



# May It Be a Little Bit More of Market Power? On Productivity Growth and Competition

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## Abstract

In its heart, competition represents an important driver of productivity growth that has slowed in European countries since the financial crisis. This study examines the non-linear relationship between productivity growth and market power, using data on Central European manufacturing firms, from 2009 to 2017. The results show concave relationships between both variables, and that firms in competitive industries respond more sensitively to market power. This study contributes to the literature by applying not only the standard firm-level measure of Lerner indexes, but also by calculating them from production functions and checking robustness with country-industry-level concentration measures.

**Keywords** Firm growth · Productivity · Market structure · Concentration · Manufacturing regulation

**JEL Classification** D22 · D24 · D47 · L11 · L51

## 1 Introduction

Many countries, especially post-soviet countries that transitioned from centrally planned to market economies, considerably liberalised industries following the dictum that competition fuels innovation and, finally, boosted economic growth. Supporters of the dictum argue that enterprises develop new products or rearrange production processes to resist market pressure. Resulting competitive advantages, however, decay, as competitors follow suit. In comparison, opponents claim that competitive advantages deteriorate too fast under fiercer market pressure, wiping out incentives to innovate. Hence, an important question to answer is whether competition between firms spurs companies to innovate or not. This question relates to the very heart of the design of economic systems. Should governments continue liberalisation or possibly roll it back? Potential gains in technical efficiency, therefore, could serve as a

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motivation to foster liberalisations and strengthen competition policy, while possible losses would favour a rollback (Backus 2020).

For many decades, the impact of competition on firm-level innovation and productivity growth has been debated controversially in the economic literature. According to Schumpeter (1934), monopolists invest more in R&D due to less market uncertainty providing greater funds and more stable sources of income. Similarly, the leading models on product differentiation by Dixit and Stiglitz (1977) and Salop (1979), and many textbook models on endogenous growth predict that more intense competition decreases postentry rents, discouraging innovation and productivity growth. Conversely, Arrow (1962) argues that innovative firms benefit more from innovation when competition is fierce. In comparison, Aghion et al. (2005) observe concave relationships between competition and innovation motivating them to build a theoretical model combining both views. Additionally, they claim that industry-specific gaps to the productivity frontier increase with intensifying competition, and that firms in competitive industries respond more strongly to competition. Their model, however, is challenged by the theoretical model by Tishler and Milstein (2009) who derive a convex relationship between competition and R&D.

Besides, the approach to measuring innovation is extensively debated in the empirical literature. Several measures of innovation and technological progress, each having particular strengths and weaknesses, are available. They relate either to inputs, outputs or quality. One strand in the literature (e.g. Beneito et al. 2015; Hashmi 2013; Jamasb and Pollitt 2011; Aghion et al. 2005; Blundell et al. 1999) quantifies innovation using the number of patents, citations or binary variables. Such measures refer to the quality of innovation (Taques et al. 2021). In comparison, productivity and its growth rates are employed in other studies (e.g. Aghion et al. 2008; Bottasso and Sembenelli 2001; Griliches 1996). This approach relates to the effectiveness of innovation (Taques et al. 2021) and is based on economic growth theory. In relevant models, technology is introduced as an input into the production function.<sup>1</sup> Being an input measure related to innovation efforts, R&D expenditures, their growth and the number of researchers are applied as innovation measures by the third strand in the literature (e.g. Atayde et al. 2021; Griffith et al. 2010; Jamasb and Pollitt 2008). Although these measures quantify different aspects of innovation, they strongly correlate with each other (Taques et al. 2021; Amable et al. 2016; Klette and Kortum 2004; Stahl and Steger 1977), i.e. research shifts the production function upwards boosting productivity (Parisi et al. 2006; Bottasso and Sembenelli 2001). Nevertheless, each approach suffers from particular problems. Effort-based measures such as R&D expenditures do not consider the output side (e.g. success and effectiveness of innovation). The same holds for the quality-based measures such as the number of patents (Hall 2011a). In comparison, productivity growth might capture other issues next to innovation. Many benefits from innovation are reflected by firm-level prices due to changes in market power. If monetary output and inputs are, however, deflated by sector-level deflators instead of the often-unavailable firm-level price indexes, then productivity growth does not properly measure innovation (Hall 2011b; Nishimizu and Page 1982).

Owing to the improving availability of firm-level data, many studies empirically examining the Schumpeterian hypothesis conclude that competition spurs innovation and productivity growth. Syverson (2004) investigates the link between productivity and competition, finding that competition raises productivity by wiping out inefficient firms. Similarly, Disney et al. (2003) conclude that competition spurs technical efficiency. Besides, Nickell (1996)

<sup>1</sup> In economic growth theory, technology is usually denoted by  $A$ . Its growth rate represents technological progress (Solow 1956).

and Nickell et al. (1997) observe that competition improves corporate productivity growth. Okada (2005) also finds positive impacts of competition on firm-level productivity. In comparison, Blundell et al. (1999) regress headcount innovation measures of major technological breakthroughs and conclude that market shares spur innovation, while market concentration decreases it. Tang (2006), following Blundell et al. (1999), shows that the relationship between competition and innovation depends on the measure of competition. The empirical and theoretical findings by Aghion et al. (2005) are supported by Hashmi (2013) (for the UK, but not for the USA), Inui et al. (2012) and Tingvall and Poldahl (2006). Contrarily, Aghion et al. (2008) observe a convex function between productivity growth and firm-level Lerner indexes in Africa. The same holds for Atayde et al. (2021) finding a convex, though insignificant, relationship between R&D variables, productivity and competition measures.

Motivated by these aspects raised by the theoretical and empirical literature, this study aims to empirically examine the relationship between competitive forces and productivity growth. Particularly, it intends to provide empirical evidence on the propositions of the theoretical model by Aghion et al. (2005). Despite the mentioned problems, I quantify technological progress with the productivity growth rate, since it is one of the best understood and, thus, most popular innovation output measures (Hall 2011b). There are two reasons. First, the effectiveness of innovation is more relevant given its influence on overall economic growth. Second, estimating the underlying production functions allows to measure firm-level market power by applying the novel approach by De Loecker and Warzynski (2012). This approach obtains Lerner indexes from the estimates of the production function.

To perform the analysis, I employ micro-data on Austrian, Czech, Hungarian, Slovak and Slovenian manufacturing firms from 2009 to 2017. I apply a two-staged framework. In the first stage, I estimate the production function for every country and two-digit NACE industry, while I establish links between productivity growth and Lerner indexes in the second stage.

Central Europe is compelling for various reasons. First, four out of five countries are post-soviet. After the collapse of the Soviet Union, many Eastern European countries considerably restructured their economic system, i.e. they implemented market mechanisms, substantially liberalised many sectors, and privatised formerly state-owned companies. Inspired by the efficiency of Western role models, post-soviet countries aimed to transition from the centrally planned system dominated by government-owned monopolies to free-market economies. Nevertheless, liberalisations were poorly implemented. In comparison, the other studies mostly analyse developed countries. Given their history, economic development and poorly implemented liberalisations, relationships plausibly differ from the relationships observed in highly developed countries. For example, the level of market power that maximises efficiency growth and innovation will plausibly be higher in the post-soviet countries. Poorly introduced liberalisations possibly did not allow manufacturing companies to get sufficiently used to employ innovation as a tool of competing with other firms. Hence, relevant firms in these regions still might require higher markups to cover innovation costs. Second, relevant countries constitute small open economies, which are more exposed to foreign competition. Consequently, competition from foreign countries plays a more important role in shaping the relationship between market power and efficiency growth and innovation. In comparison, the other studies usually analyse larger countries that do not rely as strongly on international trade as these countries do. Third, as outlined in Sect. 2, they are members of the Central European manufacturing core, an industrial region that has rapidly grown in the previous decades in contrast to other regions.

Analysing manufacturing sectors is of particular interest. First, manufacturing is considered the main source of technological progress, although the service sectors gain importance. The share of service sectors in national output is growing at the cost of manufacturing

because of changing demand structures and outsourcing (Baumol 1967). While service firms also employ other ways to compete with each other (e.g. marketing, design, organisational investment), manufacturing enterprises completely employ different production processes. In other words, they produce more research-intensively (e.g. product and process innovation) and invest more strongly in innovation to differentiate themselves from rivals (Tagues et al. 2021). Thus, results will plausibly differ, since manufacturing firms might require higher markups to cover innovation costs. The already mentioned studies also cover manufacturing sectors, but manufacturing industries in investigated countries are not that large. For instance, in the UK and USA, the shares of manufacturing in GDP vary around 10%, while in the Central European manufacturing core, the same shares lie around the double. Second, it is not common in the literature to estimate production functions of service industries.

I add to the literature in further aspects. First, my dataset covers smaller firms next to large or listed firms (e.g. Hashmi 2013), enabling a more comprehensive analysis. Second, to the best of my knowledge, this is one of the few studies that measures Lerner indexes employing the framework proposed by De Loecker and Warzynski (2012) next to the conventional return on sales-definition when examining the theoretical propositions. This novel technique of estimating markups may provide new insights into the relationship between market power and efficiency growth and innovation. In comparison to the return on sales, the primarily employed measure in the literature, these markups are corrected for the variations in output that are not related to fluctuations in the inputs (e.g. elasticities of demand, income) (De Loecker and Warzynski 2012) and, therefore, may provide different results. I check robustness with country-industry-specific measures of market concentration.

Overall, my results support the theoretical model by Aghion et al. (2005) and the empirical literature. I find concave relationships between productivity growth and market power, supporting several studies discussed above. However, the effect of average market power on country-industry-specific gaps to the productivity frontier depends on the measure of market power. Last, firms operating in competitive industries respond more strongly to market power. The results are robust when calculating productivity growth and Lerner indexes from the estimates of translog production functions.

The paper proceeds as follows. Section 2 provides an overview of the Central European manufacturing sector and the theoretical model by Aghion et al. (2005). Section 3 introduces the empirical framework and data employed to estimate the production functions and obtain productivity growth, and discusses the results. Section 4 describes the empirical strategy employed to empirically investigate the propositions of the theoretical model and the results. Last, Sect. 5 sums up and draws conclusions.

## 2 Background and Hypothesis

### 2.1 Examined Propositions

As outlined in the previous section, the models by Dixit and Stiglitz (1977) and Salop (1979) conclude that fiercer competition deteriorates postentry rents and, finally, discourages innovation and reduces the equilibrium number of entrants. Aghion et al. (2005), however, observe concave relationships between innovation and competition. They set up a theoretical model that explains this inverted-u shaped relationship, i.e. the model accounts for both, positive and negative effects of competition on innovation.

