consistent with the conventional wisdom,

Table 3 Firm-level tariffs and net employment responses with different TFP measures

	Log employment						
	Labor productivity	OLS	Augmented Olley–Pakes	Levinsohn–Petrin	ACF	System GMM	Relative SGMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign tariff (τ_{ir})	0.16*** (4.11)	2.42*** (10.22)	1.11*** (8.70)	0.81*** (5.39)	0.74*** (10.17)	2.58*** (10.47)	1.18*** (10.47)
× Productivity	− 1.92*** (− 4.51)	− 0.75*** (− 10.07)	− 0.22*** (− 8.52)	− 0.12*** (− 5.18)	− 0.24*** (− 9.96)	− 0.99*** (− 10.25)	− 4.13*** (− 10.20)
Chinese tariff (τ_{if}^*)	0.09 (1.34)	4.45*** (10.24)	1.82*** (9.47)	0.90*** (3.58)	1.34*** (10.54)	4.32*** (9.68)	2.26*** (8.61)
× Productivity	− 2.12*** (− 4.47)	− 1.45*** (− 10.32)	− 0.42*** (− 11.01)	− 0.16*** (− 4.26)	− 0.52*** (− 13.60)	− 1.75*** (− 9.75)	− 8.28*** (− 8.58)
Input tariff (λ_{it})	0.07 (0.68)	1.66* (1.76)	1.33*** (3.13)	1.03** (2.00)	0.79*** (3.25)	1.87* (1.72)	0.94** (2.34)
× Productivity	0.12 (0.13)	− 0.48 (− 1.63)	− 0.24*** (− 2.89)	− 0.13* (− 1.74)	− 0.21*** (− 2.94)	− 0.67 (− 1.60)	− 2.94** (− 2.21)
Observations	56,549	56,549	39,355	38,829	39,355	56,549	56,549
R-squared	0.41	0.43	0.44	0.43	0.45	0.45	0.43

Notes All regressions include firm fixed effects, year fixed effects, and state-owned status, foreign-owned status, export status, log capital per worker, and log sales as controls. Robust t-statistics (in parentheses) clustered at the firm level. Firm productivity is measured by value-added labor productivity in column 1, by standard OLS TFP in column 2, by augmented Olley–Pakes TFP in column 3, by the Levinsohn–Petrin TFP in column 4, by the Ackerberg–Caves–Frazer TFP in column 5, by system-GMM TFP in column 6, and by normalized system-GMM TFP in column 7

The coefficients are statistically significant at the * 10%, ** 5%, or *** 1% level

we find statistically significant evidence that SOEs, foreign firms, exporting firms, and large firms hire more workers, while firms with higher log capital per worker hire less labor.

With the exception of $p_{rs}(\varphi)$ in column 1, in all columns of Table 3 the coefficients of interest for foreign and Chinese final-good tariffs are statistically significant at a 1% level, with $\hat{\beta}_{\tau^*} > \hat{\beta}_{\tau} > 0$ and $\hat{\gamma}_{\tau^*} < \hat{\gamma}_{\tau} < 0$. The estimate for β_{λ} is positive and significant in six of the specifications, while the interaction coefficient is negative in six specifications but only significant in four of them. The positive $\hat{\beta}$'s indicate that for the least productive firms (those with $\Phi_{it} \to 0$) a decline in either type of tariff is associated with job destruction, while the magnitude of the $\hat{\beta}$'s imply that these firms' employment responds the most to Chinese liberalization in final goods and responds the least to Chinese liberalization in inputs. The negative $\hat{\gamma}$'s, on the other hand, show that as productivity increases the negative employment effect of each type of trade liberalization starts to wear off. Table 13 in the Appendix reports a mean value of 2.57 for the system-GMM TFP used in column 6, and thus $\hat{\beta} + \hat{\gamma}\overline{\Phi}$ equals 0.047 for foreign tariffs, − 0.053 for Chinese final-good tariffs, and 0.147 for Chinese input tariffs. Hence, for the firm in the mean there is slight job destruction after either a reduction in foreign tariffs or Chinese input tariffs, but slight job creation after a decline in Chinese final-good tariffs.

A drawback of using raw TFP measures is that firm-level TFP is not directly comparable across industries (see Arkolakis, 2010). To solve this problem, column 7 in Table 3 shows the estimation of (32) under a *relative* system-GMM TFP measure that normalizes the raw system-GMM TFP by two-digit industry. Specifically, we construct $\Phi_{it} \in (0, 1)$ based on the firm's TFP rank relative to its industry peers at time t: the least productive firm in the industry takes a value close to zero, the firm at the median takes a value of 0.5, and the most productive firm takes a value close to 1. This also greatly simplifies the interpretation of the results: for a given tariff, the estimated semi-elasticity of employment for the least productive firm is $\hat{\beta}$, and for the most productive firm is $\hat{\beta} + \hat{\gamma}$. Column 7 shows that each type of trade liberalization is associated with job destruction in the least productive firms ($\hat{\beta} > 0$) and with job creation in the most productive firms ($\hat{\beta} + \hat{\gamma} < 0$). The magnitude of the semi-elasticities indicate that firm-level employment responds the most to Chinese liberalization in final-good trade, and the least to Chinese liberalization in input trade.

To better gauge the effects of each type of trade liberalization along the productivity distribution of firms, we now sort firms into productivity quartiles using our relative system-GMM TFP measure. Thus, our econometric specification becomes

$$E_{it} = \sum_{l=1}^{4} \left[\beta_{\tau}^{l} \tau_{it} + \beta_{\tau^*}^{l} \tau_{it}^{*} + \beta_{\lambda}^{l} \lambda_{it}\right] 1\left\{Q_t^l\right\} + \psi_i + \upsilon_t + \kappa \Psi_{it} + \varepsilon_{it} \tag{33}$$

where $l \in \{1, 2, 3, 4\}$ indicates the quartile (low, medium–low, medium–high, and high), and $1\left\{Q_t^l\right\}$ is a dummy variable taking the value of 1 if firm i belongs to quartile ℓ at time t. Hence, for each productivity quartile, the coefficients of interest are β_{τ}^{l}, $\beta_{\tau^*}^{l}$, and β_{λ}^{l}, which directly indicate the firm-level employment semi-elasticities of firms in quartile ℓ to each type of trade cost. This is our preferred specification, and thus, all of the following results in this paper show semi-elasticities by productivity quartile.

Table 4 presents the estimation of our specification in (33). Pure processing firms face zero input tariffs and enjoy preferential treatment from their international partners (see Ludema et al., 2021). To account for this, and as a preview of our analysis by type of firm, column 1 presents the estimation using all firms, whereas columns 2 and 3 show the estimation after splitting the sample into ordinary firms and pure processing firms. All regressions include firm fixed effects, year fixed effects, and the same controls discussed above.

The three columns show that for each type of trade cost, employment semi-elasticities monotonically decrease as we move from the first to the fourth quartile, being positive and always statistically significant for low-productivity firms (first quartile) and negative and mostly statistically significant for high-productivity firms (fourth quartile). Thus, a reduction in either type of tariff reduces employment in low-productivity firms and increases employment in high-productivity firms, though the evidence is weak for high-productivity firms after a reduction in input tariffs. Firms in the second quartile also have mostly statistically significant semi-elasticities (they also destroy employment after any type of liberalization), while firms in the third quartile are not significantly affected (the exception is the third-quartile coefficient for τ^*_{it} it in column 1). In terms of coefficients' magnitudes, Chinese final-good trade liberalization has the largest effects for both job destruction in low and medium–low productivity firms, and job creation in high productivity firms.

Comparing columns 2 and 3, the most important difference between the employment responses of ordinary and pure processing firms is in the fourth-quartile coefficients for both Foreign and Chinese tariffs. Note that these are about two times larger for pure processing firms, and therefore, a decline in either type of tariff benefits employment in high-productivity pure processing firms the most.

The exercise in this section highlights the relevance of firm-level productivity for the employment effects of each type of trade liberalization. The results indicate standard Melitz's type effects, with changes in firm-level employment likely driven by trade-induced market share reallocations from low-productivity firms to high-productivity firms. Also, here we showed that the size of such employment effects depends on liberalization type and on the distinction between ordinary and pure processing firms.

Table 4 Firm-level tariffs and net employment responses by productivity quartile

	Log employment		
	(1)	(2)	(3)
Foreign tariff (τ_{it})			
First quartile	0.65*** 7.61	0.62*** 6.18	0.84*** 3.47
Second quartile	0.31*** 7.42	0.32*** 6.55	0.09 0.78
Third quartile	− 0.04 (− 1.08)	− 0.02 (− 0.46)	− 0.17 (− 1.35)
Fourth quartile	− 0.31*** (− 7.44)	− 0.28*** (− 6.23)	− 0.56*** (− 3.24)
Chinese tariff (τ_{it}^{*})			
First quartile	1.28*** 11.62	1.41*** 10.45	0.56* 1.95
Second quartile	0.47*** 7.87	0.48*** 6.64	0.52*** 3.1
Third quartile	− 0.12*** (− 2.22)	− 0.02 (− 0.27)	− 0.24 (− 1.54)
Fourth quartile	− 0.68*** (− 11.01)	− 0.54*** (− 7.70)	− 1.15*** (− 5.40)
Input tariff (λ_{it})			
First quartile	1.06*** 4.34	1.11*** 4.36	
Second quartile	0.14 1.17	0.34*** 2.62	
Third quartile	0.13 1.15	0.14 − 1.15	
Fourth quartile	− 0.14 (− 1.29)	− 0.21* (− 1.91)	
Pure processing firms	Yes	No	Only
Observations	56,549	46,443	10,106
R-squared	0.43	0.45	0.37

Notes All regressions include firm fixed effects, year fixed effects, and state-owned status, foreign-owned status, export status, log capital per worker, and log sales as controls. Robust t-statistics (in parentheses) clustered at the firm level. Firms are classified into quartiles from low- to high-productivity according to their relative system-GMM TFP
The coefficients are statistically significant at the * 10%, ** 5%, or *** 1% level

4.2 Expansions and Contractions

It may be argued that employment or tariffs are nonstationary variables, so that the results from the estimation in levels of specifications (32) and (33) are not reliable.

