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Knowledge Spillovers and Productivity Growth: Role of Absorptive Capacity in the Indian Manufacturing Sector

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Abstract
The paper explores the role of absorptive capacity in understanding the association between international knowledge spillovers and total factor productivity (TFP) growth in Indian manufacturing. Imports and FDI provide two major channels of knowledge spillovers while private research and development (R&D) and education-weighted human capital are used as proxies for domestic absorptive capacity. Applying pooled linear regression on 2-digit manufacturing sectors based on NIC 2008 (ISIC Rev. 4) for 2000–2016 in India, positive spillover effects of FDI and imports on TFP growth are confirmed. However, when looking at moderation effects, absorptive capacity is found to moderate the relationship between knowledge spillovers and domestic productivity negatively. When the manufacturing sectors are sub-grouped based on their technological intensities, interesting differences emerge. For the low-tech and medium–low-tech sectors, spillovers from FDI negatively affect TFP. In contrast, in the high-tech and medium–high-tech sectors, spillovers from imports as well as FDI have a dampening effect on productivity. With respect to interaction effects, absorptive capacity negatively moderates the relationship between FDI spillovers and TFP growth in the low-tech sectors. In the high-tech sectors, interestingly, human capital positively moderates import spillovers for productivity growth while no such moderation effect is found for R&D. Overall, results indicate that industries witnessing considerable FDI inflows and imports in recent years have not experienced direct productivity gains in the same proportion. This highlights the importance of absorptive capacity for productivity growth and the need for policy intervention at disaggregated sectoral level in India.

Keywords Absorptive capacity · R&D · Human capital · Knowledge spillovers · Total factor productivity · Manufacturing

JEL F14 · F24 · I25 · J24 · O33 · O47

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1 Introduction

The significance of knowledge spillovers in productivity growth is widely recognised in the endogenous growth literature. Prior research on technological progress (Romer 1989, Grossman and Helpman 1991, Coe and Helpman 1995) proposes that domestic productivity depends on a country's own R&D activities as well as on the knowledge, skills, and expertise acquired from foreign countries. To identify the mechanism of such knowledge spillovers, theoretical and empirical literature has so far focused on international trade and foreign direct investment (FDI) as the most important channels through which knowledge and technology are transferred across boundaries (Saggi 2002, Branstetter 2006). However, knowledge spillovers do not necessarily imply productivity growth, unless supported by domestic economic policies. Consequently, the literature suggests that an economy's ability to absorb, adapt, and diffuse new knowledge and foreign technologies depend on the quality of its education system, accumulated human capital, and knowledge stock (Kokko et al. 1996, Engelbrecht 1997, Kathuria 2002, Benhabib and Spiegel 1994, Blomström et al. 2003). An educated labour force and investment in research and development (R&D) speed up the internalisation of knowledge spillovers, thereby boosting economic growth and productivity. This has led to the investigation of domestic "absorptive capacity" to determine the effectiveness of international knowledge spillovers for productivity growth.

Absorptive capacity, a term pioneered by Cohen and Levinthal (1990), is developed through investment in own knowledge stock that enables a country, a firm, or an individual to "acquire, assimilate, transform and exploit knowledge by transforming acquired knowledge" (Zahra and George 2002). In other words, absorptive capacity measures an entity's ability to learn, combine its indigenous knowledge sources with external knowledge, and apply it successfully to build an innovation ecosystem. Part of these idiosyncratic resources is generated through path-dependent investment in R&D as well as through skill sets of the working-age population (human capital). Subsequently, it increases domestic efficiency, productivity, and economic performance (Nelson and Phelps 1966, Lucas 1988, Frantzen 2000, Kwark and Shyn 2006, Teixeira and Fortuna 2010). This is one channel through which absorptive capacity affects productivity; the other works through substantial moderation effects of absorptive capacity on international knowledge spillovers (Coe and Helpman 1995, Engelbrecht 1997, Hejazi and Safarian 1999, Ali et al. 2016). Direct and indirect effects of absorptive capacity have been extensively discussed in policy and innovation literature for productivity growth in industrialised economies. Despite the widespread consensus, the expectation is that these factors perform very differently within specific demographic, regional, or sectoral contexts. Consequently, there is demand for country-specific evidence that can explain the extent to which absorptive capacity affects the relationship between international knowledge spillovers and productivity growth in developing economies. The paper addresses this particular research gap by examining how absorptive capacity provides sufficient spillover conditions for productivity growth in the Indian manufacturing sectors.

Since the economic liberalisation of 1991 and the subsequent expansion of the domestic market, industrial investors in India have sought to build global consolidation through international knowledge networks and foreign ownership by multinational corporations (Sikdar and Mukhopadhyay 2018). Foreign investment has gone into sectors such as pharmaceuticals, chemicals, and automobiles that have been amply supported by private investments and flourished through governmental support and indigenous initiatives. In recent years, the government's emphasis has been on opening up entry routes and increasing sectoral caps for foreign investment. The insurance and defence industry has permitted foreign investment up to 49% under the automatic route. A total of 100% FDI via the automatic route is allowed in greenfield pharmaceuticals, coal and mining, telecom, and civil aviation; 100% FDI under the government route is permitted for retail trading, e-commerce, teleports, and railway infrastructure and up to 74% for brownfield pharmaceuticals and private security agencies. On the trade front, India's share of imports in high-tech commodities has been about 8% in recent years. On account of Free Trade Agreements (FTAs) signed with the Organisation for Economic Co-operation and Development (OECD) countries, foreign multinational corporations (MNCs) in India import intermediate or finished manufactured goods for local assembly or sale. Reduction in import duties has resulted in a surge of imports of products that include electrical machinery and electronics, metallurgy, chemicals, and ceramics. Evidently, India has proactively undertaken FDI and bilateral trade policies to push domestic productivity. Nevertheless, the industrial sector has been predominantly backed by the purchase of imported technologies and technology transfer agreements (Confederation of Indian Industries report 2017),[1] making the success of these economic policies less obvious.

The manufacturing sector in India accounts for 16% of the country's GDP compared to 52% by the service sector. The share of Indian manufacturing in the global markets is also low at 2.1%. The industrial sector suffers from low endowments of R&D and a mismatch in the skill composition of the workforce and employment opportunities available (Kukreja 2018). Not only has investment in R&D stagnated over the last 30 years ranging between 0.6 and 0.9% of GDP, dearth of quality vocational and higher education facilities and industry-specific skill training for shop floors have also formed critical parts of India's industrial landscape. The government incurs a large part of the country's total R&D spending, and private investment is highly concentrated in high-tech manufacturing (pharmaceuticals, biotechnology, and automobile) and service sectors (information technology). The presence of a qualified workforce and rising enrolment rates for tertiary education (for 18–23 year olds) and gross secondary education (15–16 year olds) is deemed insufficient due to growing skill-employment mismatch and low productivity of labour (Besley and Burgess 2004). The median gross hourly wage rates in manufacturing remained significantly low at Rs 211.7 in 2016 compared to Rs 386.8 in IT services and Rs 433 in financial services, banking, and insurance. Furthermore, industrial jobs fell in absolute terms from 58.9 million in 2011–2012 to 48.3 million, and the open unemployment rate jumped to 5.5% in 2016. While the Government of India has proactively undertaken policies in education, workforce training, and R&D, it is far from clear what effects such policies have on the productivity of the Indian economy. In principle, the manufacturing sector generates the strongest forward and backward linkages. Every job created has a multiplier effect in other sectors; the production processes stimulate secondary raw materials markets and growth of non-tradable goods and services (Park and Chan 1989). However, the current economic scenario in Indian manufacturing continues to be a source of concern. Barring a few high-technology sectors, India has mostly remained at the "assembly" and "development and testing" phase of production, which may not necessarily lead to capacity building and productivity growth.

[1] Manufacturing in India: Creating a Smarter Future (2017).