According to Aghion et al. (2005), the economy consists of two types of sectors: *leveled* or *neck-and-neck* sectors where firms are technological par with one another and *unleveled* sectors characterised by one leading firm (*leader*) lying one step ahead its competitors (*laggards* or *followers*). In the first group of industries, firms innovate to differentiate themselves from competitors and to temporarily escape from competition, while in the second type, laggards innovate to catchup with the leader. In case of weak product market competition, neck-and-neck firms only face weak incentives to innovate. Consequently, the overall innovation rate will be higher in unleveled industries. Thus, the industry will quickly leave the unleveled state, which it does when laggards start innovating, and slowly leaves the leveled state, which will not happen until neck-and-neck firms innovate. This implies that industries spend most of the time in the leveled state dominated by escape-competition. In other words, if competition intensity increases starting from a low level, innovation rates and productivity growth are high. Conversely, when competition intensity is high to begin with, there is hardly incentive for laggards in an unleveled state to innovate (*Schumpeterian effect*), suggesting that the industry will be slow to leave the unleveled state. In the leveled industry, however, innovation rents spur firms to innovate and escape competition (*escape-competition effect*) such that the industry quickly moves to the unleveled state where laggards innovate to catchup, while leaders do not. Summing up, in case of an intense initial competition, increasing competition drops innovation and productivity growth rates.

The second proposition of the model by Aghion et al. (2005) suggests that industry-specific expected technology gaps increase with competition. The model proposes that firms conduct more research in neck-and-neck industries when competition becomes fiercer, but less in unleveled sectors. The same holds for the entire economy due to the law of large numbers. In comparison, the static intuition of the basic textbook models suggests that intensifying competition decreases the gap by wiping out inefficient firms.

Last, the third proposition of Aghion et al. (2005) claims that firms in competitive industries respond more strongly to competition than companies in less competitive industries. In other words, the escape-competition effect is stronger in sectors in which companies are closer to the frontier, i.e. productivity growth maximising levels of competition are smaller in neck-and-neck industries.

## 2.2 Central European Manufacturing Sectors

As outlined by the studies by the European Commission (2020) and IMF (2013), Europe's manufacturing activity increasingly concentrates in a Central European core consisting of Austria, the Czech Republic, Germany, Hungary, Slovakia, Slovenia and Poland. This study examines the propositions of the discussed model using firm data on a subset of the member countries. Chosen countries are of particular interest for many reasons.

First, the chosen countries are small open economies. In comparison to Germany and Poland, Austria, the Czech Republic, Hungary, Slovakia and Slovenia are smaller and, therefore, rely more strongly on international trade.<sup>2</sup> Consequently, competition from foreign countries plays a more relevant role in the chosen countries, shaping the relationship between market power and efficiency growth and innovation.

Second, some countries are post-soviet and, therefore, have transitioned from centrally planned to market economies after the collapse of the Soviet Union. Although governments have implemented considerable institutional changes and liberalisations, their influence on the companies in these countries is still pervasive. Especially post-communist countries are

<sup>2</sup> For an overview, see <https://ec.europa.eu/eurostat/databrowser/view/tet00003/default/table?lang=en>

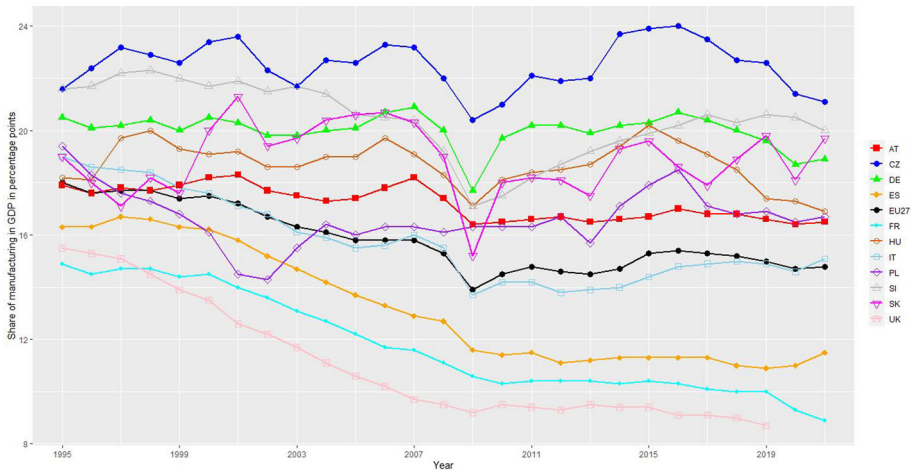
characterised by strong entry barriers, aggravating the transition to well-functioning market economies. Moreover, instead of creating open and contestable markets, poorly implemented privatisations established legal monopolies, strengthening market barriers (Buccirossi and Ciari 2018).

In comparison, the other studies investigating the relationship between competition and innovation and efficiency growth mostly apply data on developed countries. In contrast, developed countries have not experienced comparable institutional changes. Given their history, economic development and poorly implemented liberalisations, relationships between competition and efficiency growth plausibly differ between post-soviet and highly developed countries. Poorly implemented privatisations possibly did not allow companies to get used to competition sufficiently. In other words, an increase in competition might imply stronger effects on efficiency growth and innovation, suggesting steeper curves and lower efficiency growth maximising levels of competition in the relevant countries.

Third, the investigated countries benefit from strong manufacturing sectors. I focus on manufacturing industries because their production processes differ considerably from production processes in other sectors (e.g. services). Therefore, the relationship between market concentration and efficiency growth and innovation in manufacturing will be different from the ones obtained by the literature, since the literature analyses all the industries. To differentiate themselves from rivals, manufacturing enterprises rely more strongly on innovation (e.g. develop new products, invest in process innovations), while service firms also employ other ways to compete with each other (e.g. marketing, design, organisational investment) (Taques et al. 2021). Thus, manufacturing enterprises may need higher markups to cover innovation costs. However, given its unique characteristics, focusing the analysis on manufacturing companies is particularly interesting. The literature also covers manufacturing industries, but they are not really strong in the investigated countries. For instance, in the UK and USA which are analysed by Aghion et al. (2005) and Hashmi (2013), the shares of manufacturing in GDP lie around 10%, while in the member states of the Central European manufacturing core, this share is the double. Figure 1 shows the shares of the manufacturing sector in GDP by countries and years. From 1995 to 2021, the British share of manufacturing declined strongly. The analogous can be observed for other Western European countries such as France, Italy and Spain, while the shares stagnated in the Central European core. Thus, the results in the literature are not only influenced by the analysed countries' level of development, but also by the industry structure, as the relationships are likely heterogeneous across industries, and, therefore, the industry structure plays a role.

During the twentieth century, the structure of manufacturing sectors in the analysed countries changed substantially over time. In post-soviet countries, rapid industrialisation served as a key tool of the Stalinist growth and regional policies. Technological progress, however, shifted the focus gradually from the heavy industry towards chemical and electronics sectors (Siegelbaum and Suny 1993). After the collapse of the Soviet Union, the transition from centrally planned to market economies, however, substantially affected the industry structure. Formerly industrialised regions that did not adapt to the new circumstances lost wealth, while regions that adjusted successfully maintained their wealth or even benefited from the transition. For instance, the EU's Eastern European expansion implied a substantial increase in FDI in these countries. Particularly, the vehicle sectors grew considerably in these countries because of the transnational companies' massive FDI investment (e.g. Vienna-Győr-Bratislava region). Given their geographical closeness to the Western markets and the relatively inexpensive, but skilled labourforce, these countries attracted more FDI from vehicle producers than the other Eastern European countries (Pavlínek et al. 2009). Like the German manufacturing sector, the Austrian one maintained a larger share in GDP



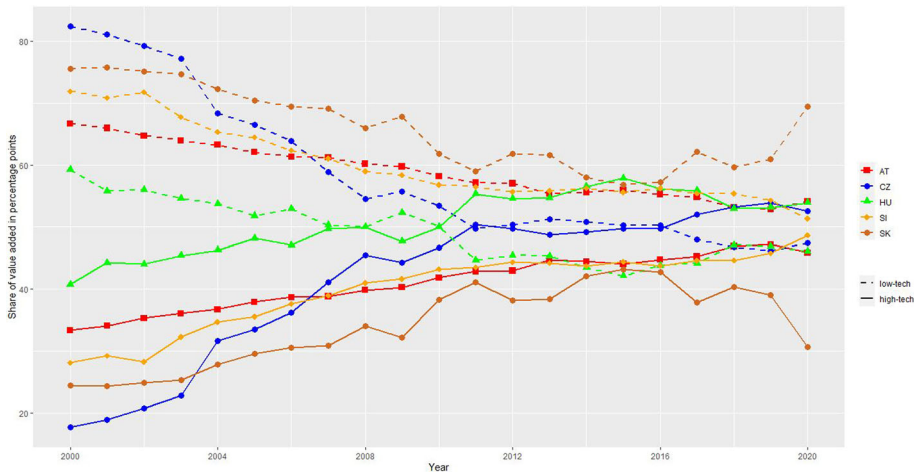


**Fig. 1** Shares of manufacturing (C) in GDP by country and year. Data source: Eurostat ([https://ec.europa.eu/eurostat/databrowser/view/NAMA\\_10\\_A10\\_custom\\_5771619/default/table?lang=en](https://ec.europa.eu/eurostat/databrowser/view/NAMA_10_A10_custom_5771619/default/table?lang=en)). Note: The figure displays the annual shares (in percentage points) of manufacturing sectors in GDP in the member states of the Central European manufacturing core and other selected member countries of the EU from 1995 to 2021. Although the manufacturing shares declined in many EU countries, they decreased only slightly or stagnated in the Central European core

after WWII in contrast to comparable industrialised countries. Nevertheless, service sectors expanded like in other countries. Over time, the manufacturing sector diversified. Nonetheless, technological progress shifted the focus from the ‘old’ industries (e.g. food, textiles, wood products sectors) towards the more ‘modern’ sectors (e.g. chemical, electronic, machinery, vehicle industries) (Klein et al. 2017; Braun 2003). Figure 2 displays the transition of the country-level manufacturing sectors towards high-tech industries from 2000 to 2020. Industries are divided into high-tech and low-tech sectors according to the European Commission’s classification scheme.<sup>3</sup> In all countries, the share of real value added of the high-tech industries in the real value added of the entire manufacturing sector grew rapidly, while the share of the low-tech industries declined. Especially, the role of Austria is interesting given its intermediate position, since it is neither an offshoring destination nor the technology leader. In comparison, Germany would be a technology leader (Stehrer and Stöllinger 2014; IMF 2013). Besides, the analysed post-soviet countries have been a part of the Austrian-Hungarian empire and, therefore, show some similarities given the common past (Klein et al. 2017). Nowadays, the focus of industrial policy in all countries shifts to the high-tech sectors. Although the considered countries historically differed in their industrial structures, food and metal industries have always contributed a large share of gross value added of the manufacturing sector. While historically large sectors (e.g. textiles) eroded over time because of corporate relocation to other parts of the world (e.g. Asia), other industries such as the vehicle industry grew strongly (Pavlínek et al. 2009).<sup>4</sup>