To account for this potential problem, in this section we use instead yearly first differences of our variables of interest. Our first-difference econometric specification is

$$\Delta E_{it} = \sum_{l=1}^{4} \left[\beta_{\tau}^{l} \tau_{it} + \beta_{\tau*}^{l} \tau_{it}^{*} + \beta_{\lambda}^{l} \lambda_{it}\right] 1\left\{Q_{t}^{l}\right\} + \Delta\upsilon_{t} + \kappa \Delta\Psi_{it} + \Delta\varepsilon_{it} \quad (34)$$

where Δ represents the first difference of a variable so that, for example, ΔE_{it} is the log change in firm i's employment from $t-1$ to t.

The estimated responses of firm-level employment to tariff changes are the result of firms' expansion and contraction decisions. For example, if firms are expected to face net job destruction after a tariff reduction, the mechanism of destruction can be through a decline in the rate of job expansion, or an increase in the rate of job destruction, or a combination of both. As a by-product of the first-difference estimation, we are able to break down firm-level employment responses to tariff reductions into their expansions and contractions components. Following Davis et al. (1996), let e_{it} represent the rate of job creation by expansion for firm i between $t-1$ and t, and let c_{it} denote the firm's rate of job destruction by contraction. Using ΔE_{it}, e_{it} and c_{it} are defined as

$$e_{it} = \max(\Delta E_{it}, 0)$$

$$c_{it} = \max(-\Delta E_{it}, 0)$$

and thus $\Delta E_{it} = e_{it} - c_{it}$. It follows that we can split our specification in (34) as

$$e_{it} = \sum_{l=1}^{4} \left[\beta_{\tau}^{le} \Delta\tau_{it} + \beta_{\tau*}^{le} \Delta\tau_{it}^{*} + \beta_{\lambda}^{le} \Delta\lambda_{it}\right] 1\left\{Q_{t}^{l}\right\} + \Delta\upsilon_{t}^{e} + \kappa^{e} \Delta\Psi_{it} + \Delta\varepsilon_{it}^{e} \quad (35)$$

$$c_{it} = \sum_{l=1}^{4} \left[\beta_{\tau}^{lc} \Delta\tau_{it} + \beta_{\tau*}^{lc} \Delta\tau_{it}^{*} + \beta_{\lambda}^{lc} \Delta\lambda_{it}\right] 1\left\{Q_{t}^{l}\right\} + \Delta\upsilon_{t}^{c} + \kappa^{c} \Delta\Psi_{it} + \Delta\varepsilon_{it}^{c} \quad (36)$$

where by construction, each coefficient in (34) is identical to the difference of the respective coefficients in (35) and (36) (e.g. $\beta_{\tau}^{l} \equiv \beta_{\tau}^{le} - \beta_{\tau}^{le}$).

Table 5 presents the first-difference estimation results. The net-employment-change regressions in columns 1, 2, and 3 can be respectively compared to the regressions in columns 1, 2, and 3 of Table 4. Comparing these columns, note that the estimated coefficients are mostly similar in sign and significance, and therefore, most of the findings from the previous section remain. A difference that stands out is that the first- and fourth-quartile foreign-tariff coefficients in the regression for pure processing firms lose their statistical significance; hence, after foreign trade liberalization, the first-difference regression indicates no statistically significant job destruction in low-productivity pure processing firms, nor job creation for high-productivity firms. Note also that in contrast to column 3 of Table 4, column 3 of Table 5 shows input-tariff coefficients for pure processing firms. This is a consequence of firms that switch status from ordinary to pure processing, with the large and significant coefficient for first-quartile firms showing that as input tariffs drop to zero, low-productivity firms that switch to pure processing status have large reductions in employment.

Using all firms, columns 4 and 7 in Table 5 show the expansions (e) and contractions (c) specifications from (35)–(36). The coefficients from column 1 are identical to the difference between the coefficients in columns 4 and 7. Hence, the result that in most rows the coefficients in the fourth and seventh columns have opposite signs shows that after a change in any type of trade cost, changes in job creation by expansion and job destruction by contraction *reinforce each* other to generate the net firm-level employment results. For example, after a 1 percentage point decline in foreign tariffs, low-productivity firms (first quartile) reduce their employment by 0.22% due to a decline in the rate of job expansions, and by 0.17% due to an increase in the rate of job contractions, for a total employment reduction of about 0.38%. On the other hand, for high-productivity firms (fourth quartile), a higher rate of job expansions increase their employment by 0.19% and a lower rate of job contractions increase their employment by 0.04%, for a net employment increase of 0.22%. Note that the majority of the effect of foreign trade liberalization on firm-level employment happens through changes in the rate of job expansions, rather than through job contractions.

Similarly, after a 1 percentage point reduction in Chinese final-good tariffs, Table 5 shows that for the associated 1.26% net job destruction in low-productivity firms (first quartile), the reduction in the rate of job expansions plays a larger role than the increase in the rate of job contractions—the former reduces employment by 0.7% and the latter by 0.55%. For high-productivity firms (fourth quartile), the associated 0.9% net job creation is driven by a 0.66% increase due to the higher rate of job expansions and by a 0.24% increase due to the reduction in the rate of job contractions. Regarding Chinese input trade liberalization, only $\hat{\beta}_{\lambda}^{le}$ is statistically significant, showing that after a 1 percentage point decline in input tariffs, the 0.75% net employment decline in low-productivity firms (first quartile) is mostly associated with a decline in job expansions (0.67%).

Table 5 shows the estimation of specifications (35) and (36) for ordinary firms in columns 5 and 8, and for pure processing firms in columns 6 and 9. The results for ordinary firms are very similar to those obtained using all firms in columns 4 and 7. For pure processing firms, the net employment increase in high-productivity firms (fourth quartile) after a decline in foreign tariffs is mostly due to an increase in the rate of job expansions. After a decline in Chinese final-good tariffs, the consequences on expansions and contractions for pure processing firms are qualitatively similar to those for ordinary firms. Lastly, the net employment reduction in low-productivity firms that switch from ordinary to pure processing firms—and who see their input tariffs drop to zero—is mainly driven by an increase in the rate of job contractions.

Table 5 First-difference estimation, expansions, and contractions

	Net employment change			Job expansions			Job contractions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Foreign tariff (τ_{it})									
First quartile	0.38*** (4.17)	0.45*** (4.34)	− 0.03 (− 0.15)	0.22*** (3.32)	0.25*** (3.30)	0.03 (0.26)	− 0.17** (− 2.50)	− 0.20** (− 2.85)	0.06 (0.36)
Second quartile	0.23*** (5.60)	0.26*** (5.69)	0.11 (1.28)	0.14*** (4.38)	0.16*** (4.33)	0.07 (1.11)	− 0.09*** (− 3.60)	− 0.10*** (− 3.74)	− 0.04 (− 0.71)
Third quartile	− 0.01 (− 0.30)	0.01 (0.26)	− 0.17 (− 1.55)	0.03 (0.83)	0.04 (1.16)	− 0.08 (− 0.95)	0.04 (1.47)	0.03 (0.96)	0.09 (1.47)
Fourth quartile	− 0.22*** (− 4.52)	− 0.22*** (− 4.30)	− 0.24 (− 1.50)	− 0.19(4***) (− 4.65)	− 0.18*** (− 4.17)	− 0.26** (− 2.20)	0.04 (1.27)	0.04 (1.41)	− 0.01 (− 0.13)
Chinese tariff (τ^*_{it})									
First quartile	1.26*** (8.20)	1.42*** (8.24)	0.65** (2.16)	0.70*** (6.91)	0.78*** (6.78)	0.39** (1.88)	− 0.55*** (− 5.54)	− 0.64*** (− 5.48)	− 0.26 (− 1.32)
Second quartile	0.41** (5.09)	0.42*** (4.70)	0.27 (1.51)	0.22*** (3.46)	0.23*** (3.34)	0.11 (0.77)	− 0.19*** (− 4.06)	− 0.19*** (− 3.63)	− 0.16 (− 1.41)
Third quartile	− 0.21*** (− 2.97)	− 0.18** (− 2.30)	− 0.37** (− 1.90)	− 0.19*** (− 3.35)	− 0.16** (− 2.53)	− 0.36** (− 2.24)	0.02 (0.43)	0.02 (0.43)	0.02 (0.13)
Fourth quartile	− 0.90*** (− 10.18)	− 0.85*** (− 9.07)	− 1.11*** (− 4.58)	− 0.66*** (− 9.11)	− 0.62*** (− 7.92)	− 0.86*** (− 4.63)	0.24*** (4.35)	0.23*** (3.97)	0.25** (1.67)

(continued)

Table 5 (continued)