The contribution of foreign R&D to productivity growth is contingent upon the particular demographic and socio-economic characteristics of the attendant local economy. There is no single top-down path to economic development in India, and a one-size-fits-all industrial policy framework is problematic. Therefore, what is needed, is a systematic evaluation of the manufacturing sector coupled with understanding how each sector conditioned upon absorptive capacity benefits from international knowledge spillovers. With the exception of a few studies on developing countries (Ferrantino 1992, Basant and Fikkert 1996, Joseph 2007, Behera 2015), limited evidence exists on the relationship between absorptive capacity and knowleldge spillovers for India. Accordingly, we posit that sectors with higher levels of absorptive capacity in the form of R&D and human capital will more efficiently manage and integrate international knowledge spillovers to boost their productivity. This is what we refer to as the moderating effect of absorptive capacity. We focus on 12 two-digit manufacturing sectors of India based on NIC 2008 (ISIC Rev. 4) to examine how our measures for absorptive capacity moderate knowledge spillovers from OECD partner countries for TFP growth during 2000–2016. Applying pooled linear regression with year and industry dummies and cluster adjusted standard errors, our major findings include positive spillover effects of FDI and imports on TFP growth. However, when looking at moderation effects, absorptive capacity is found to moderate the relationship between knowledge spillovers and domestic productivity negatively. When the manufacturing sectors are sub-grouped based on their technological intensities, interesting differences emerge with respect to direct and moderation effects. Overall, results indicate that industries witnessing considerable FDI inflows and imports in recent years have not experienced direct productivity gains in the same proportion.

The rest of the paper is organised as follows: Section 2 gives the conceptual framework; Section 3 provides the data sources and construction of variables. Section 4 discusses the core empirical methodology; Section 5 summarises the main findings; and Section 6 concludes the paper with policy implications and steps for future research.

2 Conceptual Framework

2.1 Knowledge Spillovers Through Imports and FDI

Technological progress of a country is the outcome of a complex interplay between domestic and foreign R&D investment. Earlier studies such as Grossman and Helpman (1991) and Coe and Helpman (1995) have noted that, while technology transfer agreements have a direct effect on domestic productivity, significant indirect effects are acquired through spillover channels. Following this, a considerable body of literature has looked into different transmission channels—such as bilateral trade, inward and outward FDI, labour mobility, licences and patents through which foreign technologies, knowledge, and expertise are transferred across countries (Wang and Blomström 1992, Borensztein et al. 1998, Glass and Saggi 1998, Keller 1998, Kao et al. 1999, Xu and Wang 2000, Keller 2004, Lee 2006). For the purpose of this paper, we restrict our attention to the two major conduits of knowledge spillovers viz. imports and inward FDI.[2] Griliches (1979) in his seminal paper point

[2] Our definition of knowledge spillovers includes both voluntary knowledge transfers and unintended knowledge spillovers.

out that considering multiple spillover channels can lead to biased outcomes due to the problem of multicollinearity. In other words, the estimated knowledge spillovers through channels considered in our analysis may partially account for the magnitude of knowledge flows through the other ignored channels. Looking at international trade, import of intermediate goods results in more efficient utilisation of indigenous resources. Furthermore, internalisation of the knowledge embedded in high-tech imports can stimulate productivity growth through learning about foreign technologies, R&D, and manufacturing processes. With respect to FDI, spillover effects arise from backward and forward linkages (Crespo and Fontoura 2007, Behera 2015). Inward FDI in the form of R&D activities by multinational enterprises (MNE) leads to direct productivity gains, as well as greater access to foreign technologies, expertise, and newer methods of production. When newer technologies are introduced by MNE subsidiaries, demonstration/imitation efforts by domestic firms are strongest leading to successful adoption and diffusion of such technologies. Additionally, if MNEs possess intangible resources and knowledge otherwise unavailable to the host economy, spillovers may arise through inter-industry linkages. Other channels of inward FDI spillovers include worker mobility, competition effects, and trade-induced learning from the import of high-tech intermediate inputs (Smeets 2008).

2.2 Moderating Knowledge Spillovers: Absorptive Capacity

An important policy intervention by governments globally is to attract MNEs to locate their subsidiaries in the host economies. The main rationale behind such FDI policies, as discussed above, is the belief that the presence of MNEs will boost local productivity through positive spillover effects (externalities). However, existing literature finds mixed evidence of locational benefits of MNEs on the domestic economy. Rather, it is observed that the inherent characteristics of the attendant economy determine the extent of spillover benefits. In particular, the ability of the local economy/firms/regions or sectors to utilise and benefit from external linkages depends on their absorptive capacity (Cohen and Levinthal 1990). Relating absorptive capacity to human capital, several growth economists (Nelson and Phelps 1966, Engelbrecht 1997, Blomström et al. 2003, Joseph 2007, Li 2011) postulate that in a technologically advanced economy, the more educated the innovators, the faster will be the speed of new technology adoption and diffusion. In the same breath, productivity benefits are found to be associated with greater investment in R&D and a moderate technology gap measured by local learning capacity between foreign and local firms (Kokko et al. 1996, Glass and Saggi 1998). More recently, such analysis has been conducted on sectoral levels bearing mixed results. Zhou and Lall (2005) and Chen et al. (2011) find that Chinese sectors which are technologically closer to their foreign counterparts benefit more from knowledge spillovers, while others (Haskel et al. 2007, Cameron et al. 2005) find no such relationship between technological gap and FDI spillovers for UK industries. Girma (2005) finds an inverted U-shaped relationship for UK manufacturing industries wherein productivity benefits from FDI spillovers increase with absorptive capacity until a certain threshold, beyond which it falls. Using panel data for Czech manufacturing, Kinoshita (2001) concludes that firms in oligopolistic sectors that engage in greater absorptive capacity in the form of R&D investment benefit more from FDI spillovers than firms in non-oligopolistic sectors. Taken together, all these findings suggest that the incidence of spillovers on productivity may play out very differently within specific demographic and sectoral contexts. For the paper, we contribute to this particular literature and hypothesise that there

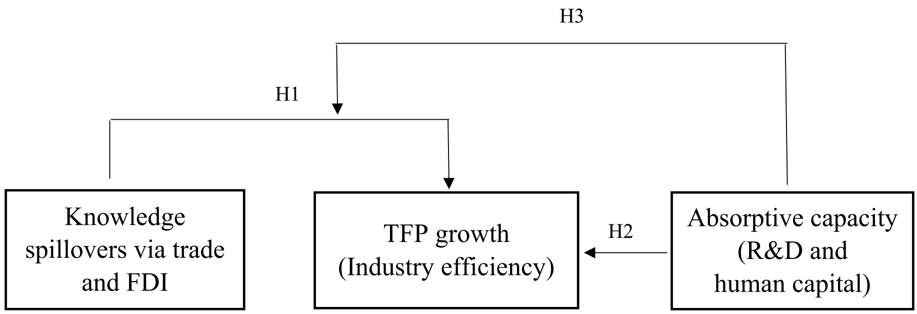

Fig. 1 Conceptual model of TFP growth in Indian manufacturing sector

exist significant differences in the extent to which industries benefit from knowledge spillovers. The underlying implication is that, if imports and FDI are technology-intensive in nature and industries do not have the adequate absorptive capacity to learn from the knowledge embedded in the imported products and technologies, then spillovers will not significantly impact their productivity. On the contrary, technologically intensive sectors with presumably higher absorptive capacity may benefit more from the absorption and diffusion of knowledge spillovers. Accordingly, the conceptual model and the hypotheses are given in Fig. 1. We test whether knowledge spillovers and absorptive capacity directly affect productivity growth. These are indicated by our hypotheses H1 and H2 respectively. Furthermore, we test whether the effect of knowledge spillovers on productivity growth is moderated by absorptive capacity in the form of R&D and human capital. This is specified by our hypothesis H3.