<sup>3</sup> [https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech\\_classification\\_of\\_manufacturing\\_industries](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech_classification_of_manufacturing_industries)

<sup>4</sup> [https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama\\_10\\_a64&lang=en](https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10_a64&lang=en)

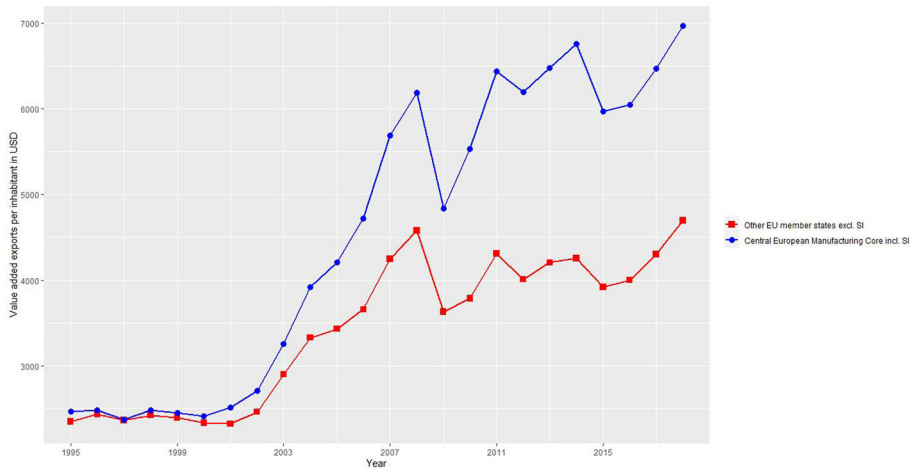


**Fig. 2** Shares of value added of high-tech and low-tech sectors in entire manufacturing sector (C). Data source: Eurostat ([https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama\\_10\\_a64&lang=en](https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10_a64&lang=en)). Note: The figure displays the annual shares (in percentage points) of real value added of the high-tech (solid lines) and low-tech (dashed lines) industries in real value added of the entire manufacturing sector in every analysed country from 2000 to 2020. Data on chained value added by countries, two-digit NACE industries and years is sourced from Eurostat. The classification of industries into high-tech and low-tech sectors is based on the European Commission's classification scheme. High-tech industries include sectors employing high (C21, C26) and medium-high (C20, C27–C30) technology, whereas low-tech sectors cover industries using medium-low (C19, C22–C25, C33) and low (C10–C18, C31, C32) technology. The shares are calculated as follows. First, for every industry, country and year, the share of real value added in the entire manufacturing sector's real value added is calculated. Second, the industries are classified according to the European Commission's classification scheme. Third, for each country and year, the aggregates are constructed for every group (high-tech, low-tech). In every country, the share of real value added of high-tech sectors in the real value added of the entire manufacturing sector increased considerably, whereas the share of low-tech industries decayed

Overall, structural shifts towards service industries were less pronounced in the Central European manufacturing core than in other countries. In contrast to the Western European countries, the shares of manufacturing in GDP only declined mildly or stagnated, as shown by Fig. 1. Furthermore, since the 2000s, the manufacturing export intensities of the member states of the Central European manufacturing core (blue line) rose more sharply than those of the other EU countries including the UK (red line), as shown by Fig. 3. The figure tracks the domestic manufacturing sectors' value added content of gross exports per inhabitant in USD. The shown variable quantifies the importance, export orientation and international competitiveness of the analysed manufacturing sectors. Before 2000, the manufacturing export intensities only differed slightly between the Central European manufacturing core and the other EU countries.<sup>5</sup> From 2000 onwards, manufacturing export intensities started to diverge, i.e. the one of the Central European manufacturing core grew more rapidly than the one of the other EU countries. While the manufacturing export intensity of the Central European manufacturing core continuously rose after the financial crises, the one of the other EU countries started to stagnate. The gap between the groups swelled over time, as the Central European manufacturing core raised its export market shares at the cost of other EU states (e.g. France, UK). As the most important manufacturing sectors, the main drivers of this development

<sup>5</sup> They also do not strongly differ back in 1995.



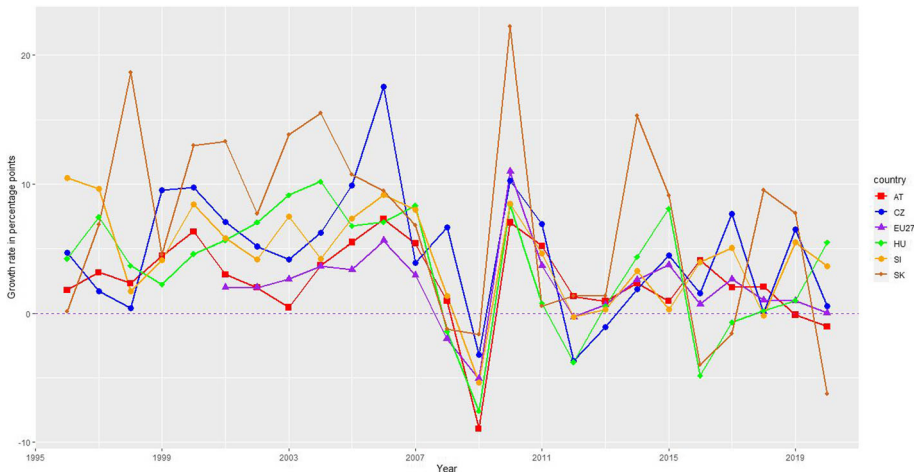


**Fig. 3** Value added exports per inhabitants in USD. Data source: Eurostat ([https://ec.europa.eu/eurostat/databrowser/view/DEMO\\_PJAN\\_\\_custom\\_5783052/default/table?lang=en](https://ec.europa.eu/eurostat/databrowser/view/DEMO_PJAN__custom_5783052/default/table?lang=en)), OECD ([https://stats.oecd.org/Index.aspx?DataSetCode=TIVA\\_2021\\_C1#](https://stats.oecd.org/Index.aspx?DataSetCode=TIVA_2021_C1#)). Note: The figure illustrates the value added content of gross exports per inhabitant from 1995 to 2018. Country-level data on the value added content of gross exports are sourced from the OECD database, while data on inhabitants are downloaded from Eurostat. First, each variable, the value added content and population, is summed across the two groups, ‘Central European manufacturing core’ and ‘other EU countries’. Second, for each group and year, the sum of value added content is divided by the sum of inhabitants. Until 2000, the gap between the manufacturing export intensity of the Central European manufacturing core (blue line) and the other EU countries (red line) stagnated at a low level, but started to swell afterwards, since the Central European core expanded its export market share at the cost of the other European countries

cover food, chemical, electrical products, machinery, metal and vehicles industries (Stehrer and Stöllinger 2014; IMF 2013).

As shown in Fig. 4, manufacturing sectors’ real labour productivity increased rapidly in the years before the financial crises. The financial crises, however, shrank the growth rate of real labour productivity in many European countries temporarily or permanently, especially in post-communist member states. After the financial crisis, labour productivity growth rates evolved differently across countries and industries. In the food, beverages and tobacco; textile, wearing apparel and leather; chemical; non-metallic minerals; basic metal; electrical equipment; machinery; motor vehicle; other transport equipment; furniture industries, the declines in the growth rates of real gross value added by working hour were only temporary. They dropped severely, but quickly recovered. Depending on the country, they recovered faster or more slowly. Contrarily, in other industries (e.g. wood; paper; printing and media; pharmaceutical; rubber and plastics; fabricated metal; computer, electronic and optical product; repair and installation), growth rates decreased permanently, as they stabilised at lower levels, particularly in the post-communist countries.<sup>6</sup>

<sup>6</sup> [https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama\\_10\\_a64&lang=en](https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10_a64&lang=en)  
[https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama\\_10\\_a64\\_e&lang=en](https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10_a64_e&lang=en)



**Fig. 4** Growth rates of real gross value added per worker in manufacturing (C) by country and year. Data source: Eurostat ([https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama\\_10\\_a64&lang=en](https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10_a64&lang=en), [https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama\\_10\\_a64\\_e&lang=en](https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10_a64_e&lang=en)). Note: The figure illustrates the growth rates of real labour productivity in the manufacturing sectors in the analysed countries from 1995 to 2020. Country-level data on chained gross value added and the total number of working hours by employed and self-employed are obtained from Eurostat. Growth rates are calculated as follows. First, chained gross value added is divided by the number of working hours. Second, the growth rate is calculated. Growth rates of real labour productivity fluctuated strongly across years. During the financial crisis, they dropped in all countries, but recovered again. Nevertheless, the average level of growth was higher in the years before crisis than in the years after the crisis

### 3 First Stage: Estimation of the Production Function

To establish links between market power and productivity growth, a two-stage procedure is employed, as described in Sects. 3 and 4. In the first stage, I estimate production functions to obtain firm-level productivity. Its growth rate is explained in the second stage. In this stage, the analysis is threefold. First, productivity growth is explained by competition at the firm-level to investigate the first proposition. Second, country-industry-specific average productivity gaps are related to competition varying at the same level. Third, the heterogeneous effects of market power are examined across competitive and not-competitive sectors.

#### 3.1 Specification of the Production Function

Following the literature (e.g. Gemmell et al. 2018; Richter and Schiersch 2017; Collard-Wexler and De Loecker 2015; Lu and Yu 2015; Du et al. 2014; Del Bo 2013; Doraszelski and Jaumandreu 2013; Crinó and Epifani 2012; De Loecker and Warzynski 2012; Arnold et al. 2011; De Loecker 2007; Javorcik 2004), I estimate three-input revenue-based Cobb-Douglas production functions, as described in Eq. 1, with the method by Akerberg et al. (2015) explained in Appendix A.  $y$  denotes logged output (dependent variable),  $k$  logged capital (state variable),  $l$  logged labour (free variable), and  $m$  logged material (proxy variable).  $\zeta$  is the sum of unobserved productivity  $\omega$  and measurement errors of productivity shocks  $\psi$ . Indices  $i$  and  $t$  represent firms and years. A Cobb-Douglas specification is chosen due to its

popularity in the literature, although translog specifications are more flexible, though data demanding (Syverson 2011).

$$y_{i,t} = \beta_k \cdot k_{i,t} + \beta_l \cdot l_{i,t} + \beta_m \cdot m_{i,t} + \underbrace{\omega_{i,t} + \psi_{i,t}}_{\xi_{i,t}} \quad (1)$$

As product-level output and input quantities are usually not available, while monetary outputs and inputs are mostly provided as firm-level aggregates, I follow the literature and estimate gross output production functions using producers' real total monetary outputs and inputs.