	Net employment change			Job expansions			Job contractions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Input tariff (λ_{it})									
First quartile	0.75*** (2.60)	0.66** (2.23)	4.00*** (3.67)	0.67*** (3.02)	0.65*** (2.88)	1.52 (1.15)	− 0.09 (− 0.52)	− 0.01 (− 0.06)	− 2.48** (− 2.07)
Second quartile	0.17 (1.12)	0.24 (1.56)	− 0.53 (− 0.98)	0.13 (1.04)	0.17 (1.34)	− 0.27 (− 0.92)	− 0.04 (− 0.46)	− 0.07 (− 0.81)	0.26 (0.63)
Third quartile	0.08 (0.59)	0.11 (0.77)	− 0.70 (− 1.46)	0.12 (1.10)	0.12 (1.08)	0.02 (0.06)	0.04 (0.49)	0.01 (0.15)	0.72** (2.55)
Fourth quartile	0.04 (0.28)	0.05 (0.37)	− 0.90 (− 1.01)	− 0.02 (− 0.17)	− 0.03 (− 0.23)	− 0.32 (− 0.37)	− 0.06 (− 0.71)	− 0.07 (− 0.95)	0.58** (2.28)
Pure processing firms	Yes	No	Only	Yes	No	Only	Yes	No	Only
Observations	16,984	14,488	2496	16,984	14,488	2496	16,984	14,488	2496
R-squared	0.38	0.39	0.38	0.25	0.25	0.25	0.21	0.21	0.22

Notes All regressions include year fixed effects and first-differences of state-owned status, foreign-owned status, export status, log capital-labor ratio, and log sales as controls. Robust t-statistics (in parentheses) clustered at the firm level. Firms are classified into quartiles from low- to high-productivity according to their relative system-GMM TFP

The coefficients are statistically significant at the * 10%, ** 5%, or *** 1% level

Given the massive Chinese economic expansion during the early 2000s, it is not surprising that (with the exception described above) in response to trade liberalization, Chinese firms' adjustments in the rate of job expansions tend to be more important than adjustments in the rate of job contractions.

4.3 Heterogenous Impact of Trade Liberalization by Firm Type

The previous results show that productivity matters for the impact of the different types of trade liberalization on firm-level employment. They also show that the effects depend on whether the firm is ordinary or pure processing. This section expands our empirical analysis by further distinguishing between the types of trading ordinary firms: nonimporting exporters, importing exporters, and importing nonexporters. We then compare the empirical results for the different types of firms against our theoretical model's predictions in Table 2 to shed light on the relative importance of each channel through which trade liberalization affects firm-level employment—competition effects, task relocation and efficiency effects, and the direct effect of foreign liberalization. Although our model does not include importing nonexporters, it still provide guidelines to understand these firms' responses.

As shown in Fig. 3, in our model a firm self-selects into each type based on its productivity and the cutoff productivity levels: there is a perfect partition of firms so that two firms with the same productivity level always have the same status $s \in \{P, N, I\}$. Thus, within the model (with $\hat{\varphi}_P < \hat{\varphi}_D < \hat{\varphi}_X < \hat{\varphi}_I$) all pure processing firms are less productive than all ordinary nonimporting firms, who are in turn less productive than all ordinary importing firms. In practice, however, there is overlapping across all types of firms (e.g., there is coexistence of high-productivity pure processing firms and low-productivity importing firms), which can be explained by other dimensions of firm heterogeneity such as differences across firms' fixed costs or managerial abilities. Recognizing this important fact, the empirical analysis in this section continues to distinguish between low, medium–low, medium–high, and high-productivity firms, but now *within* each firm type.

Table 6 reports the outcome of our specifications in (32) and (34) extended to account for different β's across the different types of firms. The first four columns show the output for the regression in levels, while the last four columns show the output for the regression in yearly first differences, with the top of each column indicating the type of firm: pure processing firms (P), nonimporting exporters (N), importing exporters (I), and importing nonexporters (I-NX).

In the two regressions, all the first-, second-, and fourth-quartile estimates of β for Chinese final-good tariffs are highly statistically significant, showing that for all types of firms, a reduction in Chinese tariffs is associated with job destruction in low- and mid-low productivity firms and with job creation in high-productivity firms. The coefficients on Foreign tariffs for the regression in levels present a similar story,

Table 6 Firm-level tariffs and net employment responses by productivity quartile and firm type

	Log employment (regression in levels)				Net employment change (regression in first differences)			
	(P)	(N)	(I)	(I-NX)	(P)	(N)	(I)	(I-NX)
Foreign tariff (τ_{it})								
First quartile	0.67*** (3.03)	0.63*** (3.99)	0.62*** (4.03)	0.74*** (2.59)	0.24 (1.02)	0.28** (2.21)	0.52*** (3.58)	0.24 (0.82)
Second quartile	0.27(** + **) (3.07)	0.39*** (5.62)	0.28*** (4.46)	0.26** (2.26)	0.07 (0.89)	0.23*** (3.48)	0.25*** (4.59)	0.32** (2.35)
Third quartile	− 0.22** (− 2.56)	0.07 (1.14)	− 0.10* (− 1.66)	0.05 (0.43)	− 0.20** (− 2.06)	0.06 (0.95)	0.00 (0.05)	− 0.10 (− 0.77)
Fourth quartile	− 0.69*** (− 4.77)	− 0.25*** (− 3.32)	− 0.23*** (− 3.59)	− 0.42*** (− 2.95)	− 0.45** (− 2.30)	− 0.15** (− 2.35)	− 0.24*** (− 3.46)	− 0.25* (− 1.77)
Chinese tariff (τ_{it}^{*})								
First quartile	1.14*** (5.29)	1.41*** (7.63)	1.20*** (5.38)	1.26*** (3.79)	1.07*** (4.60)	1.31** (6.91)	1.22*** (6.54)	1.57*** (4.61)
Second quartile	0.61*** (5.77)	0.41*** (4.62)	0.45*** (4.86)	0.38*** (2.91)	0.64*** (6.23)	0.32*** (3.29)	0.31*** (3.36)	0.49*** (3.03)
Third quartile	− 0.14 (− 1.58)	− 0.14* (− 1.72)	− 0.05 (− 0.59)	− 0.33** (− 2.26)	− 0.15 (− 1.55)	− 0.27*** (− 3.21)	− 0.23*** (− 2.74)	− 0.13 (− 0.87)
Fourth quartile	− 0.72*** (− 5.07)	− 0.76(** + **) (− 8.01)	− 0.45*** (− 4.55)	− 1.05(**t) (− 6.49)	− 0.94*** (− 5.98)	− 0.97*** (− 9.67)	− 0.76 *** (− 7.78)	− 1.03*** (− 6.24)

(continued)

Table 6 (continued)

	Log employment (regression in levels)				Net employment change (regression in first differences)			
	(P)	(N)	(I)	(I-NX)	(P)	(N)	(I)	(I-NX)
Input tariff (λ_{it})								
First quartile		1.18*** (2.67)	1.08*** (2.94)	0.65 (1.02)		0.54 (1.48)	0.47 (1.26)	1.52** (2.24)
Second quartile		0.02 (0.08)	0.17 (1.06)	0.62 (1.55)		0.23 (1.15)	0.26 (1.53)	0.02 (0.04)
Third quartile		0.15 (0.88)	0.10 (0.53)	0.07 (0.22)		0.21 (1.39)	0.02 (0.11)	– 0.12 (– 0.28)
Fourth quartile		– 0.12 (– 0.93)	– 0.54*** (– 3.21)	0.41* (1.66)		0.15 (1.15)	– 0.27 (– 1.52)	0.32 (1.54)

Notes This table reports the output of two regressions, one in levels and one in first differences. The top of the column indicates the type of firm: pure processing firms (*P*), nonimporting exporters (*N*), importing exporters (*I*), and importing nonexporters (*I*–NX). Regressions include state-owned status, foreign-owned status, export status, log capital-labor ratio, and log sales as controls. The levels regression includes 56,549 observations and the R-squared is 0.43. The first-difference regression includes 16,984 observations and the R-squared is 0.39. Robust t-statistics (in parentheses) clustered at the firm level. Firms are classified into quartiles from low- to high-productivity according to their relative system-GMM TFP

The coefficients are statistically significant at the * 10%, ** 5%, or *** 1% level

but in general they are smaller in magnitude (when compared to the coefficients on Chinese final-good tariffs) and some of them lose their statistical significance in the first-difference regression. On the other hand, the results for input tariffs are generally weak, with the few statistically significant coefficients from the regression in levels losing their relevance in the first-difference regression.

Figure 4 summarizes the results in Table 6 by showing the statistically significant estimated responses of firm-level employment—by firm type and productivity quartile—to a 1 percentage point decline in each type of tariff; i.e., Fig. 4 shows the negative of all those coefficients from Table 6 that are statistically significant at a 5% level. The figure makes evident the higher importance of Chinese final-good trade liberalization—relative to the other liberalization types—for all types of firms and across productivity quartiles.