3 Data and Variable Construction

The need for a harmonised data system that manifests the linkages between the diverse sectors of the Indian economy has been well recognised (Debroy and Santhanam 1993). It is also understood that a major drawback in devising S&T policies for the formal manufacturing sector lies in the disaggregated nature of the domestic and external conditions pertaining to it. For this paper, we use a comprehensive industry-level database that covers information on trade flows, FDI, private R&D investment, and human capital. To the best of our knowledge, such a database does not exist in India. Therefore, we aggregate data from different sources and construct a harmonised database using concordance tables to accomplish our objectives. The specific databases used in our study are as follows: (i) Annual Survey of Industries (ASI) published by the Central Statistical Organisation (CSO) Industrial Statistical wing that provides data on industry characteristics and productivity measurement, (ii) United Nations (UN) COMTRADE that provide disaggregated import flows by trading partners, (iii) Reserve Bank of India (RBI) annual reports and Open Government Data (OGD) Platform in India that produce data on country-wise and industry-wise FDI equity inflows, (iv) ProwessIQ maintained by the Centre for Monitoring Indian Economy (CMIE) that gives information on domestic R&D expenditure and OECD that provides information on foreign R&D, and (v) National Sample Survey Office (NSSO) under the Ministry of Statistics and

Programme Implementation (MoSPI) that furnishes household-level data on education and industry of employment of household members.

3.1 Total Factor Productivity by Industry

The Annual Survey of Industries is the principal data source for industrial data in India providing statistical information on factors of production, employment, investment, and costs for the organised manufacturing sector. The survey has been conducted annually since 1959 and over the years has undergone significant changes in sampling design, methodology, and National Industrial Classification (NIC). For the paper, industry data has been used from ASI 1999 to 2000 onwards, and all manufacturing units have been classified in their appropriate industry groups using concordance tables provided by MoSPI for each revised NIC. In other words, efforts have been made to convert existing industry codes (NIC 1998 and NIC 2004) to the latest versions of the NIC 2008 for maintaining international comparability of data and homogeneity over time (for more, see http://www.csoisw.gov.in).

Following this procedure, we end up with a final sample of 12 manufacturing sectors aggregated from 23 two-digit sectors for the entire period 2000–2016. Table 3 in the 10. presents the concordance table and corresponding NIC 2008 codes for the 12 aggregated sectors. Pooling of categories has also been done due to limited availability of relevant price deflators for all sectors for measuring TFP and absorptive capacity. The industrial categories have also been matched with the recently published RBI India-KLEMS[3] database for consistency. The important variables for which data is collected from ASI for calculating industrial TFP are gross value added (GVA) at the current price, labour inputs ("number of persons engaged"/employment), net fixed capital assets, depreciation, and fuels and materials consumed.

The measurement of TFP growth in the organised manufacturing sector of the Indian economy follows the standard production function for each industry i at time t given by Eq. 1.

$$Y_i(t) = F_i\left(K_i(t), L_i(t), E_i(t), M_i(t), S_i(t), t\right), \tag{1}$$

where $Y_i(t)$ is the gross industry output; $K_i(t)$ is physical capital input; $L_i(t)$ is the total number of workers employed in production; $E_i(t)$, $M_i(t)$, and $S_i(t)$ are intermediate inputs namely energy, materials, and services; and t is time and considered as an index of TFP. For the sake of brevity, the sector index t is suppressed in future notations. We also provide an alternate measure of TFP where we use gross value added (GVA) instead of the gross value of output as the output measure Y. The GVA by industry excludes intermediate inputs E, M, and S used in the production process and is related only to primary inputs capital and

[3] The India KLEMS database is part of an ongoing research project supported by the Reserve Bank of India (RBI) that provides data for analysing productivity of the Indian economy at disaggregate industry level. It covers 27 industries based on the NIC classification and provides measures of economic growth, capital formation, and productivity from 1980 to 1981 onwards. The input measures incorporate various categories of capital (K), labour (L), energy (E), material (M), and services (S) inputs, while the output measures provide information on total factor productivity (TFP), value added, and labour and capital estimates at the disaggregated level. The database is constructed using data compiled from the Central Statistical Office (CSO), NSSO, ASI, and Input–Output tables and harmonized for uniformity across industrial classification and aggregation levels.

labour. Data on gross output, GVA, capital, and labour inputs for the manufacturing sector at current prices have been collected from ASI. Time series on intermediate inputs *E*, *M*, and *S* have been extracted from the RBI India-KLEMS database based on the input–output methodology proposed by Jorgenson et al. (2005) and Timmer et al. (2010).

Real gross output and gross value-added at constant prices are arrived at by deflating the nominal series by the wholesale price index (WPI) for the manufacturing industries at 2011–2012 constant prices. Weights used in the WPI are value weights and not quantity weights. The traded values of manufactured products, i.e., total production + excise duty + imports – exports, have been extracted from CSO. An important point to note here is that the industrial classification followed by ASI has undergone two significant changes in 2003–2004 and 2007–2008. Therefore, due adjustments are made in the WPI indices by splicing the old one with 1993–1994 base prices to the new one with 2004–2005 base prices using appropriate linking coefficients. Unfortunately, CSO does not provide linking factors for detailed individual commodity indices before 2004–2005. We use the linking factor for the aggregated manufacturing price index for transforming the 2000–2004 WPI series.

For labour input, the literature recommends using employment data in manufacturing viz. number of employees engaged directly in production. Other alternatives, such as man-hours or total wages/salaries, can be used to measure total factor productivity. However, the lack of time-series data on man-hours for the Indian manufacturing industry drives the choice of using employment as the ideal measure for labour input.

The measurement of capital input is the most complex of all input measures and subjected to extensive debate and research in recent years. In productivity literature, it is now being discussed that capital "services" provide the closest approximation to understanding capital input for production than capital "stock." Using the traditional method, one would ideally construct initial capital stock by using the gross fixed capital formation series reported in the earliest ASI volume (1964–1965) and adjust it with the long-term growth rate of capital investments and the rate of depreciation (De La Fuente and Doménech 2006). Capital stocks in subsequent years should then be calculated by adding current year fixed capital to the previous year's capital stock after accounting for depreciation (perpetual inventory method, PIM). In other words, the annual additions are deflated by the wholesale price indices and added to the initial capital stock to construct the series on capital stock at base year prices. However, this method, while being widely acknowledged, disregards the differences in composition and marginal productivities of assets (Erumban and Das 2014). Therefore, for this paper, we follow Jorgenson (1963) and construct a series of capital services after accounting for asset heterogeneity. For this, we require data on current capital formation by asset type, investment prices of capital assets, and depreciation rate. RBI-KLEMS India, CSO and ASI provide detailed information on these along with gross fixed capital formation by asset type for the manufacturing sector. The National Accounts Statistics estimate of net fixed capital stock by asset type in 1964 is used as the benchmark capital stock for subsequent calculation using PIM (see https://rbi.org.in/).