To consider heterogenous input elasticities  $\beta$  across countries, I follow the majority of studies (e.g. Fons-Rosen et al. 2021; Levine and Warusawitharana 2021; Gemmell et al. 2018; Olper et al. 2016) and estimate Eq. 1 for each two-digit NACE industry-country combination. As productivity is the residual, it measures the shifts in output while keeping inputs constant. Owing to the logged dependent variable, productivity is also logged, as shown in Eq. 2 (Javorcik 2004; Olley and Pakes 1996).

$$\log(TFP_{i,t}) = y_{i,t} - \beta_k \cdot k_{i,t} - \beta_l \cdot l_{i,t} - \beta_m \cdot m_{i,t} \quad (2)$$

### 3.2 Data

In this work, I use the same data as in Steinbrunner (2021). Firm-level data are sourced from the Orbis database published by Bureau van Dijk. Orbis contains accounting data, legal form, industry activity codes and incorporation date for a large set of public and private companies worldwide. I include active and inactive; medium sized, large and very large<sup>7</sup> European manufacturing companies (NACE C1000 - C3320), incorporated in five countries: Austria, the Czech Republic, Hungary, Slovakia and Slovenia. The final sample is a 9-year unbalanced panel dataset, from 2009 to 2017, containing 18,060 firms with 123,101 observations of 24 two-digit NACE industries (94 three-digit and 265 four-digit NACE industries).<sup>8</sup>

Output is defined as real operating revenues, being the sum of net sales, other operating revenues and stock variations excluding VAT (Bureau van Dijk 2007) deflated by annual gross value added deflators from the OECD database,<sup>9</sup> varying across countries, two-digit NACE industries and years. Next, capital is approximated with tangible fixed assets (e.g. machinery) deflated by uniform investment good price indexes from the same database,<sup>10</sup> varying across countries and years. Third, labour is a physical measure of the number of employees included in the company's payroll. Fourth, material is measured by real material expenditures, being the sum of expenditures on raw materials and intermediate goods deflated by uniform intermediate good price indexes from the same database,<sup>11</sup> varying across coun-

<sup>7</sup> Orbis considers firms to be 'medium sized', when operating revenues  $\geq 1$  mill. EUR or total assets  $\geq 2$  mill. EUR or employees  $\geq 15$ . Orbis defines firms to be 'large', when operating revenues  $\geq 10$  mill. EUR or total assets  $\geq 20$  mill. EUR or employees  $\geq 150$ . Firms are 'very large', when operating revenues  $\geq 100$  mill. EUR or total assets  $\geq 200$  mill. EUR or employees  $\geq 1,000$  or the company is listed (Bureau van Dijk 2007).

<sup>8</sup> Observations with implausible output and input values (e.g. negative values, values almost zero), missing values, unknown activity status or industry affiliation are dropped.

<sup>9</sup> [https://stats.oecd.org/Index.aspx?DataSetCode=SNA\\_TABLE6A](https://stats.oecd.org/Index.aspx?DataSetCode=SNA_TABLE6A)

<sup>10</sup> [https://stats.oecd.org/Index.aspx?DataSetCode=MEI\\_PRICES\\_PPI](https://stats.oecd.org/Index.aspx?DataSetCode=MEI_PRICES_PPI)

<sup>11</sup> [https://stats.oecd.org/Index.aspx?DataSetCode=MEI\\_PRICES\\_PPI](https://stats.oecd.org/Index.aspx?DataSetCode=MEI_PRICES_PPI)

tries and years (Castelnovo et al. 2019; Richter and Schiersch 2017; Newman et al. 2015; Du et al. 2014; Nishitani et al. 2014; Baghdasaryan and la Cour 2013; Javorcik and Li 2013; Crinó and Epifani 2012; Higón and Antolín 2012; Javorcik 2004).

However, one set of econometric issues results from employing deflated monetary values of inputs instead of quantities. Potential differences in input prices across firms, implied by differences in the access to input markets or monopsony positions, might cause the ‘input price bias’. When ignoring this issue, the framework implicitly assumes that all firms face identical input prices. Hence, derived estimates would suffer from input price biases, in case of input price differences. Resulting coefficients are biased downwards, while constructed productivity, finally, is biased upwards. In this work, I only rely on two deflated monetary inputs, capital and material, potentially causing biased coefficients, while labour is measured physically (De Loecker and Goldberg 2014). Furthermore, Gandhi et al. (2020) show that material demand may not completely reflect productivity complicating the identification of revenue-based production functions. To tackle these problems, I follow the literature (e.g. Doraszelski and Jaumandreu 2021; Gandhi et al. 2020; Garcia-Marin and Voigtländer 2019; Doraszelski and Jaumandreu 2018; Lu and Yu 2015; Doraszelski and Jaumandreu 2013; De Loecker and Warzynski 2012) and introduce a demand shifter  $\alpha$ . Usually, these papers involve firm-level lagged real input prices, exports, etc. Like Doraszelski and Jaumandreu (2021), Gandhi et al. (2020), Doraszelski and Jaumandreu (2018) and Doraszelski and Jaumandreu (2013), I include the lagged input price of labour, the lagged average real wage per worker.<sup>12</sup> It does not enter the production function as an input but affects the demand for material and, therefore, is part of the polynomial used to proxy for unobserved productivity. In other words, omitted firm-level input prices are assumed to be a reduced-form function of the demand shifter which is interacted with deflated inputs (Gandhi et al. 2020; Doraszelski and Jaumandreu 2018; Lu and Yu 2015; De Loecker and Warzynski 2012). Given the lag, every firm’s first observation will be dropped. Data on firm-level wage costs are sourced from Orbis as well, which are deflated by national consumer price indices, downloaded from Eurostat,<sup>13</sup> and divided by firm-level employment. Alternatively, some studies (e.g. Raval 2023) suggest to calculate the production function’s coefficients non-parametrically as the shares of input costs in output assuming a Cobb-Douglas production function with constant returns to scale. Relevant methods might generally be applicable to manufacturing sectors. For some particular industries, however, the assumption is too restrictive.

Next, a further set of econometric issues is implied by applying deflated monetary values of output instead of quantities (‘output price bias’). Although firm-level or even product-level price indices would be necessary, they are usually not available. Price indices, however, are only available at some industry-level. Applying industry-level price indices to firm-level operating revenues causes biased coefficients of the production function, if firm- or product-level prices deviate from the development of the industry-level price index, which are captured by the error term. The direction of each coefficient’s bias is not straightforward and can go in either direction (De Loecker 2011; De Loecker and Goldberg 2014; Klette and Griliches 1996). To solve this problem, in the spirit of Klette and Griliches (1996), De Loecker (2011) proposes a framework, based on including industry-specific aggregate demand shifters, which, however, fails to correctly identify the coefficients, because multiplying all asymmetrically biased input coefficients with a constant cannot yield unbiased

<sup>12</sup> Doraszelski and Jaumandreu (2018) also show that the real price of labour is more relevant than the real price of material. Besides, as fossil fuels and raw materials are traded at the stock exchange, only little variation across firms is expected. Hence, average real wages are the preferred choice.

<sup>13</sup> [https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=prc\\_hicp\\_aind&lang=de](https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=prc_hicp_aind&lang=de)

input coefficients (Ornaghi 2006). Consequently, the first stage estimates will suffer from output price biases.

Summary statistics of the variables used in the first and second stage of the analysis are shown in Table 1. The first part of the table provides summary statistics of the variables employed in the first stage, while the second part displays those of the ones used in the second stage. The sample includes lots of smaller and medium sized companies, as can be seen from the number of employees. Lerner indexes strongly vary. Many firms compete strongly with other companies and, therefore, are characterised by smaller Lerner indexes. In comparison, there are many companies that only compete weakly with other enterprises given the higher values of the markups.

### 3.3 Results

Tables 5–9 in Appendix C summarise the results of the production function estimations for each two-digit NACE industry-country combination. In every table, columns (1)–(3) provide the elasticities of output with respect to the considered inputs. Columns (4) and (5) display the numbers of observations and firms. The sum of input elasticities supplies an estimate of the degree of returns to scale. Therefore, column (6) shows the  $p$ -value of the Wald tests examining whether this sum significantly differs from one. Usually, the production function estimations consider attrition by introducing an additional stage into the estimation framework modelling the firms' entrance and exit behaviour. In some industries, too few firms exit the market not allowing to consider attrition. Column (7), thus, provides information on whether attrition can be and is considered or not.<sup>14</sup>

Overall, results are consistent with the literature (e.g. Richter and Schiersch 2017; Lu and Yu 2015; Du et al. 2014; Arnold et al. 2011). Labour elasticities mostly vary between 0.20 and 0.40 (Richter and Schiersch 2017; Arnold et al. 2011). In some industries, coefficients lie between 0.05 and 0.20 as in Lu and Yu (2015) and Du et al. (2014). As in these studies, capital elasticities are usually small between 0 and 0.10. In Hungary, some of them, however, are larger, suggesting that the relevant industries produce more capital-intensively. Depending on the study, material elasticities vary between 0.40 and 0.90, confirming my results.

Nevertheless, there are some abnormalities. Particularly, one coefficient exceeds one (Hungary: C21) and, similarly to Lu and Yu (2015), the elasticity of capital falls below zero in eleven combination (Austria: C18, C25, C26, C28, C31 and C32; Hungary: C16, C25 and C33; Slovakia: C25 and C26).

Figures 5 and 6 show average Lerner indexes for two-digit NACE industries important to the Central European core. Average return on sales-style Lerner indexes are quite stationary, fluctuating around 0.33. Although Lerner indexes obtained from the production function take on similar values, they seem to develop in the opposite direction in some industries. When not correcting the shares of material expenditures for fluctuations in output unrelated to variations in inputs, these, however, exhibit similar developments, as they also include such variations which are completely reflected by the return on sales highlighting the importance of the correction.