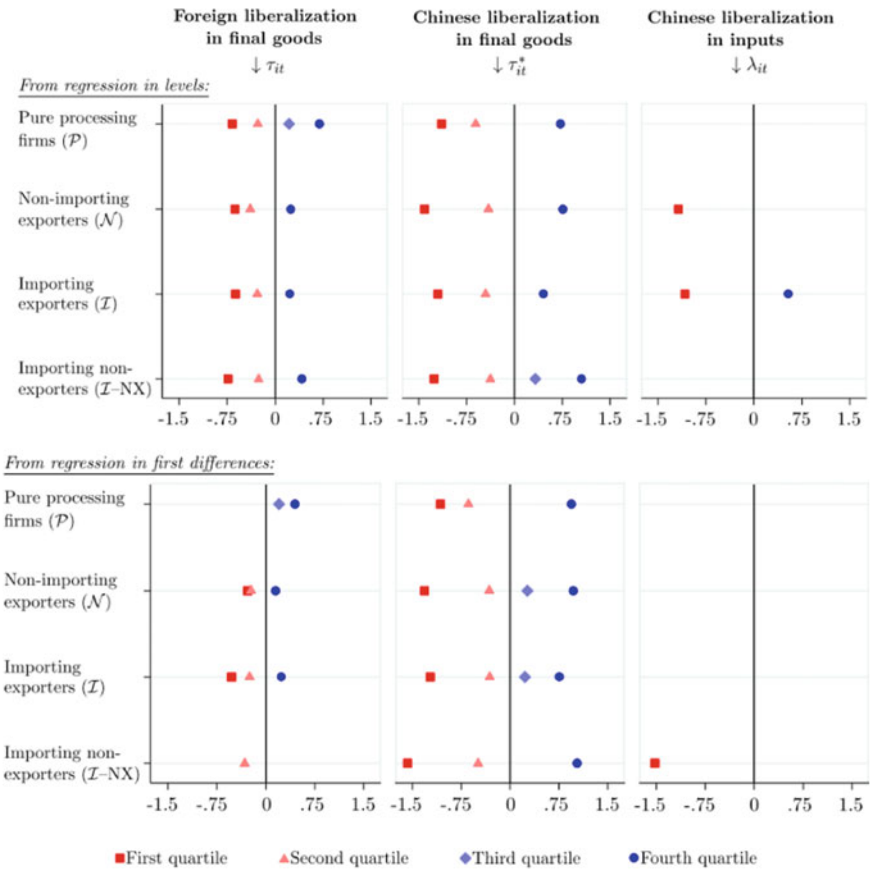

Fig. 4 Employment responses to a 1 percentage point decline in tariffs (statistically significant at a 5% level). Colour figure can be viewed at wileyonlinelibrary.com

Using as guide the theoretical results summarized in Table 2, the destruction in low and mid-low productivity firms after foreign or Chinese trade liberalization in final goods can be explained by competition effects: trade liberalization increases competition, driving down aggregate prices—which shifts to the left the residual demand each firm faces—and causing firm-level employment reductions in low-productivity firms. There is lower destruction after a decline in foreign tariffs because in that case only the foreign market becomes tougher and there are more countervailing forces, such as an easier competitive environment in the domestic market, the expansive direct effect on exporters (who become instantly more competitive in the foreign market), and possible efficiency gains for new pure processing firms and importers.

After Home trade liberalization in final goods, Table 2 shows sources of job creation only for firms that switch from nonimporting to pure processing (from efficiency gains and market size effects) and for firms that switch from importing to nonimporting (from task relocation effects). Hence, although the model provides insights on the channels that can explain job creation in high-productivity pure processing firms after a reduction in Chinese final-good tariffs, it faces limitations to explain the estimated job creation in other types of high-productivity firms. Combined with the observed job destruction in low-productivity firms, a potential explanation is the existence of market share reallocation effects from low and mid-low productivity firms to high-productivity firms within each firm type. This is a channel that is absent from our model, which obtains that all firms with the same status have the same employment elasticities to tariff changes.

After Chinese input trade liberalization, the regression in levels show statistically significant job destruction in low-productivity nonimporting exporters, which by Table 2 can be explained by tougher competition in both markets. There is also job destruction in low-productivity importing exporters, which is explained by competition effects as well as by task relocation effects.

High-productivity importing exporters show statistically significant job creation after input trade liberalization, which can be explained by sufficiently large efficiency gains—their marginal costs decline ($c(\hat{\alpha}_I)$ falls)—that allow them to charge lower prices and capture larger market shares. These results, however, lose their statistical significance in the first difference regression, which only shows job destruction in low productivity importing nonexporters.

Table 7 breaks down the first-difference regression results of Table 6 into its expansions and contractions components. After a decline in Foreign tariffs, an increase in expansions drives job creation in all types of high-productivity firms, while a reduction in expansions and an increase in contractions play a more balanced role in the net job destruction of low- and mid-low productivity firms. Similar results hold for a decline in Chinese final-good tariffs, with the additional result that mid-high productivity (third quartile) firms—with the exception of importing nonexporters—also have statistically significant job expansions. The result that after any type of final-good trade liberalization—but especially after a reduction in Chinese tariffs—job contractions also play an important role on net job destruction in low and mid-low productivity firms indicates that within firm type, there are large labor reallocation effects from low and mid-low productivity firms to mid-high and high-productivity firms. Lastly, after a decline in input tariffs, a reduction in expansions drives job destruction in the least productive importing nonexporters.

4.4 Employment Responses of Switchers

The summary of our model in Table 2 includes a description of the employment responses to trade liberalization for firms that change their status to either pure processing (P), nonimporting exporter (N), or importing exporter (I). This section looks at how switchers in our data respond to each type of tariff, and relies on the model's implications to guide the interpretation of the observed empirical responses. Using first-difference regressions (for net employment changes, expansions, and contractions), Table 8 presents our results for switching firms.

For firms that switch to pure processing status, there is statistically significant job destruction by contraction for low-productivity firms after foreign trade liberalization. According to Table 2, the predicted job destruction by contraction is a consequence of the task relocation effect. However, the net employment effect is not statistically significant, likely as a consequence of expansions due to efficiency gains (firms have reductions in their marginal costs, which allow them to charge lower prices and capture larger market shares) and access to foreign markets that are larger than the no-longer accessible domestic market.

For switchers to P after Chinese liberalization in final goods (a reduction in τ^*), we observe large and statistically significant net job creation for both mid-high and high-productivity firms. The main driver of the net effect is a decline in the rate of job contractions, but job expansions also play a significant role for the most productive firms. From Table 2, the net job creation for these switchers is likely a consequence of efficiency gains and a larger foreign market size. Note that there is also mildly statistically significant evidence of less job contraction for low and mid-low productivity switchers, though the predicted net job creation is not statistically significant. To sum up, these switching Chinese firms saw the decline in domestic tariffs as an opportunity to restructure and expand: facing a threat in the domestic market due to lower τ^*, these Chinese firms decided to escape competition in the domestic market altogether by switching to pure processing status and, while focusing on a narrower set of tasks, expanded their employment to meet foreign demand.

For firms that switch to nonimporting exporter status (N), there is statistically significant net job destruction in mid-low and mid-high productivity firms after a decline in foreign tariffs, whereas there are net job destruction in low-productivity firms and net job creation in mid-high and high productivity firms after a decline in Chinese final-good tariffs. From Table 2, the model does not predict switchers to N (from P or I), and therefore, the net job destruction in switchers to N is explained by channels that are not captured by our model, such as market share reallocations within each firm type. The net job creation in high-productivity N switchers after Chinese liberalization in final goods can also be explained by within-type market

Table 7 Firm-level employment expansions and contractions by firm type

	Job expansions				Job contractions			
	(P)	(N)	(I)	(I-NX)	(P)	(N)	(I)	(I-NX)
Foreign tariff (τ_{it})								
First quartile	0.22 1.56	0.18* 1.73	0.20* 1.81	0.27 1.38	− 0.02 (− 0.12)	− 0.11 (− 1.53)	− 0.32*** (− 2.89)	0.03 0.15
Second quartile	0.11* 1.76	0.13*** 2.87	0.14*** 2.77	0.18* 1.75	0.04 0.95	− 0.10** (− 2.36)	− 0.11*** (− 3.34)	− 0.14 (− 1.59)
Third quartile	− 0.08 (− 1.19)	0.09* 1.8	0.05 1.06	− 0.13 (− 1.27)	0.11** 2.13	0.03 0.81	0.05 1.04	− 0.04 (− 0.40)
Fourth quartile	− 0.35*** (− 2.58)	− 0.14*** (− 2.66)	− 0.17*** (− 2.96)	− 0.27*** (− 2.60)	0.1 1.01	0.01 0.25	0.07* 1.7	− 0.02 (− 0.25)
Chinese tariff (τ^*_{it})								
First quartile	0.67*** 4.58	0.65*** 5.41	0.79*** 5.95	0.77*** 3.18	− 0.40*** (− 2.86)	− 0.65*** (− 4.73)	− 0.43*** (− 3.84)	− 0.80*** (− 4.14)
Second quartile	0.33*** 4.18	0.17** 2.35	0.17** 2.25	0.27**** 2.38	− 0.32*** (− 4.94)	− 0.15** (− 2.55)	− 0.14*** (− 2.65)	− 0.22** (− 2.39)
Third quartile	− 0.17** (− 2.20)	− 0.22*** (− 3.26)	− 0.19*** (− 2.86)	− 0.16 (− 1.21)	− 0.01 (− 0.20)	0.05 0.91	0.04 0.77	− 0.03 (− 0.31)
Fourth quartile	− 0.63*** (− 5.03)	− 0.69*** (− 8.43)	− 0.61*** (− 7.55)	− 0.74*** (− 5.54)	0.31*** 3.65	0.28*** 4.6	0.15** 2.36	0.30*** 2.8

(continued)

Table 7 (continued)