Finally, intermediate inputs for measuring TFP with gross output are extracted from the input–output tables that give the flows of all commodities, produced domestically or imported, within the economy. Energy, materials, and service inputs are further classified using the two-digit NIC classification, and a time series of proportions of each in total intermediate inputs for each sector is calculated. The intermediate input series at constant prices are obtained from RBI-KLEMS. Compiling these input measures for the 12 manufacturing sectors over 2000–2016, we calculate sectoral TFP growth as the difference between the growth of output and weighted averages of growth of primary inputs capital and labour (K, L) and intermediate inputs energy, materials, and services (E, M, S). Weights $(\overline{\vartheta})$ are the two-period average value shares of each input in the nominal value of output. The growth rates are also matched with the KLEMS database for robustness. Equation 2 presents the notational form of TFP growth across sectors j and time t. Figure 2 shows trends in annual growth rates across all manufacturing sectors during 2000–2016.

$$\Delta lnTFP_{t,j} = \Delta lnY_{t,j} - \overline{\vartheta_{K,j}}\Delta lnK_{t,j} - \overline{\vartheta_{L,j}}\Delta lnL_{t,j} - \overline{\vartheta_{E,j}}\Delta lnE_{t,j} - \overline{\vartheta_{M,j}}\Delta lnM_{t,j} - \overline{\vartheta_{S,j}}\Delta lnS_{t,j} \tag{2}$$

3.2 Knowledge Spillovers via Trade

The present study requires annual sectoral data on imports to India from the rest of the world for the period 2000–2016. The United Nations COMTRADE database provides the most comprehensive international trade statistics by goods and service categories and partner countries from 1962. Import data is available in several commodity classifications (Harmonized System HS, Standard International Trade Classification SITC and Broad Economic Categories BEC) at the disaggregated level, allowing international comparisons (see https://unstats.un.org/unsd/trade/classifications/correspondence-tables.asp). The Harmonized System (HS) comprises about 5000 commodity groups, each associated with a unique six-digit code, and updated every 5–6 years to achieve uniformity. It allows for a comprehensive analysis of changes in trade classification over time and constitutes the most preferred source of data among the available ones. HS versions 1996, 2002, and 2007

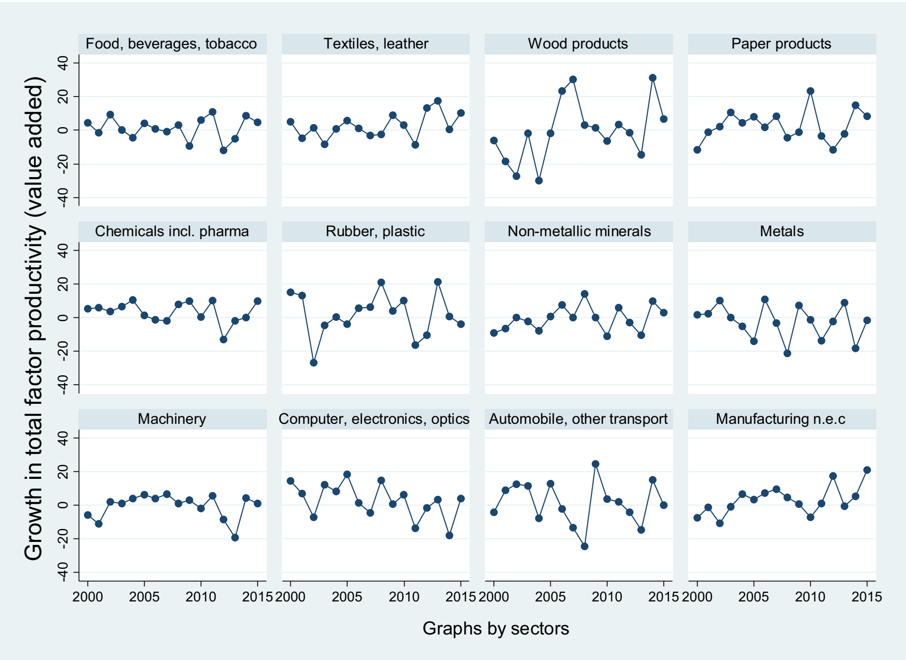

Fig. 2 TFP growth rates (value added based) by sectors 2000–2016

are used in the paper to extract data on import flows for India at the commodity level and subsequently matched with NIC 2008 on the two-industry level. Since no concordance tables are readily available between HS and NIC 2008, we manually harmonise the trade and industry classifications below.

Data harmonisation is attempted in two stages: (a) import data at the six-digit product level are aggregated to 92 two-digit product levels for each year of our sample across all versions of HS, and (b) the two-digit product data are matched with 23 two-digit NIC 2008 (ISIC Rev 4) manufacturing industries engaged in merchandise trade in India. This process entails many-to-one mapping from HS six-digit to NIC two-digit and has methodological limitations that are refined in subsequent steps. First, there is a significant mismatch in the harmonised system when data is converted from older to newer classifications. For example, when converting product codes from HS 1996/HS 2002/HS 2007 to a uniform two-digit NIC code, it is likely that some of the converted codes constitute more or less products than what is implied by the broader commodity head. In other words, what product composition NIC code “20 Manufacturing of chemical and chemical products” would have according to HS 1996 might be different from that in HS 2002. *Second*, in several cases, the product classification in one category of goods is found to be produced in more than one industry as defined by NIC. This yields multiple non-unique mappings and makes a strict distinction between industry classes impossible. Manual adjustments are made in both these scenarios. Table 4 in the 10. gives a snapshot of the data harmonisation process for a particular ISIC 2-digit code.[4]

The import spillover index $Importspill_{j,t}$ is constructed for the top 25 OECD countries that are the biggest trading partners of India and for which data on foreign R&D and imports are available. Each country’s knowledge stock is approximated by its R&D capital stock, and the assumption here is that, through imports, a portion of this knowledge stock gets transferred across countries. Trade-related spillovers for individual partner countries are then aggregated across sectors j to identify sectoral composition. Formally, they are defined by the import-share weighted average of the foreign R&D stocks of the trading partners k as:

$$Importspill_{j,t} = \sum_{k=1}^{25} \frac{Imports_{j,k,t}}{realGDP_{j,t}} R\&D^{OECD}_{j,k,t} \tag{3}$$

3.3 Knowledge Spillovers via FDI

The Reserve Bank of India annual reports and Open Government Data (OGD) Platform in India (https://data.gov.in) provide secondary data on FDI equity inflows to India in the manufacturing and service sectors. According to the Department for Promotion of Industry and Internal Trade (DPIIT), cumulative FDI inflows (including equity inflows, reinvested earnings, other capital and excluding foreign remittances) in India during 2000–2016 amounted to US$ 324,357 million. The service sector attracted the highest cumulative inflows (US$ 58,345 million) for the entire period, followed by construction development (US$ 24,287 million), telecommunications (US$ 23,921 million), computer software and

[4] Stata do-files for matching of six-digit HS 1996, HS 2002, and HS 2007 codes to two-digit NIC 2008 manufacturing categories are available from the author upon request.

hardware (US$ 22,832 million), automobile industry (US$ 16,518 million), and drugs and pharmaceuticals (US& 14,537 million). Other manufacturing sectors, however, have experienced significantly low FDI inflows. In terms of the top five investing countries in India, Mauritius has been at the forefront with 33.52% of total inflows during 2000–2016, followed by Singapore (16.34%), Japan (7.77%), the UK (7.51%), and the USA (6.13%). For the paper, we extract data on FDI equity inflows during 2000–2016 from the sources mentioned above for 23 manufacturing sectors according to two-digit NIC 2008 and subsequently aggregate them to 12 broad manufacturing sectors to maintain uniformity with ASI classification.

For the calculation of the FDI spillover index, we use a similar methodology as Eq. 3 and use data on global inward $FDIstock_{j,t}$ to approximate knowledge spillovers through FDI for India.

3.4 Absorptive Capacity: R&D Stock

The current study draws upon domestic R&D data from the ProwessIQ database. Aggregated foreign R&D data for the top 25 OECD countries, on the other hand, is collected from the OECD database that provides information on business enterprise R&D expenditure (BERD) in manufacturing by ISIC Rev 4 industry classification since 1995.

ProwessIQ is maintained by the Centre for Monitoring Indian Economy (CMIE) and provides financial performance data for over 48,000 listed and unlisted Indian companies since 1989. Information provided includes general characteristics, corporate indicators, and business undertakings of companies that can be classified into 22 two-digit manufacturing industries. The industrial classification followed by Prowess is quite disaggregated, which allows for matching with NIC 2008 reasonably well. Each company-industry mapping is based on the distribution of companies amongst industry heads in which a company derives more than half of its sales. In case a particular company derives its sales from multiple industries, it is classified under diversified industry. Therefore, when matching individual NIC 2008 codes with the Prowess codes, we aggregate two or more NIC items as and when necessary. Using this method, we arrive at 12 two-digit manufacturing industries in the final sample that provides domestic R&D expenses in current and capital account (in Rs million) since 2000–2001.