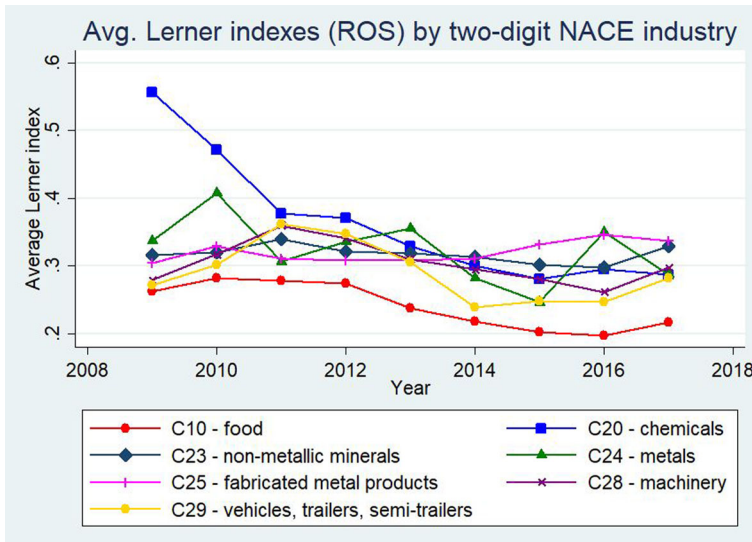
<sup>14</sup> I exclude tobacco (C12) and coke and petroleum (C19) industries because of too few observations. Industries with less than 15 firms whose analysis does not allow to consider attrition are also dropped due to not-meaningful results.

**Table 1** Descriptive statistics

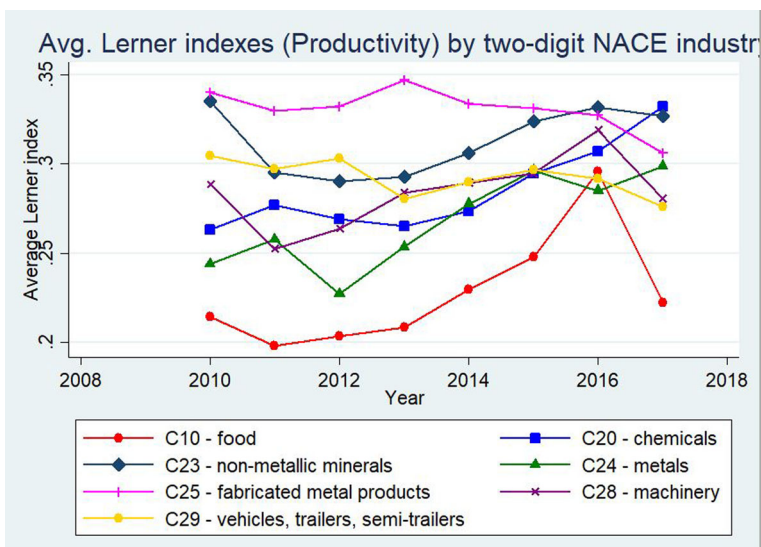
Variable	Unit	Mean (SD)	Min - Med - Max	IQR (CV)	Observations
<b>First stage</b>					
Real operating revenues	Mill. Euro	22.3 (168.2)	0.0 < 3.0 < 14,089.2	8.8 (7.6)	123,813
Real material expenditures	Mill. Euro	13.5 (122.4)	0.0 < 1.4 < 10,179.1	4.5 (9.0)	123,813
Real tangible assets	Mill. Euro	9.2 (1,286.4)	0.0 < 0.8 < 452,504.6	2.6 (140.5)	123,813
Number employees	Integer	125.6 (333.3)	1.0 < 38.0 < 15,000.0	109.0 (2.7)	123,813
<b>Second stage</b>					
log(TFP)		4.5 (1.9)	-26.1 < 4.4 < 12.5	1.8 (0.4)	102,856
$\Delta \log(\text{TFP})$		-0.0 (0.2)	-11.2 < -0.0 < 5.8	0.2 (-73.1)	83,973
Lerner index (ROS)	Percent	0.3 (0.2)	0.0 < 0.3 < 1.0	0.2 (0.5)	116,750
Lerner index (De Loecker & Warzynski)	Percent	0.3 (0.2)	0.0 < 0.3 < 1.0	0.3 (0.7)	74,549
HHI		0.1 (0.1)	0.0 < 0.1 < 1.0	0.1 (1.3)	123,813
CR4		0.4 (0.2)	0.1 < 0.4 < 1.0	0.4 (0.5)	123,813
Theil's L		1.0 (0.4)	0.0 < 0.9 < 4.6	0.5 (0.4)	123,813
Theil's S		1.0 (0.4)	0.0 < 0.9 < 3.5	0.5 (0.4)	123,813
Theil's T		1.0 (0.4)	0.0 < 0.9 < 3.3	0.5 (0.4)	123,813
Real total assets	Mill. Euro	7.0 (58.3)	0.0 < 0.8 < 8,512.2	2.9 (8.3)	123,798
Average real wage	Thsd. Euro	18.9 (170.7)	0.0 < 14.2 < 48,415.7	10.2 (9.1)	122,824
Number entrants	Integer	1,005.8 (1,349.8)	0.0 < 352.0 < 6,336.0	1,108.0 (1.3)	123,813
Productivity gap	Percent	0.7 (0.3)	0.0 < 0.8 < 1.0	0.3 (0.4)	102,856
SD of log(TFP)		0.4 (0.2)	0.0 < 0.4 < 6.0	0.2 (0.6)	102,856
Industry-level average productivity gap	Percent	0.7 (0.2)	0.0 < 0.7 < 1.0	0.3 (0.3)	102,856
Country-level average of industry-level average productivity gap	Percent	0.5 (0.1)	0.0 < 0.5 < 0.6	0.0 (0.1)	102,856
Neck-and-neck	Binary	0.2 (0.4)	0.0 < 0.0 < 1.0	0.0 (1.9)	102,856

*Note:* Mean denotes the average, SD the standard deviation, Min the minimum value, Med the median, Max the maximum value, IQR the interquartile range, CV the coefficient of variation, and Observations the number of available observations





**Fig. 5** Average Lerner indexes (ROS) by two-digit NACE industry. Note: The figure displays the annual averages of the return on sales for selected two-digit NACE industries. They evolve quite stably over time, fluctuating around 0.33



**Fig. 6** Average Lerner indexes (DLW) by two-digit NACE industry. Note: The figure displays the annual averages of the Lerner indexes obtained from the production function for selected two-digit NACE industries. They generally resemble the annual averages of the return on sales

## 4 Second Stage: Determinants of Firm Behaviour

This section describes the second stage of the empirical analysis employed to empirically examine the propositions of the theoretical model by Aghion et al. (2005). Innovation represents an important part of productivity growth, i.e. if a firm innovates, its productivity will rise. Nevertheless, productivity growth also captures technology adoption (e.g. a firm adopts innovation generated by another firm). Despite its weaknesses, the productivity growth rate is one of the best understood and, thus, most popular innovation output measures (Hall 2011b). There are several reasons. First, the effectiveness of innovation is more relevant to economic growth, i.e. although an innovation is protected by a patent, it does not necessarily influence production processes. It only influences production processes, if its application is economically beneficial.<sup>15</sup> Second, estimating the underlying production functions allows to measure firm-level market power by applying the novel approach by De Loecker and Warzynski (2012), which obtains Lerner indexes from the estimates of the production function. Third, the various available measures strongly correlate with each other (Taques et al. 2021; Amable et al. 2016; Klette and Kortum 2004; Stahl and Steger 1977).

### 4.1 First Proposition: Concave Relationship Between Productivity Growth and Competition

#### 4.1.1 Empirical Strategy

To examine the first proposition, I employ fixed effects regressions of firm-level productivity growth on Lerner indexes, their squares, some covariates and nested country-year and industry-year dummies (Inui et al. 2012; Aghion et al. 2008), as described in Eq. 3. The indices  $i$ ,  $t$ ,  $s$  and  $c$  denote firms, years, three-digit NACE industries and countries.  $S$  and  $C$  represent the total numbers of three-digit NACE industries and countries.

$$\Delta \log(TFP_{i,t}) = \delta_1 \cdot LI_{i,t} + \delta_2 \cdot LI_{i,t}^2 + \beta \cdot X_{i,t-1} + \alpha_i + \sum_{c=1}^C \sum_{t=2011}^{2017} \gamma_{c,t} \cdot D_c \cdot D_t + \sum_{s=1}^S \sum_{t=2011}^{2017} \sigma_{s,t} \cdot D_s \cdot D_t + \epsilon_{i,t} \quad (3)$$

The dependent variable is the firm-level growth rate of productivity that approximates technological progress. It is the first difference in logged productivity (Inui et al. 2012). The firm-level Lerner index  $LI$  is the variable of interest. I expect it to show a concave relationship with the dependent variable. Unlike Atayde et al. (2021), Inui et al. (2012), Aghion et al. (2008) and Aghion et al. (2005), I do not use its inverse  $1 - LI$ , but introduce market power  $LI$  itself.<sup>16</sup> This approach allows to verify robustness by applying market concentration measures, particularly the not invertible ones (e.g. Theil indexes).<sup>17</sup>

<sup>15</sup> Effort-based measures such as R&D expenditures do not consider the output side (e.g. success and effectiveness of innovation). The same holds for the quality-based measures such as the number of patents (Hall 2011a).

<sup>16</sup> This approach does not influence the functional form, as regressions involving  $LI$  instead of the inverse  $1 - LI$  provide the analogous results.

<sup>17</sup> Note that higher market concentration does not necessarily result in greater market power. For a discussion on the advantages and disadvantages of approximating market power with market concentration measures, see Berry et al. (2019) or Syverson (2019).

I employ two measures of Lerner indexes. The first one is the return on sales, being the share of variable profits in revenues. This indicator, however, only serves as a valid proxy, if marginal costs are constant (Syverson 2019). Despite this shortcoming, return on sales are frequently applied in the literature (e.g. Atayde et al. 2021; Inui et al. 2012; Aghion et al. 2008). As the dataset does not contain data on profits, I define real profits as the difference between the real operating revenues and the sum of real material costs and wage expenditures following Aghion et al. (2008). Then, this difference is divided by the real operating revenues.<sup>18,19</sup>

The second measure applied is the Lerner index derived using the algorithm by De Loecker and Warzynski (2012). This approach, as explained in Appendix B, directly calculates firm-level Lerner indexes from the estimates of the production function. Given the firm's optimisation problem, firm-level price–cost ratios equal the ratio of the marginal effect of the input free of adjustment costs, and this input's share of expenditures in operating revenues.<sup>20</sup> The expenditure share is adjusted by variations in output unrelated to fluctuations in input demand. Resulting price–cost ratios are then transformed to compute Lerner indexes. Following the majority of studies (e.g. Lu and Yu 2015; De Loecker and Warzynski 2012), I use material as the input free of adjustment costs. In contrast to labour, material is more flexible and less prone to adjustment costs, i.e. hiring and firing is costly, while adjusting material stocks is less expensive given the advanced inventory management (De Loecker and Warzynski 2012). Moreover, the algorithm by Akerberg et al. (2015) backs picking material. It assumes that labour is chosen prior to other flexible inputs or is dynamic and subject to adjustment costs. On the other hand, the choice of the variable free of adjustments is crucial, as pointed out by some studies (e.g. Doraszelski and Jaumandreu 2021; Raval 2023), since the results depend on the variable chosen.<sup>21</sup> Like the return on sales, the Lerner index or price–cost ratios obtained using De Loecker and Warzynski (2012) are frequently criticised in the literature. For instance, Bond and et al. (2021) show that, when imposing the demand system by Hall (1986) and assuming identical own-price elasticities and zero cross-price elasticities, the obtained Lerner indexes should be zero for every firm and year, if the model is correctly specified. Thus, estimated markups do not provide any information on the true ones. However, in models with heterogeneous markups (e.g. Klenow and Willis 2016; Atkeson and Burstein 2008; Kimball 1995) own-price demand elasticities vary across firms and, therefore, at least one company exhibits a markup different from zero. In this case, the estimator is the sum of the average of the true markups and a weighted average of the demand elasticities of the firms sharing the same production function. Thus, the estimator is informative, since the true markup and the estimator are correlated. As the applied method does not impose assumptions on the underlying demand system and own-price demand elasticities plausibly differ across enterprises, the second case may likely be true.