	Job expansions				Job contractions			
	(P)	(N)	(I)	(I-NX)	(P)	(N)	(I)	(I-NX)
Input tariff (λ_{it})								
First quartile		0.5 1.54	0.42 1.52	1.24** 2.4		– 0.04 (– 0.19)	– 0.05 (– 0.24)	– 0.27 (– 0.66)
Second quartile		0.11 0.73	0.21 1.46	0.06 0.18		– 0.12 (– 0.95)	– 0.04 (– 0.48)	0.04 0.16
Third quartile		0.2 1.62	0 0.01	0.19 0.58		– 0.01 (– 0.10)	– 0.02 (– 0.18)	0.31 1.52
Fourth quartile		0.07 0.58	– 0.17 (– 1.07)	0.12 0.75		– 0.09 (– 1.18)	0.1 – 1	– 0.2 (– 1.45)

Notes This table breaks down the results from the last four columns of Table 6 into its expansions and contractions components—the difference between the expansions and contractions coefficients yield the net employment coefficient. The top of the column indicates the type of firm: pure processing firms (P), nonimporting exporters (N), importing exporters (I), and importing nonexporters (I–NX). Regressions include first differences of state-owned status, foreign-owned status, export status, log capital-labor ratio, and log sales as controls. Each regression includes 16,984 observations and the R-squared is 0.25 for the job expansions regression and is 0.21 for the job contractions regression. Robust t-statistics (in parentheses) clustered at the firm level. Firms are classified into quartiles from low- to high-productivity according to their relative system-GMM TFP

The coefficients are statistically significant at the * 10%, ** 5%, or *** 1% level

Table 8 Estimation of employment response of switchers

	Switchers to pure processing firm (P)			Switchers to nonimporting exporter (N)			Switchers to importing exporter (I)		
	(ΔE ≡ e − c)	(e)	(c)	(ΔE− ≡ e − c)	(e)	(c)	(ΔE− ≡ e − c)	(e)	(c)
Foreign tariff (τ_{it})									
First quartile	0.17 (0.42)	− 0.28 (− 0.83)	− 0.45** (− 2.4)	0.35 (0.99)	0.18 (0.82)	− 0.17 (− 0.52)	− 0.19 (− 0.79)	− 0.14 (− 0.68)	0.05 (0.45)
Second quartile	0.11 (0.48)	− 0.03 (− 0.22)	− 0.14 (− 0.86)	0.29**** (2.08)	0.07 (0.55)	− 0.22*** (− 2.84)	0.12 (0.83)	0.06 (0.53)	− 0.06 (− 0.74)
Third quartile	0.12 (0.35)	0.30* (1.69)	0.17 (0.53)	0.25* (1.81)	0.24** (2.14)	− 0.01 (− 0.18)	− 0.12 (− 0.55)	− 0.02 (− 0.1)	0.10 (1.37)
Fourth quartile	− 0.42 (− 1.16)	− 0.16 (− 0.6)	0.27 (1.35)	− 0.02 (− 0.12)	0.05 (0.34)	0.07 (0.75)	− 0.63* (− 1.84)	− 0.60* (− 1.8)	0.03 (0.46)
Chinese tariff (τ_{it}^{*})									
First quartile	− 0.32 (− 0.8)	0.2 (0.63)	0.53* (1.66)	0.93**** (2.4)	0.67** (2.28)	− 0.26 (− 0.99)	0.20 (0.27)	0.16 (0.33)	− 0.04 (− 0.11)
Second quartile	− 0.40 (− 1.2)	0.12 (0.55)	0.52* (1.89)	0.39 (1.45)	0.28 (1.19)	− 0.10 (− 0.84)	− 0.06 (− 0.2)	− 0.00 (− 0.02)	0.06 (0.30)
Third quartile	− 1.05****** (− 3.3)	− 0.16 (− 0.9)	0.89*** (3.34)	− 0.36* (− 1.7)	− 0.22 (− 1.27)	0.14 (1.24)	− 0.32 (− 0.98)	− 0.41 (− 1.56)	− 0.09 (− 0.38)
Fourth quartile	− 1.33*** (− 3.64)	− 0.45** (− 2.52)	0.88*** (2.74)	− 0.86*** (− 3.24)	− 0.64*** (− 2.79)	0.22* (1.72)	− 0.97*** (− 2.95)	− 0.87*** (− 3)	0.10 (0.50)

(continued)

Table 8 (continued)

	Switchers to pure processing firm (P)			Switchers to nonimporting exporter (N)			Switchers to importing exporter (I)		
	($\Delta E \equiv e - c$)	(e)	(c)	($\Delta E - \equiv e - c$)	(e)	(c)	($\Delta E - \equiv e - c$)	(e)	(c)
Input tariff (λ_{it})									
First quartile	− 0.43 (− 0.13)	− 2.17 (− 0.82)	− 1.74 (− 1.31)	0.33 (0.35)	− 0.15 (− 0.19)	− 0.48 (− 1.44)	1.38 (1.32)	0.47 (0.79)	− 0.91 (− 1.04)
Second quartile	0.86 (0.90)	0.1 (0.21)	− 0.75 (− 1.18)	0.20 (0.26)	0.30 (0.44)	0.10 (0.22)	0.33 (0.61)	0.31 (0.83)	− 0.02 (− 0.09)
Third quartile	0.92 (0.74)	0.56 (1.02)	− 0.35 (− 0.42)	− 0.06 (− 0.13)	0.02 (0.05)	0.09 (0.39)	− 0.43 (− 1.14)	0.18 (0.57)	0.61** (2.21)
Fourth quartile	− 0.48 (− 0.37)	− 0.18 (− 0.18)	0.30 (0.43)	− 0.66 (− 1.3)	− 0.43 (− 1.01)	0.24 (0.81)	0.30 (0.7)	0.63 (1.38)	0.33* (1.76)
Observations	487	487	487	1548	1548	1548	1013	1013	1013
R-squared	0.36	0.17	0.3	0.37	0.27	0.18	0.42	0.3	0.24

Notes All regressions include year fixed effects and first-differences of state-owned status, foreign-owned status, export status, log capital-labor ratio, and log sales as controls. Robust t-statistics (in parentheses) clustered at the firm level. Firms are classified into quartiles from low- to high-productivity according to their relative system-GMM TFP

The coefficients are statistically significant at the * 10%, ** 5%, or *** 1% level

share reallocations, but also by strong task relocation effects from firms that stop importing inputs.

For switchers to importing exporter status (I), there is statistically significant net job creation (driven mostly by expansions) in high-productivity firms after reductions in either foreign tariffs or Chinese final-good tariffs. According to Table 2, the employment growth in these firms after a decline in foreign tariffs implies that job creation from easier domestic competition, the direct positive effect on exporters, and efficiency gains dominate the job destruction associated with task relocation effects and the tougher competitive environment abroad. The model does not predict switchers to I after Chinese liberalization in final goods (it predicts destruction in I firms due to tougher environments at home and abroad, along with switchers from I to N). An explanation is that these firms switch to I status to become more efficient competitors in both markets: facing tougher environments in both markets, the opportunity cost of restructuring to reduce marginal costs (by procuring inputs from abroad) declines. As firms switch to I, those with high productivity increase their employment as a result of efficiency gains and within-type reallocation effects.

5 Robustness

In the previous estimations, all types of trade liberalization were treated as exogenous. However, tariff formation could be endogenous in the sense that firm employment could have a reverse causality effect on tariff changes: with a fall in employment, workers could blame free trade policies and form labor unions to lobby the government for temporary trade protection (Bagwell & Staiger, 1990; Grossman & Helpman, 1994). Although this happens in developed countries like the United States (Goldberg & Maggi, 1999), it is less likely to happen in China because its labor unions are symbolic organizations (see, e.g., Branstetter & Feenstra, 2002; Chen et al., 2017). Nevertheless, for the sake of completeness, we use an instrumental variables (IV) approach to control for such possible reverse causality.

Identifying a qualified instrument for tariffs is always a challenging task. Following Trefler (2004) and Amiti and Davis (2011), we use one-year lagged tariffs as instruments of the first difference in tariffs. Abstracting from firm type, Table 9 presents the IV second-stage results for the first difference of our specification in (32), with one-year lags of firm-level Chinese final-good tariffs, Chinese input tariffs, and foreign tariffs serving as instruments of their corresponding first-difference values. Column 1 in Table 9 shows first-difference OLS estimates, using normalized TFP as our measure of productivity (as in column 7 of Table 3). Column 3, which presents the IV estimation, shows coefficients that are all very close to their counterparts in column 1. All the estimates for β are positive and significant, whereas all the estimates for γ are negative, larger in magnitude, and significant. Such results are consistent with our findings in the previous tables.