The benchmark model we use for our analysis is Coe and Helpman (1995), which explains variations in a country's total factor productivity by variations in its domestic and foreign R&D stocks transferred through the international trade channel. Long time-series data on domestic R&D capital stock is not available for Indian manufacturing. Therefore, we calculate R&D stock from private R&D expenditures using the perpetuary inventory method for each of the 12 manufacturing sectors in the following way:

$$R\&D^{stock}_{j,t} = R\&D^{flow}_{j,t} + (1-\delta)R\&D^{stock}_{j,t-1} \tag{4}$$

where, $R\&D^{flow}_{j,t}$ is R&D expenditure by industry j in time t, $R\&D^{stock}_{j,t-1}$ is the R&D stock of sector j in period $t-1$, and δ is the depreciation rate of investment taken as 0.15 following Coe and Helpman (1995). Since the first year for which sectoral R&D data is available for India is 1999, we use R&D expenditure flows in 1999 as the initial stock of R&D. Figure 3 provides trends in private R&D expenditures as a percentage of gross output by manufacturing sectors in India. The most R&D-intensive manufacturing sectors include

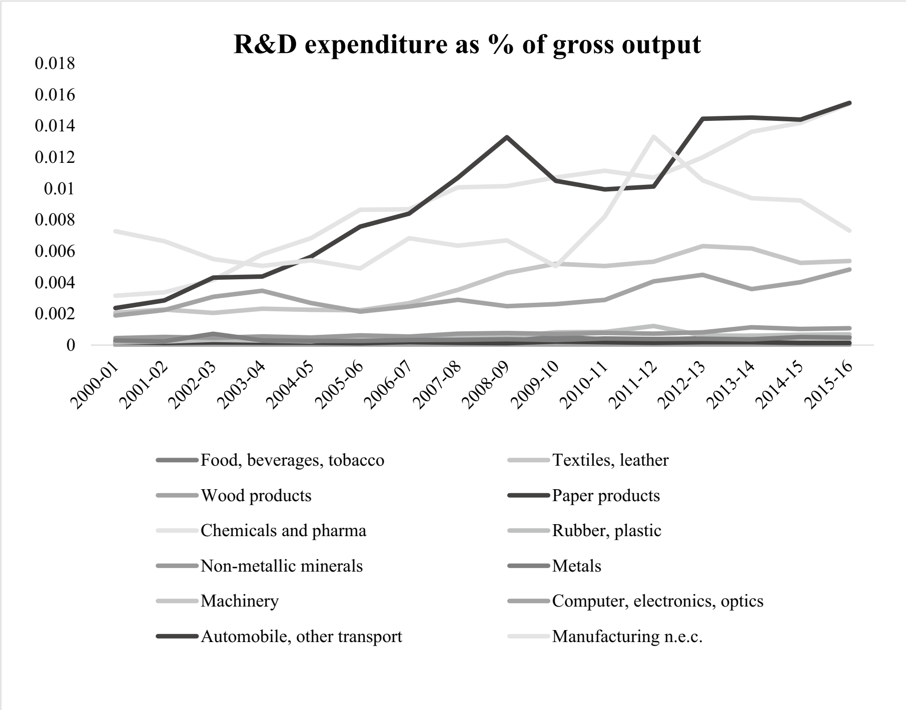

Fig. 3 Trends in sectoral R&D expenditure 2000–2016

transport and automobile, chemicals, and pharmaceuticals, followed by machinery, computers, and electronics.

For foreign R&D stock of OECD countries, the initial R&D stock year is taken as 1995, and the same procedure is followed to calculate trade partners' cumulative R&D stock. For countries such as Austria, China, and Switzerland, where available data start from 1998, initial capital stock is calculated for available years and missing data is linearly extrapolated as necessary. Similarly, linear interpolation is used to fill in missing R&D flow values for countries such as Germany, Ireland, and Norway. China, Germany, South Korea, Japan, and the USA demonstrate increasing R&D spending, accounting for 66.7% of global R&D.

3.5 Absorptive Capacity: Education-Weighted Human Capital

The National Sample Survey Office (NSSO) is the primary source of data in India on various indicators on the educational attainment of the country like literacy rates, average years of schooling, attendance ratios, incentives received by students, social consumption on education and health expenditures, costs incurred for education, etc. Employment and unemployment information are available for a large sample size of households at the national and state levels from the NSSO 38th round (October 1973) onwards. For this paper, we have used all available rounds of NSSO since 1990 (55th, 61st, 64th, 66th, and 68th) and estimated the share of employment with various educational qualifications (illiterate, primary, middle, secondary, higher secondary, diploma/certificate, graduate or post-graduate) in each industry employment during 2000–2016.

In the paper, we are interested in identifying the direct relationship between quality-adjusted human capital and TFP and include education-weighted human capital as a separate entity. Ideally, changes in human capital composition by industries need estimation based on age, gender, and educational composition of the workforce to disentangle quantity and quality of labour. For this paper, we use NSSO rounds data to extract the skill composition of the manufacturing workforce and categorise education into six distinct categories based on years of schooling: no education (0 years), primary (4 years), middle (7 years), secondary (10 years), higher secondary (12 years), and graduate and above (15 years). To construct the education-weighted human capital index, we simply calculate the weighted average of the share of employment in each sector by years of schooling. In other words, we simply multiply the share of sectoral employment with their respective years of schooling, and divide the sum by 100.

Looking only at employment growth, Fig. 4 presents the quantity indicator of human capital, where we see that in recent years employment growth has been most significant in medium–low and medium–high-tech industries such as rubber, metallurgy, computers, electrical machinery, and transport equipment, including automobile. However, when looking at human capital through the lens of skills, Fig. 5 (panels A, B, and C) paints an altogether different picture. Lack of education is a widespread occurrence among labourers in the manufacturing industry, particularly in the low-paying labour-intensive sectors.