<sup>18</sup> This share simplifies to one minus the shares of real wages and real material costs in real operating revenues.

<sup>19</sup> Although this measure does not include capital costs (e.g. interest costs), as they are mostly missing, potential biases will be small. For example, Aghion et al. (2008) show that deducting capital costs barely changes the estimated coefficients.

<sup>20</sup> In a Cobb Douglas production function, the marginal effect of this input equals this input's coefficient.

<sup>21</sup> As pointed out in Sect. 3.2, Raval (2023) suggests to calculate the production function's coefficients non-parametrically as the shares of input costs in revenues assuming a Cobb-Douglas production function with constant returns to scale. Nevertheless, the assumption of constant returns to scale may be too restrictive for some industries.

For both specifications, only observations with  $LI \in [0, 1]$  are included, as Lerner indexes lying outside the interval imply either that prices do not cover marginal costs, some products of multi-product firms are complements, or that marginal costs are negative (Tirole 1994). In other words, observations with Lerner indexes lying outside the interval do not provide information on the degree of market power and, therefore, would bias results and turn them meaningless. Negative values, for instance, result either from losses or, for the case of the second measure, from corrected shares of material expenditures in operating revenues substantially exceeding the coefficient of material. Excluding relevant observations is relevant, as firms with negative Lerner indexes also suffer from low productivity growth implying biased coefficients.

Vector  $X$  includes the control variables, capturing other drivers of technological progress and reorganisation within firms. They also aim to control for the parts of productivity growth that do not result from innovation. To overcome reverse causality, they are lagged by one year (Franco and Marin 2017; Inui et al. 2012). As productivity growth also responds to wage costs, labour market regulation and human capital, I involve the logged firm-level average real wages (Del Bo 2013). In comparison, Commins et al. (2011) employ the shares of aggregate labour costs in value added and Franco and Marin (2017) the logged industry-specific average wages, but they suffer from multicollinearity. Their lagged value serves as the demand shifter in the first stage. Data on firm-level wage costs are obtained from Orbis, deflated by country-level HCPIs sourced from Eurostat<sup>22</sup> and divided by firm-level employment. Their impact is ambiguous. Although more human capital allows firms to produce more efficiently and higher wage costs encourage capital substitution, higher wages may also signal inflexible and inefficient production processes. Depending on whether labour costs increase more or less strongly than labour productivity, the effect will be positive or negative.

Besides, following Castelnovo et al. (2019), Del Bo (2013) and Inui et al. (2012), I include the firm's logged real total assets to capture the effects of firm size. I expect a positive effect, as firm size represents an important driver of productivity growth (Inui et al. 2012). Total assets are obtained from Orbis and deflated by the same price index as the tangible fixed assets.

Furthermore, I include fixed effects for firms  $\alpha_i$ , capturing unobserved firm-level heterogeneity (e.g. country, NACE industry, legal form). I also involve nested country-year dummies  $D_c \cdot D_t$ , capturing countrywide shocks (e.g. profit taxes, electricity and fuel prices, institutional quality, business activity), and three-digit NACE industry-year dummies  $D_s \cdot D_t$ , controlling for industry-specific technological developments, propensities to innovate and European regulations (Hashmi 2013).

Regarding causality, the correlation between productivity growth and market power and its causes are a critical issue, i.e. does the observed correlation between the productivity growth rate and the Lerner index result from changing incentives to innovate, or is it implied by selection into markets?<sup>23</sup> If selection is driving the conditional correlation, then the regressions would detect a relationship between market power and productivity growth even in the absence of a causal effect. Nevertheless, the literature on developed and developing countries (e.g. Álvarez and Gonzalez 2020; Backus 2020) finds no or only weak evidence for selection impacts, suggesting that the estimated effects may only suffer little from selection biases.

<sup>22</sup> [https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=prc\\_hicp\\_aind&lang=de](https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=prc_hicp_aind&lang=de)

<sup>23</sup> Backus (2020) calls the first channel 'treatment effect' that refers to the causal impact of market power on productivity growth, while the second one, the 'selection effect', claims that the observed conditional correlation is driven by selection into markets, i.e. in competitive industries, selection processes are more aggressive. In other words, less efficient firms will die quickly, whereas the efficient firms survive.

Concerning endogeneity, three issues are worth discussing. First, endogeneity may be caused by reverse causality. If a given firm's productivity grows more rapidly, its marginal costs decline more strongly, affecting its Lerner index. Hence, when estimating Eq. 3 using OLS, the estimated coefficients will be inconsistent, as Lerner indexes are treated as exogenous variables. For instance, Aghion et al. (2008) introduce the inverted Lerner indexes as exogenous variables given the lack of sufficiently strong instrument variables (IVs), causing considerable biases.<sup>24</sup>

To solve this problem, the literature (e.g. Hashmi 2013; Tingvall and Poldahl 2006; Aghion et al. 2005) usually relies on various IVs (e.g. dummies for liberalised industries, import penetration and weighted exchange rates, industry profits, antitrust penalties, etc.). They, however, likely do not satisfy the exclusion restriction or respond to technological progress, i.e. if productivity growth rises, imports into the given industry will decline given the improved international competitiveness (Hashmi 2013). Despite their weaknesses, these variables are frequently used as IVs in the literature. Following the literature, I applied these variables as IVs for the potentially endogenous Lerner indexes. As in Hashmi (2013), they were not sufficiently relevant, violating IV relevance. If the IVs are weak, then they imply large biases even at small deviations from the IV exogeneity assumption. To avoid these biases, I follow Inui et al. (2012) who employ lagged changes in the Lerner index. They argue that firms only respond to the level of competition but not to its changes. Furthermore, companies are more likely to decide on the level of Lerner indexes by reorganising production to affect efficiency growth rather than on the change in market power. If many lags are involved, then many observations will be dropped. To avoid burning too many observations, I use  $\Delta LI_{i,t-1}$  as Inui et al. (2012) and Li et al. (2019) do in their baseline analysis, and the lagged difference in the squared Lerner indexes,  $\Delta(LI^2)_{i,t-1}$ .<sup>25</sup> Using lagged differences in Lerner indexes is associated with advantages and disadvantages. On the one hand, given the strong positive relationships between current values of the Lerner indexes and their lagged changes, the IVs will be highly relevant. On the other hand, IV exogeneity may be violated for the same reason. If contemporaneous Lerner indexes are endogenous, then the positive relationship between present and past values may cause a correlation between the IVs and the error term. Consequently, estimates may still be biased and inconsistent.<sup>26</sup> Additionally, I involve the number entries into a given industry as a third instrument like in Le et al. (2021) and overspecify the equation.<sup>27</sup> According to Audretsch (1999), small firms enter because they want to innovate, finally raising competitive pressures. Fiercer competition forces the incumbents to innovate and produce more efficiently. Besides, market entry likely satisfies the exclusion restriction, since new entries are external to the incumbents (Inui et al. 2012). Besides, the number of entries will likely not respond to the productivity growth of single

<sup>24</sup> The need for IVs is illustrated by treating Lerner indexes as exogenous variables as in Aghion et al. (2008). As in this study, the relevant regressions suggest convex relationships rejecting the theoretical model.

<sup>25</sup> The regression introducing the return on sales uses observations from 2011 onwards. Given the lagged demand shifter applied in the first stage, every firm's first observation is dropped. Next, employing the growth rate of productivity burns every firm's second observation. No further observations except for NAs are dropped, as the return on sales can be calculated for the entire time horizon. The Lerner indexes obtained by De Loecker and Warzynski (2012) exclude every firm's third observation as well, since they are calculated from the production function estimates that uses data starting from 2010. Employing their first difference lagged by 1 year as instrument, therefore, drops every firm's third observation.

<sup>26</sup> Nonetheless, the bias would be small given the strength of the instruments, providing informative conclusions even under noteworthy deviations from the instrument exogeneity assumption (Conley et al. 2012; Wooldridge 2010).

<sup>27</sup> Similarly, Inui et al. (2012) introduce the number of firms lagged by two years.

companies in the market, as the entrants aim to achieve innovation and improve the available product variety instead of forcing incumbents to innovate. Data on the number of entrants in each country, two-digit NACE industry and year is obtained from Eurostat.<sup>28,29</sup> In the regressions, IV exogeneity is evaluated using the Hansen test, the pendant of the Sargan applied under heteroskedasticity, since particularly the first differences in the Lerner indexes lagged by one year are prone to violate the assumption.

Second, I introduce important drivers of reorganisation within firms, firm-level fixed effects and nested dummies to solve omitted variable biases implied by confounding factors.