As described above, our firm-level Chinese final-good tariffs are constructed using Eq. (30), which makes the strong assumption that exported and domestic shares of

Table 9 First-difference IV estimation

	OLS		IV				
	Relative SGMM	De Loecker	Relative SGMM				De Loecker
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign tariff (τ_{it})	0.51*** (4.75)	0.40*** (3.30)	0.44*** (3.36)	0.39 (1.58)	0.48*** (3.04)	0.14 (1.03)	0.23 (1.15)
× Productivity	− 1.78*** (− 4.92)	− 0.75*** (− 3.30)	− 1.57*** (− 3.51)	− 1.23 (− 1.57)	− 1.81*** (− 3.26)	− 0.60 (− 1.35)	− 0.39 (− 1.00)
Chinese tariff (τ_{it}^{*})	2.36*** (11.84)	0.72*** (3.41)	2.08*** (7.68)	2.56*** (5.00)	1.77*** (5.29)	2.70*** (11.26)	1.10** (2.30)
× Productivity	− 8.97*** (− 14.37)	− 1.76*** (− 4.91)	− 9.22*** (− 10.60)	− 11.43*** (− 6.59)	− 8.05*** (− 7.97)	− 9.45*** (− 12.52)	− 3.37*** (− 3.74)
Input tariff (λ_{it})	0.85** (2.22)	0.60 (1.43)	1.22** (2.26)	0.12 (0.12)	1.93*** (2.99)	1.02* (1.89)	0.54 (0.48)
× Productivity	− 2.47** (− 2.03)	− 1.10 (− 1.40)	− 3.58** (− 1.96)	− 0.21 (− 0.07)	− 5.67*** (− 2.58)	− 2.99 (− 1.64)	− 0.76 (− 0.33)
Chinese tariff level	Firm	Firm	Firm	Firm	Firm	Industry	Firm
Included industries	All	All	All	High GSC	Low GSC	All	All
Observations	16,975	9709	16,975	6021	10,954	14,848	9709

Notes All regressions include year fixed effects and first-differences of state-owned status, foreign-owned status, export status, log sales, and log capital per worker as controls. Robust t-statistics (in parentheses) clustered at the firm level The coefficients are statistically significant at the * 10%, ** 5%, or *** 1% level

a product are identical. However, China plays an important role in global supply chains and produces some intermediate goods that cannot be used in the domestic production sector, and as a consequence, the product composition of Chinese exports may be very different from the composition of products sold in the domestic market (Kee & Tang, 2016). Since this problem would bias the measure of firm-level final-good tariffs differently depending on the industry, we experiment with two robustness checks.

First we separate all firms into two groups: those belonging to highly-integrated global supply chain (GSC) sectors, and those belonging to lowly-integrated GSC sectors. After calculating each industry's ratio of value added to gross industrial output, the GSC-integrated indicator takes the value of one if the ratio of an industry is lower than the mean ratio and is zero otherwise. The coefficients on input tariffs for high GSC industries in the IV estimates of column 4 are insignificant and much smaller than their counterparts for low GSC industries in column 5. This is exactly what we expect: input tariffs in the high GSC sectors should be insignificant as such sectors heavily engage in duty-free processing imports. Second, following Yu (2015), we check whether our estimation results are sensitive to our particular measure of firm-level final-goods tariffs by using instead conventional industry-level tariffs. Column 6 in Table 9 reports our IV estimation that replaces firm-level Chinese final-good tariffs with industry-level tariffs. Compared to column 3, our results remain robust.

Thus far, firm productivity is assumed to be exogenous and would not be affected by trade liberalization. However, there is a growing literature exploring firm-level productivity improvements in response to trade liberalization. Ignoring such productivity gains from trade liberalization may generate some estimation bias. To address this concern, we follow De Loecker (2013) and develop an augmented Olley–Pakes TFP by allowing firm-level productivity to react to changes in both foreign and home tariffs over time. Hence, the OLS estimates in column 2 and the IV estimates in column 7 use "De Loecker's TFP" to measure firm productivity. Although the magnitudes of the coefficients are not directly comparable to those in columns 1 and 3—because of the different productivity measures—they yield qualitatively similar results for the effects of foreign tariffs and Chinese final-good tariffs (the coefficients on inputs tariffs are statistically insignificant under De Loecker's TFP).

Lastly, Table 10 presents an IV robustness check that splits firms by status (pure processing firms, nonimporting firms, importing firms, and importing nonexporters) and uses the high-TFP indicator as our measure of productivity. The table shows first-difference IV regressions for net employment changes using two sets of firms. The first four columns report the estimation results for all trading firms, which are comparable to the first-difference OLS estimates shown in the last four columns of Table 6. Note that although some of the estimated coefficients for low-productivity firms lose statistical significance, the IV estimation results are very close to the OLS results for high-productivity firms. The last four columns in Table 10 verify whether ownership status matters by estimating a separate IV regression for foreign-invested firms. The results are qualitatively similar to those presented in the first four columns. Hence, our main estimation results remain robust.

6 Conclusion

Using firm-level tariff measures, this paper separates out the effects of foreign and Chinese trade liberalization in final goods, as well as of Chinese trade liberalization in inputs, on Chinese employment in trading firms. We distinguish firms according to their productivity and type—pure processing, nonimporting exporter, importing exporter, and importing nonexporter—and found that (i) for all types of firms, reductions in Chinese and foreign final-good tariffs are associated with job destruction in low-productivity firms and job creation in high-productivity firms, (ii) that after a reduction in input tariffs, there is job destruction in low-productivity firms, but not statistically significant job creation in high-productivity firms, and (iii) that of the three types of liberalization, Chinese trade liberalization in final goods generates the largest firm-level employment responses.

Table 10 First-difference IV estimation by type of firm

	All firms				Foreign invested firms			
	(P)	(N)	(I)	(I-NX)	(P)	(N)	(I)	(I-NX)
Foreign tariff (τ_{it})								
First quartile	0.43 1.2	0.01 0.08	0.16 0.9	0.91** 2.27	0.58 1.41	0.26 1.46	0.25 1.27	0.71** 2.14
Second quartile	0.1 0.8	0.24** 2.23	0.09 1.05	0.44** 2.12	0.14 1.04	0.40*** 2.96	0.12 1.36	0.21 0.88
Third quartile	− 0.19 (− 1.33)	0.08 0.92	− 0.11 (− 1.12)	− 0.1 (− 0.47)	− 0.16 (− 0.98)	0.04 0.42	− 0.1 (− 0.92)	− 0.19 (− 0.68)
Fourth quartile	− 0.75*** (− 3.24)	− 0.15 (− 1.38)	− 0.32*** (− 2.72)	− 0.12 (− 0.49)	− 0.74*** (− 2.79)	− 0.12 (− 0.83)	− 0.39*** (− 2.74)	− 0.37* (− 1.70)
Chinese tariff (τ^*_{it})								
First quartile	0.4 1.18	0.75** 2.47	0.73*** 2.6	0.63 1.25	0.38 0.96	0.51* 1.78	0.58** 1.98	0.37 0.73
Second quartile	0.03 0.19	− 0.40** (− 2.50)	− 0.40** (− 2.52)	0.01 0.03	0.13 0.69	− 0.36** (− 2.01)	− 0.41** (− 2.34)	− 0.04 (− 0.17)
Third quartile	− 0.62*** (− 3.61)	− 0.90*** (− 5.62)	− 0.79*** (− 4.79)	− 0.39 (− 1.42)	− 0.51** (− 2.55)	− 0.78*** (− 4.23)	− 0.70*** (− 3.75)	− 0.52* (− 1.65)
Fourth quartile	− 1.14*** (− 4.39)	− 1.48*** (− 7.12)	− 1.20*** (− 6.17)	− 1.47*** (− 4.72)	− 1.02*** (− 3.52)	− 1.38*** (− 5.36)	− 1.02*** (− 4.59)	− 1.45*** (− 4.49)
Input tariff (λ_{it})								
First quartile		0.05 0.09	− 0.34 (− 0.74)	1.55 1.3		− 0.31 (− 0.32)	− 0.58 (− 1.12)	0.98 0.95
Second quartile		− 0.16 (− 0.56)	− 0.22 (− 1.07)	− 0.47 (− 1.00)		− 0.49 (− 1.33)	− 0.21 (− 0.87)	− 0.58 (− 1.10)
Third quartile		− 0.44* (− 1.94)	− 0.51* (− 1.70)	− 0.41 (− 0.86)		− 0.62* (− 1.78)	− 0.61* (− 1.84)	− 0.64 (− 1.02)
Fourth quartile		0.08 0.23	− 0.26 (− 0.79)	1.03* 1.83		− 0.24 (− 0.50)	− 0.61 (− 1.40)	0.02 0.04

Notes This table reports the output of two first-difference IV regressions, one using all trading firms, and the other using foreign-invested firms. The top of the column indicates the type of firm: pure processing firms (*P*), nonimporting exporters (*N*), importing exporters (*I*), and importing nonexporters (*I*–NX). Regressions include state-owned status, foreign-owned status, export status, log capital-labor ratio, and log sales as controls. The first regression (all trading firms) includes 16,984 observations and the second regression (foreign-invested firms) includes 12,864 observations. Robust t-statistics (in parentheses) clustered at the firm level. Firms are classified into quartiles from low- to high-productivity according to their relative system-GMM TFP

The coefficients are statistically significant at the * 10%, ** 5%, or *** 1% level

Theoretically, the model that we introduce to guide the interpretation of the empirical results describes channels of job creation and destruction in response to changes in every type of tariff. It cannot explain, however, the large positive employment responses of all types of high-productivity firms to reductions in Chinese final-good tariffs. This empirical result presents a theoretical challenge, as it is difficult to explain with conventional mechanisms the employment expansion of firms due to a shock that brings tougher competition from foreign firms.

A possible explanation to this result is the existence of *escape-competition* effects as described by Aghion et al. (2005): facing tougher competition, some firms decide to invest and expand as a way to "escape competition". This type of effect can be included in our model by introducing a lumpy investment decision with nonconvex adjustment costs: tougher competition causes a reduction in the opportunity cost of investing, driving some firms to invest and expand. Another possible explanation is the existence of market share reallocations from low- to high-productivity firms within firm type. This is absent from our model because all firms of the same type have identical employment elasticities to tariff changes. Model's extensions that would capture within-type reallocations include assuming random fixed costs of trading activities, or assuming preferences with endogenous markups.

Due to data limitations, our analysis focuses on the intensive margin of employment: job creation and destruction due to expansions or contractions of existing trading firms. Hence, we miss all the job creation and destruction due to births and deaths of firms. Although more recent Chinese firm-level data is more reliable for the study of the extensive margin of employment, gathering and processing this data is a challenge by itself; this forces us to leave the study of the responses of the extensive margin of Chinese employment to trade liberalization as a future project.