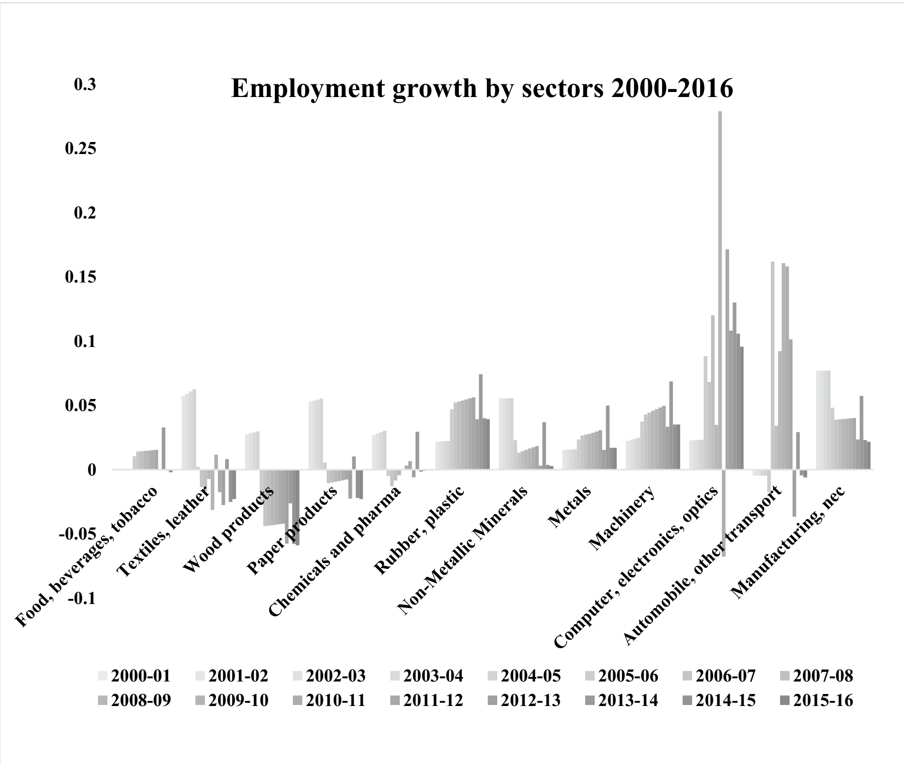

Fig. 4 Employment growth by sectors

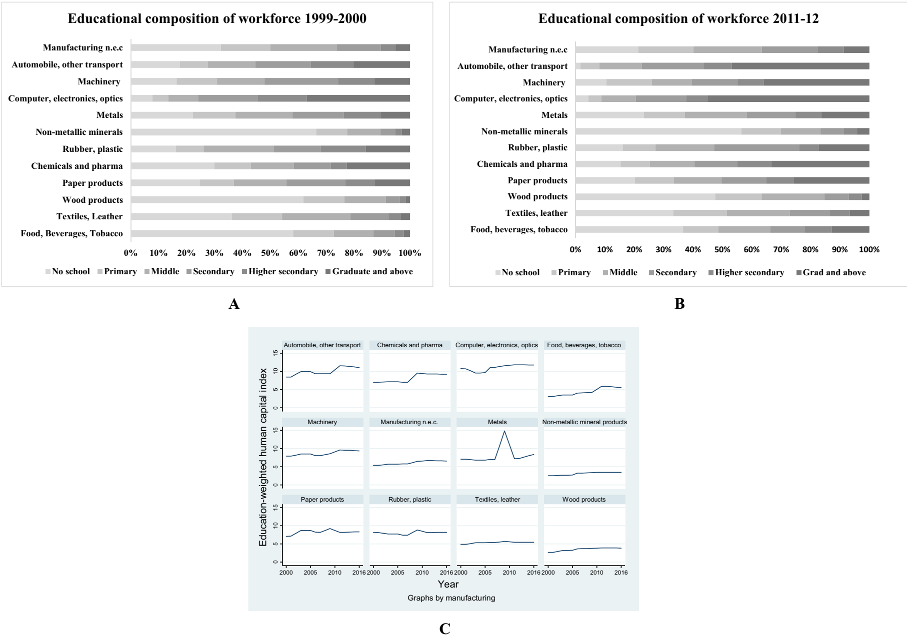

Fig. 5 Educational composition of the workforce by sectors

The share of skilled workforce raises with the degree of technology intensity of a sector. Higher education is predominant among workers in high-tech sectors such as chemicals and pharmaceuticals, computers and electronics, and machinery and automobile. A large share of graduates is also employed in low-tech manufacturing sectors such as food and beverages, paper, rubber, and metallurgy industry in 2011–2012, while the share of skilled employment in low-tech sectors was significantly less in 1999–2000. In recent years, this education-employment mismatch and non-overlapping demand and supply in the labour market are an interesting case in point for our study.

4 Econometric Model Setting

In this section, we specify the core equations and the econometric model used in our analysis. In an open economy with international trade and FDI, a country's technological efficiency depends not only on its own R&D efforts but also on the R&D efforts of its trading partners (Grossman and Helpman 1991, Eq. 1.3). In this view, innovation feeds on the knowledge generated through cumulative R&D activities and at the same time contribute to this stock of knowledge. The benefits of foreign knowledge stock consist of direct learning about new technologies and production processes as well as indirect learning from the knowledge embedded in traded products and services. To examine the implications of foreign R&D, we extend Coe and Helpman model and consider the effects of knowledge spillover indices on domestic productivity growth (Eq. 5) and the moderating role of R&D and human capital (Eqs. 6 and 7 respectively). Formally,

$$\Delta lnTFP_{j,t} = \beta_0 + \beta_1 lnFDIstock_{j,t-1} + \beta_2 Importspill_{j,t-1} + \beta_3 lnR\&D^d_{j,t-1} + \beta_4 lnHCQ^d_{j,t-1} + \in_{j,t} \quad (5)$$

$$\Delta lnTFP_{j,t} = \beta_0 + \beta_1 lnFDIstock_{j,t-1} + \beta_2 Importspill_{j,t-1} + \beta_3 lnR\&D^d_{j,t-1} + \beta_4 lnHCQ^d_{j,t-1} + \beta_5 lnFDIstock_{j,t-1} * lnR\&D^d_{j,t-1} + \beta_5 Importspill_{j,t-1} * lnR\&D^d_{j,t-1} + \in_{j,t} \quad (6)$$

$$\Delta lnTFP_{j,t} = \beta_0 + \beta_1 lnFDIstock_{j,t-1} + \beta_2 Importspill_{j,t-1} + \beta_3 lnR\&D^d_{j,t-1} + \beta_4 lnHCQ^d_{j,t-1} + \beta_5 lnFDIstock_{j,t-1} * lnHCQ^d_{j,t-1} + \beta_5 Importspill_{j,t-1} * lnHCQ^d_{j,t-1} + \in_{j,t} \quad (7)$$

Our final analysis covers the period from 2000–2001 to 2015–2016 and a sample of 12 two-digit manufacturing sub-sectors categorised based on OCED technology intensity classification as shown by Fig. 6. We end up with a pooled dataset of (12*15) 180 observations at the industry level and subsequently employ pooled linear regression with year and industry dummies and cluster adjusted standard errors for measuring total factor productivity growth. Explanatory variables are lagged to reduce the potential simultaneity problem. As robustness check, we have also provided fixed effects estimation results in the 10. (Table 3) to account for any unobserved heterogeneity in the analysis.

5 Results and Discussion

Following the empirical strategy mentioned in Section 4, we start by estimating growth in TFP for the entire manufacturing sample. Column 1 of Table 1 corresponds to Eq. 5 where no moderation is included. The overall fit of the model indicates poor predictability of the explanatory variables, thus reinforcing the importance of considering moderation effects of absorptive capacity. Columns 2 and 3 extend the baseline specification and introduce the spillover effects of FDI and trade through R&D and human capital respectively (Eqs. 6 and

High-technology industries	**Medium-high-technology industries**
Chemicals including pharmaceuticals	Electrical machinery and apparatus
Computers, electronics, communications and optical instruments	Machinery and equipment
	Motor vehicles, Railroad and other transport equipment
Medium-low-technology industries	**Low-technology industries**
Rubber and plastic products	Wood products
Non-metallic mineral products	Paper and paper products, printing and publishing of media
Basic metals and fabricated metal products	Food products, beverages and tobacco
	Textiles, wearing apparel, leather and footwear

Fig. 6 Manufacturing sectors based on OECD technology intensity classification

Table 1 Growth in TFP in total manufacturing

	TFP growth		
$lnFDIstock_{t-1}$	1.041 (1.988)	−2.406 (2.014)	7.186** (3.428)
$lnImportspillovers_{t-1}$	1.919 (1.338)	2.797* (1.249)	−3.462 (4.741)
$lnR\&Dintensity_{t-1}$	2.123 (2.406)	8.851* (5.094)	2.424 (1.990)
$lnSkillemplindex_{t-1}$	0.871 (7.986)	1.858 (8.066)	38.128* (20.04)
$lnFDIstock_{t-1}$*$lnR\&Dintensity_{t-1}$	-	−0.694** (0.349)	-
$lnImportspillovers_{t-1}$*$lnR\&Dintensity_{t-1}$	-	0.587 (0.636)	-
$lnFDIstock_{t-1}$*$lnSkillemplindex_{t-1}$	-	-	−4.551*** (1.64)
$lnImportspillovers_{t-1}$*$lnSkillemplindex_{t-1}$	-	-	−3.011 (2.484)
Constant	8.935 (19.865)	29.422* (16.445)	−50.712 (40.306)
F	1.06*	1.39*	1.67**
R^2	0.135	0.175	0.2

Number of observations = 180, number of groups = 12.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Cluster-adjusted standard errors in parentheses.

OLS regression with year and sector dummies.