Third, output price biases still contaminate productivity and the Lerner indexes obtained from the production function, while input price biases can be avoided by introducing the demand shifter. This issue is particularly relevant because it represents a further channel for correlation between Lerner indexes and productivity growth. Particularly, resulting measurement errors enter both, the dependent variable and the variable of interest. Consequently, the assumption of IV exogeneity may not be satisfied, possibly biasing the results.<sup>30</sup> Nevertheless, larger parts of these measurement errors are eliminated by the firm-level fixed effects and nested dummies. Permanent firm-specific measurement errors in productivity are killed by differencing technical efficiency to calculate its growth rate. Furthermore, the introduced firm-level fixed effects control for firm-specific trends in the underlying level of productivity and for permanent measurement errors in the Lerner indexes. Additionally, the nested year dummies also help to eliminate some parts of the correlated measurement errors. They drop those varying across countries and year, or industries and years, possibly resulting from the estimation framework applied in the first stage. Overall, only smaller parts of the measurement errors (e.g. parts of the transient measurement errors) survive. They, however, should be dealt with by using 2SLS. Alternative estimators (e.g. Ronning and Rosemann 2008; Schaalje and Butts 1993), do not consider the simultaneity between the dependent and explanatory variable. Thus, 2SLS appears to be the better approach (Ronning and Rosemann 2008).<sup>31</sup>

#### 4.1.2 Results

Table 2 displays the estimates of Eq. 3 used to examine the model's first proposition. Productivity growth is regressed on the return on sales in column (1), while it is regressed on the Lerner index obtained from the production function estimates in column (2). Standard errors

<sup>28</sup> [https://ec.europa.eu/eurostat/databrowser/view/BD\\_9BD\\_SZ\\_CL\\_R2\\_\\_custom\\_5699495/default/table?lang=de](https://ec.europa.eu/eurostat/databrowser/view/BD_9BD_SZ_CL_R2__custom_5699495/default/table?lang=de)

<sup>29</sup> For some industries, data are only available at the group-level, i.e. C10, C11 and C12 form one group. For them, only the sum of the numbers of entrants across the three industries is provided.

<sup>30</sup> In comparison to quantity-based output measures, revenue-based ones capture equilibrium markups (Klette and Griliches 1996). Hence, productivity constructed from revenue-based production functions and related markups derived from these functions are, finally, automatically correlated resulting in biased second-stage coefficients (Backus 2020). Although quantity-based output measures avoid output price biases, data on output quantities are rarely available.

<sup>31</sup> Day et al. (2004) show that biases are small, when measurement errors are weakly correlated (below 0.7) and the explanatory variable is exogenous. Although Lerner indexes are endogenous given the simultaneities, the correlation between the measurement errors, however, will not be large because of the differencing, fixed effects and nested year dummies.



**Table 2** Results of examination of first proposition

	<i>Dependent variable: <math>\Delta \log(TFP)</math></i>	
	Lerner index (ROS) (1)	Lerner index (DLW) (2)
Lerner index <sub><i>t</i></sub>	1.630** (0.658)	0.881** (0.363)
Squared lerner index <sub><i>t</i></sub>	-7.447*** (1.251)	-2.927*** (0.577)
Log(real total assets <sub><i>t-1</i></sub> )	0.016*** (0.006)	0.025*** (0.006)
Log(average real wage <sub><i>t-1</i></sub> )	-0.220*** (0.013)	-0.212*** (0.016)
Observations	74,193	41,542
Units	13,733	9592
<i>Underidentification</i>		
Kleibergen-Paap rk LM statistic	191.365	478.495
<i>p</i> -value	0.000	0.000
<i>Weak identification</i>		
Cragg-Donald Wald F statistic	548.677	400.757
Kleibergen-Paap rk Wald F statistic	60.575	177.052
Stock-Yogo weak ID test critical values		
10% maximal IV size	13.43	13.43
15% maximal IV size	8.18	8.18
20% maximal IV size	6.40	6.40
25% maximal IV size	5.45	5.45
<i>Overidentification test all IVs</i>		
Hansen statistic	0.112	2.908
<i>p</i> -value	0.738	0.088
<i>Endogeneity</i>		
Endogeneity test	996.286	73.847
<i>p</i> -value	0.000	0.000
Firm-FE	Yes	Yes
Country-year dummies	Yes	Yes
Industry-year dummies	Yes	Yes
Model type	2SLS-FE	2SLS-FE

*Note:* The table shows the results of the regressions of Eq. 3. The dependent variable is  $\Delta \log(TFP)$  in all columns. All standard errors, in parenthesis, are clustered at the firm-level. In column (1), the variable of interest is the return on sales ('ROS'), while column (2) displays the results of the regression introducing the Lerner index derived from the production function ('DLW'). The model type "2SLS-FE" denotes the 2SLS regressions augmented with fixed effects that are used to estimate the equation. Variables of interest are instrumented with their first differences lagged by one period and the number of entrants in a given country, two-digit NACE industry and year. Variance inflation factors (VIFs) are computed manually from the within-R2s of fixed effects regressions of each covariate on the other covariates, firm-level fixed effects and nested country-year and industry-year dummies, using the data from 2010 to 2017. Observations of 2009 are dropped due to the lagged variables. VIFs of the controls, slightly exceeding one, do not suggest multicollinearity. On the other hand, the VIFs of the Lerner indexes vary between 5.75 and 7.55 due to the inclusion of its squared term suggesting multicollinearity, but decrease severely when excluding its square

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

are clustered at the firm-level to overcome residual serial correlation.<sup>32</sup> They are regressed by applying 2SLS as declared by the last row of the table.<sup>33</sup> In all the columns, underidentification, weak-identification tests and endogeneity tests are satisfied.<sup>34</sup> Although the first differences in the Lerner indexes lagged by one period appeared to be prone to violate IV exogeneity, the Hansen tests suggest that the chosen instruments are exogenous.<sup>35</sup>

Confirming the literature (e.g. Hashmi 2013; Inui et al. 2012; Aghion et al. 2005), relationships between market power and productivity growth are inverted-u shaped. Concerning the interpretation, suppose the following example. In column (1), a rise in the Lerner index, starting from 0.30 ( $\sim$  mean, median), by one percentage point decreases productivity growth by 2.8 percentage points. In column (2), productivity growth declines by 0.9 percentage points. Productivity growth maximising Lerner indexes  $LI^*$  are identified by taking first-order derivatives, setting them equal to zero and solving for  $LI$ .  $LI^*$  lies around 0.109 in column (1), while it equals 0.150 in column (2). In comparison, Hashmi (2013), Inui et al. (2012) and Aghion et al. (2005) estimate the impacts of the inverted Lerner indexes  $1 - LI$  and find optimising values around 0.95. Being generally consistent with these studies, the inverses of my optimising values  $1 - LI^*$  are 0.891 in column (1) and 0.850 in column (2).

The first one lies closer to 0.95, while the second one differs slightly more from the literature. Despite being in line with the literature, my estimates are generally smaller. There are many reasons. First, Hashmi (2013), Aghion et al. (2005) and Inui et al. (2012) analyse almost all the industries in the given countries, while I focus on manufacturing sectors, as estimating production functions for service industries is not common in the literature. Escape-competition effects are plausibly stronger in manufacturing than in other sectors (e.g. services that make up the largest parts of nowadays economies) due to its special characteristics. Manufacturing industries represent the main driver of technological progress (Baumol 1967) and, therefore, produce more research-intensively than service sectors, i.e. to escape competition, manufacturing companies must develop new products, which is costly and, thus, larger markups are required to cover the high research costs. In comparison, service firms are more prone to marketing, design and organisation investment than to conventional R&D (Tagues et al. 2021).<sup>36,37</sup>

<sup>32</sup> To check whether results are driven by industries showing abnormal production function estimates, I exclude relevant industry-country combinations. The results, however, barely change. Since the numbers of firms are large in industries C25 and C28, the results may be driven by these sectors. To check sensitivity, I run one regression excluding both industries and one regression only covering these two sectors. As all regressions show concave relationships, I can rule out that results are driven by this issue.

<sup>33</sup> The last rows of all the regression tables show whether fixed effects regressions ('FE'), treating the variables of interest as exogenous variables, or 2SLS augmented with fixed effects ('2SLS-FE') are employed. If the latter is used, the instruments include the differences in the variables of interest lagged by one year and the number of entrants in the relevant country, two-digit NACE industry and year.

<sup>34</sup> The critical values by Stock-Yogo have to be interpreted with caution, as they actually refer to Cragg-Donald Wald F statistic that assumes i.i.d. errors and can only be tabulated for up to three endogenous variables. Alternatively, the Kleibergen-Paap rk Wald F statistic can be cautiously compared with the 'rule of thumb' by Staiger and Stock (1997). The results do not suffer from weak instruments, if the F statistics on the joint significance of the instruments in the first stage regressions exceed ten (Baum et al. 2007).

<sup>35</sup> Nevertheless, the Hansen statistic is slightly insignificant with a  $p$ -value around 0.09 in column (2).

<sup>36</sup> For an overview about research intensities by industries, see <https://www.statista.com/statistics/1103594/research-intensity-industry-oeecd/>.

<sup>37</sup> The descriptive table in De Loecker et al. (2020) also shows that markups are generally higher in manufacturing than in service industries. They are, however, higher in particular fast growing industries such as information technology.

Second, I investigate the Central European manufacturing core. Four out of five countries are post-communist and have transitioned from centrally planned to market economies. Despite the liberalisation, the governments' role is still pervasive. Particularly, socialist planning supported large monopolies by missallocating resources. Poorly implemented privatisations did not create contestable markets, but established legal monopolies, fostering market barriers (Buccirosi and Ciari 2018). As the studies discussed analyse developed economies (e.g. the UK, USA, Japan) characterised by well-functioning markets, derived efficiency growth maximising inverted Lerner indexes may be plausibly higher. As analysed post-communist countries still suffer from strong market barriers and not perfectly-working markets, enterprises might have not got sufficiently used to operate in more competitive environments, to innovate to resist market pressures and to eliminate inefficiencies because of the poorly implemented liberalisations. These failures may limit the firms' possibilities to catchup with market leaders. If competition is weak, an increase in competition may move the industry slower from the unlevelled to the leveled state, as poorly implemented liberalisation aggravates catchup processes. In comparison, if competition is strong, the laggards' incentives to catchup with the leader may be even weaker because of these policies. Thus, competition impacts productivity growth more strongly, positively and negatively, in the relevant countries. Hence, the concave relationship turns steeper, decreasing optimal levels of competition  $1 - LI^*$ .

Besides, the values by Hashmi (2013) and Aghion et al. (2005), however, are calculated from the regressions of the numbers of patents, while Inui et al. (2012) regress the growth rates of efficiency derived by DEA. They also investigate different time horizons (1997–2003, 1973–1994). Next, I also cover smaller firms. Unlike Inui et al. (2012), I follow Aghion et al. (2005) and employ contemporaneous Lerner indexes instead of the values lagged by one period. Differences also result from the different IVs applied. Analogous to Inui et al. (2012), I involve the lagged first differences in market concentration as instruments because the frequently used instruments (e.g. import shares, firm numbers, antitrust penalties) lack IV relevance as in Hashmi (2013) and Aghion et al. (2008). Last, unlike these studies, I include a large set of nested dummies to avoid omitted variable biases.