Notes

1. An exception is Ma et al. (2015), who provide a picture of the evolution of Chinese job flows from 1998 to 2007.
2. In the same vein, Groizard et al. (2014) construct a heterogeneous-firm model of offshoring that describes the effects of input trade liberalization on firm-level employment. They derive similar effects to those described in this paper, but do not consider final-good trade costs, nor the existence of processing firms, which are very important in the Chinese manufacturing industry.
3. More generally, we could assume that $y_S(\alpha) = A_L a_L(\alpha)l + A_{Ms} a_M(\alpha)m$, which follows closely Acemoglu and Autor (2011). For the purposes of this paper it is enough to normalize A_L and $a_L(\alpha)$ to 1, and think of A_{Ms} and $a_M(\alpha)$ as productivity factors that indicate the comparative advantage of materials with respect to labor.
4. In China, pure processing firms perform (on average) few and very specific tasks, for example, assembly and packaging (which are very unskilled tasks).
5. Combes et al. (2012) estimate that firm-level productivity of French firms is a mix 95% lognormal and 5% Pareto, and that restricting to a 100% lognormal yields parameters $\mu = -0.02$ and $\rho = 0.35$.
6. We tried several combinations of parameter values and never found an scenario that contradicts the results in Table 1.
7. In 2006, the total value added of all the firms included in the survey was RMB 9107 billion, which accounted for 99% of the value added of all firms in the manufacturing sector (RMB 9131 billion), as reported by the 2007 China's Statistics Yearbook.

8. We keep observations if all of the following hold: (1) total fixed assets cannot exceed total assets; (2) liquid assets cannot exceed total assets; (3) the net value of fixed assets is less than that of total assets; (4) number of employees cannot be less than eight; (5) the firm's identification number exists and is unique, and (6) the established time is valid.
9. See Yu (2015) for a detailed description. Also, some of the firms in the data are pure trade intermediaries that do not have production activities. To ensure the precision of our estimates, we exclude these firms from the sample. Trade intermediaries are identified according to the procedures of Ahn et al. (2011).
10. In spite of including firm-level fixed effects in every specification, we are still able to estimate coefficients for the SOE and foreign-owned indicators. This is possible because some firms switch their ownerships during the sample period (Hsieh & Song, 2015).
11. Relatedly, Groizard et al. (2015) use establishment level data from California from 1992 to 2004 to estimate the effects input and final-good trade costs on firm-level employment. Similar to our results, they find evidence of trade-induced job destruction in low-productivity firms and job creation in high-productivity firms. They also report that in the California data, the employment effects of input trade liberalization are more important than the effects of final-good trade liberalization. In contrast to our empirical analysis, they cannot distinguish between domestic and foreign final-good tariffs, and they have limited information on each establishment, which prevents them from identifying each firm's type and from obtaining firm-level tariffs.
12. Table 14 in the Appendix provides statistics about the composition of firms in our sample of trading firms. Most firms in our sample are nonimporting exporters, accounting for 70.4% of all firms in 2000, and for 56.1% in 2006. Pure processing firms accounted for 10.4% of trading firms in 2000, and for 8.3% in 2006. Importing firms made up for the decline in the fraction of pure processing and nonimporting exporters from 2000 to 2006, with importing exporters raising their share from 12.5 to 16.8%, and importing nonexporters increasing their share from 6.7 to 18.8%.
13. Similar to column 3 in Table 4, pure processing firms face a zero input tariff and hence, there are no input-tariff coefficient estimates for this type of firm in the first column of Table 6. Recall from Table 5 that the first-difference regression would yield input-tariff coefficients for firms that switch to P status. For purposes of comparison, we exclude input tariffs for pure processing firms in the first-difference regression in Table 6 (we look at responses of switchers in Sect. 4.4).
14. In addition, the case for tariff endogeneity is weaker for firm-level specifications. Using plant-level specifications for employment growth in Canada, Trefler (2004) strongly rejects tariff endogeneity and mentions that "this likely reflects the fact that tariffs, even if endogenous to the industry, are exogenous to the plant."

15. As a perfect example of a high-GSC integrated product, the iPhone is assembled by China but its parts and intermediates are made by several countries. Accordingly, the value-added of China on the iPhone production is very low.
16. Similar to De Loecker (2013), a firm's productivity process is given by $\varphi_{it+1} = g\left(\varphi_{it}, \tau_{it}, \tau_{it}^{*}, \lambda_{it}\right) + \varsigma_{it+1}$ where ς_{it+1} is the productivity innovation. This process adopts a fourth-order polynomial form, $g(\cdot) = \Sigma_{sm}\beta_{sm}\left(\varphi_{it}^{s}\tau_{it}^{m} + \varphi_{it}^{s}\tau_{it}^{*m} + \varphi_{it}^{s}\lambda_{it}^{m}\right)$ for $s \in \{1, 2, 3, 4\}$ and $m \in \{1, 2, 3, 4\}$, with $E(\varsigma_{it+1}\tau_{it}) = 0$, $E\left(\varsigma_{it+1}\tau_{it}^{*}\right) = 0$, and $E(\varsigma_{it+1}\lambda_{it}) = 0$.

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Data Availability Statement The data that support the findings of this study are available on request from the authors. The data are not publicly available due to privacy restrictions.

Appendix 1: Theoretical Appendix: Proofs

Proof of Lemma 1 We know that for every s, there exists a cutoff $\hat{\alpha}_S$ so that tasks in the range $0, \hat{\alpha}_S)$ are produced inside the firm (with hired domestic labor), and tasks in the range $\left[\hat{\alpha}_S, 1\right]$ are procured using outside materials. From (3) and given $\hat{\alpha}_S$, it follows that $y_S(\alpha) = l$ if $\alpha < \hat{\alpha}_S$ and $y_S(\alpha) = A_{Ms}a_M(\alpha)m$ if $\alpha \geq \hat{\alpha}_S$, so that $Y_S = \left[\int_0^1 y_S(\alpha)^{\frac{\theta-1}{\theta}} d\alpha\right]^{\frac{\theta}{\theta-1}}$ can be rewritten as

$$Y_s = \left\{\int_0^{\hat{\alpha}_S} l(\alpha)^{\frac{\theta-1}{\theta}} d\alpha + \int_{\hat{\alpha}_S}^{1} \left[A_{Ms}a_M(\alpha)m(\alpha)\right]^{\frac{\theta-1}{\theta}} d\alpha\right\}^{\frac{\theta}{\theta-1}} \tag{37}$$

Optimality conditions require that $\frac{dY_S}{dl(\alpha)} = \frac{dY_S}{dl(\alpha')}$ and $\frac{dY_S}{dm(\alpha)} = \frac{dY_S}{dm(\alpha')}$ and therefore, $l(\alpha) = l\left(\alpha'\right)$ and $a_M(\alpha)^{1-\theta}m(\alpha) = a_M\left(\alpha'\right)^{1-\theta}m\left(\alpha'\right)$.

Let L_S and M_S denote the total amounts of labor and materials used for the production of the task aggregator Y_S, so that

$$L_S = \int_0^{\hat{\alpha}_S} l(\alpha)d\alpha \tag{38}$$

$$M_S = \int_{\hat{\alpha}_S}^{1} m(\alpha) d\alpha \tag{39}$$

Given that $l(\alpha) = l(\hat{\alpha})_S$, it follows from (38) that $L_S = \hat{\alpha}_S l(\hat{a}_S)$, and then

$$l(\alpha) = \frac{L_S}{\hat{\alpha}_S} \tag{40}$$

Similarly, we know that $a_M(\alpha)^{1-\theta} m(\alpha) = a_M(\hat{\alpha}_S)^{1-\theta} m(\hat{\alpha}_S)$, which plugged into (39) yield $M_S = a_M(\hat{\alpha}_S)^{1-\theta} m(\hat{\alpha}_S) \int_{\hat{\alpha}_S}^{1} a_M(\alpha)^{\theta-1} d\alpha$. It follows that

$$m(\alpha) = \frac{a_M(\alpha)^{\theta-1} M_S}{\int_{\hat{\alpha}_S}^{1} a_M(\alpha)^{\theta-1} d\alpha} \tag{41}$$

Plugging in (40) and (41) into (37) yields

$$Y_s = \left(\hat{\alpha}_S^{\frac{1}{\theta}} L_S^{\frac{\theta-1}{\theta}} + v_S(\hat{\alpha}_S)^{\frac{1}{\theta}} M_S^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}} \tag{42}$$

where

$$v_S(\hat{\alpha}_S) = \int_{\hat{\alpha}_S}^{1} [A_{Ms} a_M(\alpha)]^{\theta-1} d\alpha \tag{43}$$

Note that if $\theta = 1$, $v_S(\hat{\alpha}_S) = 1 - \hat{\alpha}_S$.