7). First, knowledge spillovers from FDI and imports are found to significantly impact TFP growth, thereby confirming the findings of Coe and Helpman (1995). Absorptive capacity in terms of R&D intensity is found to be crucial for technological progress, implying that an increase in private R&D promotes TFP growth. The quality of human capital measured in terms of the skill-employment index has a weak but positive effect. While interpreting the coefficients of FDI spillovers in column 3, the switch of sign from positive to negative deserves an explanation. For moderation effects, interpretation of the overall effect has to be done jointly with the interaction term. In our case, since the magnitude of the overall effects for FDI spillover is positive (7.186–4.551), we can conclude that the overall effect of FDI spillovers on TFP growth is always positive. Results remain robust when we use fixed effects regression to account for industry-level unobserved heterogeneity (see 10.).

Interestingly, the most surprising results are found when we look at the moderation effects. Both R&D and skill employment index negatively moderate the relationship between FDI and TFP growth. In other words, the interaction between FDI and domestic absorptive capacity is negatively related to TFP growth indicating statistically lower partial correlation coefficients of FDI on TFP. Intuitively, this result signifies that higher absorptive capacity dampens the direct positive effect of FDI on productivity. Concerning import spillovers, however, no interaction effect is found, which means that absorptive capacity is not important for the absorption of knowledge through imports. These results are not in line with our theoretical predictions of positive moderation effects yet presents a vital distinction between developed and developing economies with respect to threshold requirements of absorptive capacity.

Digging deeper into the manufacturing sector, as the next step, we split the pooled manufacturing sample into two industry classes based on their technology intensity: (low tech, medium low-tech) and (medium low-tech, high-tech). The a priori assumption is that spillovers and absorptive capacity play out differently for different industry classes, and therefore it is essential to run the analysis for individual samples. Table 2 corresponds to Eqs. 6 and 7 and captures the sectoral heterogeneity with respect to our explanatory variables. For the low-tech and medium–low-tech sectors (models 1 and 2), spillover from FDI stock is found to significantly affect TFP. One explanation for the negative coefficient of productivity spillovers from FDI in model 1 is competition effects from foreign firms acquiring greater market share through cost advantages and reducing domestic demand for inputs. This is particularly true in the low-tech sectors such as food, beverages, paper, and textiles, where negative horizontal externalities from MNCs reduce domestic productivity in the short run. Both our measures of absorptive capacity are found to impact TFP growth.

When looking at the moderation effects, significant and negative coefficients of the interaction terms for FDI indicate that as absorptive capacity increases, conditional spillover effects of FDI on productivity decreases. This result again points towards threshold requirements of absorptive capacity (R&D and human capital) in the low-tech sectors, below which technological spillovers do not contribute to positive productivity growth. The picture is significantly different in the medium–high-tech and high-tech sectors (models 3 and 4). FDI spillover is weakly significant for productivity growth, while spillover

Table 2 Growth in TFP by industrial class

	TFP growth			
	Low and medium–low tech		Medium–high and high-tech	
	Model 1	Model 2	Model 3	Model 4
$\ln FDIstock_{t-1}$	− 3.629*** (0.936)	5.353** (1.573)	5.973 (5.890)	− 16.697* (5.637)
$\ln Importspillovers_{t-1}$	0.872 (1.154)	-3.487 (2.794)	5.926 (6.735)	− 64.957** (19.368)
$\ln R\&Dintensity_{t-1}$	5.204 (2.471)	1.135* (0.596)	19.687 (15.737)	8.214* (3.201)
$\ln Skillemplindex_{t-1}$	− 2.133 (2.654)	35.587** (13.884)	2.494 (21.919)	− 42.022 (28.685)
$\ln FDIstock_{t-1}{*}\ln R\&Dintensity_{t-1}$	− 0.679** (0.281)	-	–1.522 (1.774)	-
$\ln Importspillovers_{t-1}{*}\ln R\&Dintensity_{t-1}$	0.106 (0.280)	-	–0.421 (3.947)	-
$\ln FDIstock_{t-1}{*}\ln Skillemplindex_{t-1}$	-	4.369*** (1.173)	-	12.483** (2.782)
$\ln Importspillovers_{t-1}{*}\ln Skillemplindex_{t-1}$	-	2.658 (1.533)	-	31.431** (7.618)
Constant	27.998 (11.845)	–44.549 (24.357)	–30.225 (80.480)	41.310 (70.158)
R^2	0.223	0.252	0.405	0.519

Number of observations = 120 (columns 1 and 2), 60 (columns 3 and 4).

$*p<0.10$; $**p<0.05$; $***p<0.01$.

Cluster-adjusted standard errors in parentheses.

Linear regression with year and industry dummies.

from imports has a strong negative effect. This implies that technology-based industries such as automobile, metals, and machinery that have witnessed considerable high-tech imports in recent years have not experienced productivity benefits. When markets are imperfect, an increased influx of high-tech imports causes domestic markets to shrink and productivity to eventually fall. Another reason could be insufficient absorptive capacity and poor R&D and labour infrastructure. Our moderation results (model 4) confirm this, which shows that the negative effect of import spillovers on productivity becomes smaller in absolute value as human capital increases ($-64.957+31.431$). The finding suggests that in high-tech sectors, technological efficiency is achieved not through spillover effects of trade and FDI but through their interaction with absorptive capacity and subsequent knowledge absorption and diffusion. Expectedly, R&D intensity has a significant and positive effect on TFP growth, while the effect of human capital is negative but insignificant. This points towards education-employment mismatch in the high-tech and medium–high-tech manufacturing sectors and the low productivity of labour in general. No significant moderation effect is found with respect to FDI, R&D and human capital.

6 Conclusion and Policy Implications

Among the reasons for India's unsatisfactory economic performance and low industrial output compared to technological frontier countries such as China and South Korea, emphasis has been put on regulatory and infrastructural bottlenecks so far (Kumar 2009). Indeed, the Government of India has undertaken policies in FDI and international trade, education, and R&D to increase industrial productivity. Yet, drawing general conclusions as to how such policies affect productivity growth without considering the role of indigenous factors such as R&D and human capital is problematic. Given that India is a large country with substantial sectoral heterogeneity in terms of investment in R&D and skills, it may be straightforward to expect sectoral variation in the spillover effects from foreign investment and trade openness. Taking a cue from this backdrop, the current paper contributes to the literature on absorptive capacity and total factor productivity for developing countries and disentangles the direct and indirect effects. Classifying the manufacturing sectors into two industry classes based on their technology intensity, we propose that sectors with higher levels of absorptive capacity in the form of R&D and human capital will more efficiently manage and integrate international knowledge spillovers to boost their productivity. Results from the linear regression analysis confirm positive spillover effects of FDI and imports and negative moderation effect of absorptive capacity on TFP growth for the entire sample. However, when the manufacturing sectors are sub-grouped, significant differences emerge with respect to the direct and moderation effects. In the low- and medium–low-tech sectors, we find that absorptive capacity negatively moderates knowledge spillovers for productivity growth, while in the medium–high- and high-tech sectors, absorptive capacity in the form of human capital has a positive and significant interaction with the spillover variables. Overall, our results confirm that considering absorptive capacity for devising policies to promote TFP growth is essential for Indian industries. Based on our findings, in the section below, we provide suggestions for policy intervention at the industry and central government levels.

(i) *Data unavailability and homogenisation issues*: The biggest challenge in undertaking a sectoral level multi-factor analysis is poor data infrastructure which needs to be addressed. For this paper, we have used multiple databases for extracting disaggregated information on FDI, trade flows, private R&D, and human capital. When looking at the industry classification, the paper has clubbed different unrelated industries together. For example, one may argue that a firm in food processing may have little to learn from a firm in the tea industry, although both are clubbed under the "food products, beverages and tobacco" category. Ideally, disaggregated levels of industries at 3-digit or 4-digit levels should be considered. However, methodological limitations in combining multiple databases along with limited availability of disaggregated data are challenging to bypass. When considering private R&D, the only database available for recent years is privately procured ProwessIQ, which gives information on R&D expenditures in the capital and current account (other being data.gov.in that gives sectoral information on R&D units recognised by the Department of Scientific and Industrial Research only up to 2009–2010). However, this aggregated information coupled with a low response rate is seldom beneficial for answering innovation-related queries. For skill composition of employment at the sectoral level, NSSO provides information only up to the graduate level. No information on higher education, number of researchers, and PhD students and above in industry employment is provided at a disaggregated level—this seriously constraints skill-employment analysis and correct determination of human capital quality. Lastly, the need for a comprehensive and harmonised database in India cannot be stressed enough. In the absence of such database, combining data from multiple sources requires constructing concordance tables manually for harmonisation and international comparability. Therefore, efforts should be taken to provide disaggregated data on economic indicators using uniform NIC codes as well as updated private R&D and human capital data by NSSO and NSTMIS.

(ii) *Industrial R&D policies* should prioritise high-tech sectors where productivity benefits are mostly visible. Investing in R&D units of MNCs, building government-supported industry-specific R&D consortia (such as BIRAC in India, SEMATECH in the USA) and establishing links with universities and research institutes are absolutely necessary. In the low-tech manufacturing sectors, the "crowding out" effect of FDI inflows is evident, which dampens productivity growth. When interacted with R&D and human capital, results do not change, implying that any positive spillovers from FDI and imports to the local economy are offset by competition effects and poor absorptive capacity. Policy intervention by MHRD and DPIIT should address this issue and formulate FDI incentives in the low-tech sectors in conjunction with R&D and education-employment policies. Also, attention should be paid to the type of FDI, whether greenfield investment or brownfield.

(iii) *On the job front*, while initiatives have been undertaken in skill training under the National Skill Development Mission, building synergies with economic and R&D policies has been overlooked. The creation of jobs is not sufficient. In the high-tech sector, what is needed are better quality jobs, reallocation of resources, and reduction in the education-employment mismatch. Low labour productivity and low wage rates loom large, subsequently lowering TFP growth. However, regression results from the high-tech sector confirm positive moderation effects of human capital and

> import spillovers for productivity growth. Thus, attempts should be made to mandate training and hiring of PhD graduates and research scholars in sectors that experience a greater influx of high-tech imports in intermediate goods, such as automobiles, electronics, chemicals, and pharmaceuticals. Only then will import spillovers and foreign technological knowledge be beneficial for productivity. Devising trade policies conditioned upon absorptive capacity is therefore crucial. Simply allowing 100% FDI or imports is not enough for achieving technological efficiency in the high-tech manufacturing sector.

The broad contribution of this research, therefore, is (a) to identify the nuances of imports and FDI from OECD partner countries to India and to understand sectoral heterogeneity in knowledge spillovers when instituting incentives for trade and inward FDI, (b) to formulate an industry-human capital interface to enable foreign technologies and skills to be successfully absorbed and adopted, (c) to support reallocation of human resources to the organised manufacturing sector to enable quality job creation and growth, and (d) to build upon the academic research on knowledge spillovers and absorptive capacity from a hitherto overlooked developing country perspective**.** The practical implications include providing suggestions for policy intervention by clusters of stakeholders in India such as the Department of Science and Technology (DST), Confederation of Indian Industry (CII), Federation of Indian Chambers of Commerce and Industry (FICCI), DPIIT, and Ministry of Human Resource Development (MHRD).

While the study offers new insights into the discussion on the role of absorptive capacity and knowledge spillovers within the Indian manufacturing setting, it is not free from limitations. First, cross-industry studies on FDI spillovers face a selection problem in the sense that FDI often gravitates toward productive industries. Consequently, the observed spillovers resulting from cross-industrial data tend to overstate the impact of foreign firms due to the potential endogeneity of FDI. To overcome this endogeneity issue, long panels of firm-level data may be used (Demena and van Bergeijk 2017) subject to data availability. Second, to dig deeper into the spillover domain, one could examine the effect of knowledge spillovers on the productivity of domestic firms in intermediate sectors—the so-called vertical spillovers. This would enhance our understanding of what proportion of overall productivity increase in the Indian economy could be attributed to the growth of productivity of firms in the intermediate inputs sector. Lastly, recent studies in the field of evolutionary economics (Amsden 2009) have pointed out that very little technological transfer may take place between subsidiaries of MNCs located in developing countries. Most of the R&D activities take place in the headquarters of the firms which are located in developed countries, which is why accumulation of technological capabilities occur within domestic firms rather than within subsidiaries of foreign-owned firms. While the evidence is limited, future research should acknowledge the possibility while evaluating the importance of international knowledge spillovers in productivity growth.

Appendix

Table 3 Matching of NIC 1998, NIC 2004, and NIC 2008 codes

NIC 2008	Manufacturing sectors Revised	Revised categories	Description
10	Food products	10, 11, 12	Food products, beverages and tobacco
11	Beverages		
12	Tobacco products		
13	Textiles	13, 14, 15	Textiles, leather products, apparel
14	Wearing apparel		
15	Leather and related products		
16	Wood and wood products, except furniture	16	Wood and wood products
17	Paper and paper products	17, 18	Paper products, printing and publishing
18	Printing, reproduction of recorded media		
20	Chemicals and chemical products	20, 21	Chemicals, drugs and pharmaceuticals
21	Pharmaceuticals		
22	Rubber and plastics products	22	Rubber and plastics
23	Other non-metallic mineral products	23	Other non-metallic minerals
24	Basic metals	24, 25	Basic and fabricated metals
25	Fabricated metal products		
26	Computer, electronic and optical products	26, 27	Electricals, electronics and optical equipments
27	Electrical equipment		
28	Machinery and equipment n.e.c	28	Machinery n.e.c
29	Motor vehicles, trailers and semi-trailers	29, 30	Transport equipment
30	Other transport equipment		
19	Coke and refined petroleum products	19, 31, 32	Other manufacturing
31	Furniture		
32	Other manufacturing		

Table 4 HS 2007 product composition of manufacturing of chemicals acc. to NIC 2008

6-digit HS 2007 code	Product description	Two-digit HS 2007	Two-digit NIC 2008
151800	Animal/vegetable fats and their fractions, boiled/oxidised	15	20: Manufacture of chemicals and chemical products
152000	Glycerol, crude; glycerol waters, and glycerol lyes	15	
260300	Copper ores and concentrates	26	
261610	Silver ores and concentrates	26	
270730	Xylol	27	
270820	Pitch coke obtained from coal tar/other mineral tar	27	
280120	Iodine	28	
281000	Oxides of boron, boric acids	28	
283010	Sodium sulphides	28	
290314	Carbon tetrachloride	29	
293020	Thiocarbamates and dithiocarbamates	29	
300670	Gel preparations designed to be used in human/veterinary	30	
310250	Sodium nitrate	31	
320210	Synthetic organic tanning substance	32	
320820	Paints and varnishes based on acrylic	32	
321511	Printing ink, black	32	
330119	Essential oils of citrus fruit	33	
340111	Soap and organic surface-active products and preparations	34	
350300	Gelatine	35	
350691	Adhesives based on polymers/rubbers	35	
360300	Safety fuses; detonating fuses	36	
370210	Photographic film in rolls, unexposed, of any material	37	
380210	Active carbon	38	
381129	Additives for lubricating oils	38	
390190	Polymers of ethylene, in primary forms	39	
391000	Silicones, in primary forms	39	
400291	Synthetic rubber and factice derived from oils, latex	40	
540231	Textured yarn other than sewing thread, of nylon/others	54	
550110	Synthetic filament tow, of nylon/other polyamides	55	
710410	Piezo-electric quartz	71	
852340	Optical media for the recording of sound	85	

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Declarations

Compliance with ethical standards The manuscript is original and has not been published nor is under consideration for publication elsewhere.

Conflict of Interest The authors declare no competing interests.

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