The second step is to obtain the unit cost for Y_S, which we call $c(\hat{\alpha}_S)$. For a firm with status s, $c(\hat{\alpha}_S)$ is the minimum cost, $L + p_{Ms} M_S$, such that $Y_S = 1$. The Lagrangean is then given by

$$\mathcal{L} = L + p_{Ms} M_S + \varpi \left[1 - \left(\hat{\alpha}_S^{\frac{1}{\theta}} L_S^{\frac{\theta-1}{\theta}} + v_S(\hat{\alpha}_S)^{\frac{1}{\theta}} M_S^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}}\right]$$

The first order conditions are

$$1 - \varpi \left(\hat{\alpha}_S^{\frac{1}{\theta}} L_S^{\frac{\theta-1}{\theta}} + v_S(\hat{\alpha}_S)^{\frac{1}{\theta}} M_S^{\frac{\theta-1}{\theta}}\right)^{\frac{1}{\theta-1}} \hat{\alpha}_S^{\frac{1}{\theta}} L_S^{\frac{-1}{\theta}} = 0 \tag{44}$$

$$p_{Ms} - \varpi \left(\hat{\alpha}_S^{\frac{1}{\theta}} L_S^{\frac{\theta-1}{\theta}} + v_S(\hat{\alpha}_S)^{\frac{1}{\theta}} M_S^{\frac{\theta-1}{\theta}}\right)^{\frac{1}{\theta-1}} v_S(\hat{\alpha}_S)^{\frac{1}{\theta}} M_S^{\frac{-1}{\theta}} = 0 \tag{45}$$

$$\hat{\alpha}_S^{\frac{1}{\theta}} L_S^{\frac{\theta-1}{\theta}} + v_S(\hat{\alpha}_S)^{\frac{1}{\theta}} M_S^{\frac{\theta-1}{\theta}} = 1 \tag{46}$$

From (44) and (45) we get

$$M_S = \frac{v_S(\hat{\alpha}_S) L_S}{p_{Ms}^{\theta} \hat{\alpha}_S} \tag{47}$$

which combined with (46) yields

$$L_{s,Y_s=1} = \frac{\hat{\alpha}_S}{\left[\hat{\alpha}_S + v_S(\hat{\alpha}_S) p_{Ms}^{1-\theta}\right]^{\frac{\theta}{\theta-1}}} \tag{48}$$

$$M_{s,Y_s=1} = \frac{v_S(\hat{\alpha}_S) p_{Ms}^{-\theta}}{\left[\hat{\alpha}_S + v_S(\hat{\alpha}_S) p_{Ms}^{1-\theta}\right]^{\frac{\theta}{\theta-1}}} \tag{49}$$

It follows that $c(\hat{\alpha}_S) = L_{S,Y_S=1} + p_{Ms} M_{S,Y_S=1}$ is

$$c(\hat{\alpha}_S) = \left[\hat{\alpha}_S + v_S(\hat{\alpha}_S) p_{Ms}^{1-\theta}\right]^{\frac{1}{1-\theta}} \tag{50}$$

From (4) we know that $p_{Ms} = A_{Ms} a_M(\hat{\alpha}_S)$, which along with (43) implies that $v_S(\hat{\alpha}_S) p_{Ms}^{1-\theta} = \int_{\hat{\alpha}_S}^{1} \left[\frac{a_M(\hat{\alpha}_S)}{a_M(\alpha)}\right]^{1-\theta} d\alpha$. Hence, we rewrite (50) as

$$c(\hat{\alpha}_S) = \left\{\hat{\alpha}_S + \int_{\hat{\alpha}_S}^{1} \left[\frac{a_M(\hat{\alpha}_S)}{a_M(\alpha)}\right]^{1-\theta} d\alpha\right\}^{\frac{1}{1-\theta}} < 1 \tag{51}$$

Taking the derivative of $c(\hat{\alpha}_S)$ with respect to $\hat{\alpha}_S$ we get

$$\frac{dc(\hat{\alpha}_S)}{d\hat{\alpha}_S} = \left\{\int_{\hat{\alpha}_S}^{1} \left[\frac{a_M(\hat{\alpha}_S)}{a_M(\alpha)}\right]^{1-\theta} d\alpha\right\} \frac{c(\hat{\alpha}_S)^{-\theta} a_M'(\hat{\alpha}_S)}{a_M(\hat{\alpha}_S)} > 0$$

because $a_M(\alpha)$ is strictly increasing in α. Note from (51) that $\lim_{\hat{\alpha}_S \to 1} c(\hat{a}_S) = 1$. Given that $\hat{a}_P < \hat{\alpha}_I < \hat{a}_N$, it is also the case that $c(\hat{\alpha}_P) < c(\hat{\alpha}_I) < c(\hat{\alpha}_N)$.

Proof of Lemma 2 From the proof of Lemma 1 we know that the firm-level demand for domestic labor to produce for market r of a Home firm with productivity φ and status s is given by $L_{rs}(\varphi) = \hat{\alpha}_S c\left(\hat{\alpha}_S\right)^{\theta} Y_{rs}(\varphi)$. Given the production function and the iceberg trade cost the firm faces when exporting, the amount of task aggregator it requires to produce for market r is $Y_{rs}(\varphi) = \frac{\tau^{1\{r=X\}} Z_{rs}(\varphi)}{\varphi}$. Equations (27) and (28) then follow after noting that $Z_{rs}(\varphi) = \frac{\sigma \pi_{rs}(\varphi)}{p_{rs}(\varphi)}$, with $\pi_{rs}(\varphi)$ given by (8), and $p_{rs}(\varphi) = \left(\frac{\sigma}{\sigma-1}\right) \frac{\tau^{1\{r=X\}} c\left(\hat{\alpha}_S\right)}{\varphi}$. The two exceptions are a consequence of the ordering of the cutoff levels $\left(\hat{\varphi}_P < \hat{\varphi}_D < \hat{\varphi}_X < \hat{\varphi}_I\right)$ and of the assumption that pure processing firms are not allowed to access the domestic market.

Appendix 2: Supporting Tables and Figures

See Fig. 5 and Tables 11, 12, 13 and 14.

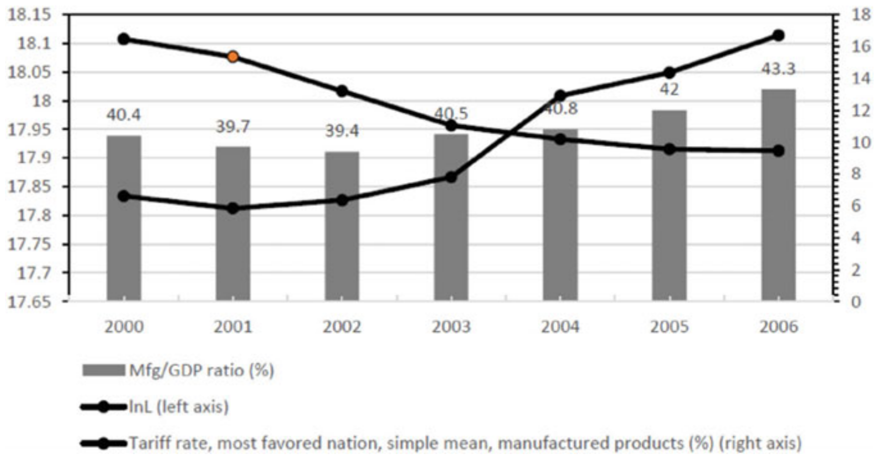

Fig. 5 Chinese employment in the manufacturing sector and the MFN tariff rate. Colour figure can be viewed at wileyonlinelibrary.com

Table 11 Numerical comparative statics to tariff reductions

	Benchmark	Foreign trade liberalization	Home trade liberalization	
	$(\tau = \tau^* = 2, \lambda = 1.6)$	$(\tau = 1.6)$	In final goods $(\tau^* = 1.6)$	In inputs $(\lambda = 1.4)$
$\hat{\alpha}_t$	0.498	0.498	0.498	0.438
P	0.789	0.802	0.748	0.747
P*	0.747	0.698	0.745	0.735
$\hat{\varphi}_p$	0.544	0.465	0.545	0.553
$\hat{\varphi}_D$	0.674	0.926	0.778	0.758
$\hat{\varphi}_X$	1.204	1.031	1.208	1.224
$\hat{\varphi}_I$	1.494	1.424	1.56	1.257
$\hat{\varphi}_D^*$	0.498	0.533	0.5	0.506
$\hat{\varphi}_X^*$	0.99	0.973	0.836	1.045
$\hat{\alpha}_P$	0.283	0.283	0.283	0.283
$\hat{\alpha}_N$	0.683	0.683	0.683	0.683
$\hat{\alpha}^*$	0.556	0.556	0.556	0.556

Table 12 Summary statistics for firm-level tariffs

Year	Foreign tariff (τ_{it})		Chinese tariff (τ_{it}^*)		Input tariff (λ_{it})	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
2000	7.71	7.2	15.57	12.03	2.54	4.9
2001	8.16	7.72	12.39	9.4	2.37	5.06
2002	8.72	8	9.63	8.22	1.68	3.53
2003	7.46	6.88	8.82	7.51	1.94	3.7
2004	6.91	6.76	7.59	7.08	1.87	3.59
2005	6.9	6.64	7	6.78	1.71	3.53
2006	7.61	7.14	7.46	6.46	2.18	3.72
All years	7.47	7.1	8.29	7.65	1.98	3.82

Table 13 Summary statistics of key variables (2000–2006)

	Mean	Std. dev.
Log of firm employment	5.54	1.18
System-GMM TFP	2.57	0.408
Relative system-GMM TFP	0.277	0.086
High TFP indicator	0.517	0.499
Log of firm sales	10.84	1.38
SOE indicator	0.015	0.121
Foreign indicator	0.739	0.439
Exporter indicator	0.849	0.357

Table 14 The types of Chinese trading firms

	Fraction of each firm type (within sample)	
	2000	2006
Pure processing firms (P)	10.4	8.3
Nonimporting exporters (N)	70.4	56.1
Importing exporters (I)	12.5	16.8
Importing nonexporters	6.7	18.8

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