While the inverse of the optimising Lerner index  $1 - LI^*$  in column (1) is closer to 0.95, the pendant in column (2) differs slightly more from this benchmark. The reason is that material shares and, finally, the Lerner index by De Loecker and Warzynski (2012) are corrected for variations in output unrelated to fluctuations in inputs (e.g. elasticities of demand, income level). In comparison, the return on sales completely reflects them given its formula. It follows a downwards biased optimal Lerner index, highlighting the importance of the correction (De Loecker and Warzynski 2012). This can be seen from a regression on the Lerner indexes whose underlying share of material expenditure is not corrected, providing optimising values around 0.98 close to 0.95. Thus, the results obtained by the other studies that employ the return on sales could be possibly biased because of these factors. Consequently, the literature might suggest too high optimal levels of competition.

The conclusion might be interesting for designing competition policies. Poorly implemented liberalisation may aggravate transition processes, possibly shrinking the optimal level of competition. Thus, the consequences of possibly poorly implemented liberalisation should be addressed, i.e. especially in not-competitive industries, market barriers should be eliminated. In competitive industries, however, poor liberalisation may impede catchup processes.

As expected, firm size, as measured by logged real total assets, significantly increases productivity growth (Inui et al. 2012). An increase by one percent raises the productivity growth rate by 0.016–0.025 percentage points. Conversely, average real wages per employee

significantly decrease productivity growth. A rise by one percent drops the dependent variable by 0.212–0.220 percentage points.

Another interesting aspect is whether responses differ across high-tech and low-tech industries. To examine this issue, I perform regressions separately for each type of sectors. Industries are classified using the definition of the EU Commission.<sup>38</sup> I use the industry classification schema for the two-digit NACE industries, but results are robust when employing the classification for the three-digit NACE industries. When involving the return on sales, productivity growth maximising Lerner indexes  $LI^*$  are higher in the high-tech than in the low-tech sectors, suggesting that high-tech industries require higher markups to cover research costs. In comparison, the regressions introducing the Lerner indexes obtained from the production function draw the opposite conclusions. This result again highlights the importance of the correction of the material shares when calculating the Lerner indexes from the production function. Now, Schumpeterian effects dominate in high-tech industries that may often be characterised by a small number of market leaders. Conversely, escape-competition effects dominate in low-tech industries in which competition is stronger due to larger firm numbers.

In the literature, market concentration variables are popular proxies for market power because of their linkage between them. Despite their popularity, the relationship is, however, imperfect. For instance, higher market concentration does not necessarily result in greater market power (Berry et al. 2019; Syverson 2019).<sup>39</sup> In face of this shortcoming, I check robustness by applying frequently employed market concentration measures as proxies for market power. Particularly, I aim to examine whether the estimated functional form, the concave relationship, sensitively responds to the approach to quantifying market power. Therefore, I re-estimate the models using country-industry-specific measures of market concentration frequently used in the literature: Herfindahl-Hirschman index (HHI), CR4, and Theil indexes (Atayde et al. 2021; Opoku et al. 2020; Lu and Yu 2015; Inui et al. 2012). Variables are discussed and results are shown in Appendix D. Again, contemporary market concentration is instrumented with its lagged first differences and the number of entrants. Despite the strong instruments, the HHI and CR4 are exogenous as suggested by the endogeneity tests. Therefore, columns (1) and (2) provide the results of the fixed effects regressions. All the columns display the concave relationship between market concentration and productivity growth, although both coefficients are only significant in the regressions that investigate the impacts of the Theil indexes.<sup>40</sup> For the other regressions, standard errors might be inflated too much by multicollinearity, resulting in partially insignificant coefficients.

Besides, the results might respond to the functional form applied in the first stage. To check robustness, I estimate translog production functions for every country and two-digit NACE industry. From these estimates, I construct the productivity growth rate, and the Lerner index using the algorithm by De Loecker and Warzynski (2012). The results of the regression of productivity growth on the return on sales barely change, while the regression introducing the Lerner indexes constructed from the production function shows a convex relationship.

<sup>38</sup> [https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech\\_classification\\_of\\_manufacturing\\_industries](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech_classification_of_manufacturing_industries)

<sup>39</sup> Suppose the following example. A given industry is characterised by monopolistic competition. Despite the atomistic nature of firms and the possibly resulting low market concentration, single companies may face inelastic residual demand functions, allowing them to charge prices above marginal costs (Syverson 2019).

<sup>40</sup> Instead of the number of entrants in a given country, two-digit NACE industry and year, I introduce their logged value as an instrument, as they are more powerful.

Hence, the chosen functional form of the production function might crucially influence the results of the second stage. As all the other regressions except for this one, however, display a concave relationship, my results generally confirm the theoretical model by Aghion et al. (2005). In each regression, the instruments are relevant and strong. Additionally, the Hansen tests consider them exogenous.

## 4.2 Second Proposition: Industry-Level Productivity Gaps Rise with Competition

### 4.2.1 Empirical Strategy

To examine the second proposition, the relevant equation is estimated at averages. First, I identify the most productive firm (leader) in every country, three-digit NACE industry and year. Its technical efficiency is the frontier,  $max_{c,s,t}(TFP_{i,t})$ . Second, I calculate the gap between the firm’s productivity and the frontier for every firm and year  $TFP\ gap_{i,t} = \frac{max_{c,s,t}(TFP_{i,t}) - TFP_{i,t}}{max_{c,s,t}(TFP_{i,t})}$  (Atayde et al. 2021; Aghion et al. 2005).<sup>41</sup> Third, I average all the firm-level variables (productivity gaps, Lerner indexes, controls) at the country-three-digit NACE industry-year-level. Fourth, I estimate the equation at averages, as shown in Eq. 4.  $\bar{W}$  covers two dependent variables: the annual average gap to the frontier  $\overline{TFP\ gap}_{c,s,t}$  in every country and three-digit NACE industry, and the annual standard deviation of logged productivity  $SD[\log(TFP)]_{c,s,t}$ . The standard deviation is regressed to compare my results with Inui et al. (2012). It is computed from firm-level productivity for every country, three-digit NACE industry and year. Following Inui et al. (2012) and Aghion et al. (2005), average Lerner indexes  $\bar{L}I$  are introduced as exogenous variables.  $\alpha_{c,s}$  represent nested country-three-digit NACE industry-level fixed effects.

$$\begin{aligned} \bar{W}_{c,s,t} = & \delta_1 \cdot \bar{L}I_{c,s,t} + \beta \cdot \bar{X}_{c,s,t-1} \\ & + \alpha_{c,s} + \sum_{c=1}^C \sum_{t=2011}^{2017} \gamma_{c,t} \cdot D_c \cdot D_t + \sum_{s=1}^S \sum_{t=2011}^{2017} \sigma_{s,t} \cdot D_s \cdot D_t + \bar{\epsilon}_{c,s,t} \end{aligned} \tag{4}$$

### 4.2.2 Results

Table 3 shows the results of the outlined fixed effects regressions. Columns (1) and (2) provide the outcomes of the regressions of the average gaps to the frontier, while columns (3) and (4) display the regression results of the standard deviations of logged firm-level productivity. Columns (1) and (3) show the results when using the first definition of the Lerner index, while columns (2) and (4) provide the same for the second definition.

In every column, average market power widens the gap to the frontier and boosts productivity dispersion. Hence, the positive effect (wiping out inefficient firms) dominates the negative effect (falling innovation rates). If the average Lerner index rises by one percentage point, the average gap and the standard deviation significantly increase by 0.271–0.588 percentage points.<sup>42</sup> Nonetheless, the results contradict the conclusions by Inui et al. (2012) and

<sup>41</sup> When using the 90<sup>th</sup> or 99<sup>th</sup> percentile instead of the maximum value, results of the empirical investigation of the second and third propositions, however, barely change.

<sup>42</sup> Results are robust when applying the country-industry-specific measures of market concentration: HHI, CR4 and Theil indexes.

**Table 3** Results of examination of second proposition

	<i>Dependent variable:</i>			
	<i>Average gap to frontier</i>		<i>Standard deviation of <math>\log(TFP)</math></i>	
	Lerner index (ROS)	Lerner index (DLW)	Lerner index (ROS)	Lerner index (DLW)
	(1)	(2)	(3)	(4)
Lerner index <sub><i>t</i></sub>	0.294*** (0.078)	0.271*** (0.081)	0.588*** (0.171)	0.508*** (0.123)
Log(real total assets <sub><i>t-1</i></sub> )	-0.011*** (0.004)	-0.009** (0.004)	-0.012 (0.007)	-0.013** (0.006)
Log(average real wage <sub><i>t-1</i></sub> )	-0.023 (0.023)	0.004 (0.041)	-0.111 (0.068)	-0.013 (0.054)
R-squared	0.341	0.342	0.403	0.434
Observations	2607	1993	2519	1965
Units	430	394	411	386
Country-industry-FE	Yes	Yes	Yes	Yes
Country-year dummies	Yes	Yes	Yes	Yes
Industry-year dummies	Yes	Yes	Yes	Yes
Model type	FE	FE	FE	FE

*Note:* The table shows the results of the regressions of Eq. 4. The dependent variables are the annual average gaps to the country-industry specific productivity frontier in columns (1) and (2), and the annual country-industry specific standard deviations of  $\log(TFP)$  in columns (3) and (4). All standard errors, in parenthesis, are clustered at the country-industry-level. In columns (1) and (2), the variable of interest is the return on sales ('ROS'), while columns (3) and (4) display the results of the regressions introducing the Lerner index derived from the production function ('DLW'). The model type "FE" denotes fixed effects models that are applied to estimate the relevant equation. Variance inflation factors (VIFs) are computed manually from the within-R2s of fixed effects regressions of each covariate on the other covariates, firm-level fixed effects and nested country-year and industry-year dummies, using the data from 2011 to 2017. Observations of 2009 and 2010 are dropped due to the specification of the production function and lagged variables. VIFs of the covariates, varying between 1.76 and 4.11, do not suggest multicollinearity

\*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

Aghion et al. (2005). In these studies, the return on sales significantly decreases the chosen dependent variables, suggesting that competition widens the industry-specific average gap to the frontier and productivity dispersion. Despite being insignificant, Hashmi (2013) finds mixed effects.

One reason for observing the opposite relationship might be the history of the analysed countries. Four out of five countries have transitioned from centrally planned to market economies. Although governments have considerably liberalised industries, the R&D intensities have risen mildly except for Slovenia.<sup>43</sup> As firms might not have been used to compete that intensively with each other and use innovation as a tool to do so, fiercer competition has primarily driven inefficient firms out of the market instead of providing sufficient incentives to innovate.

<sup>43</sup> For a quick overview, see <https://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS?locations=CZ-AT-BE-DK-FI-FR-DE-HU-IT-IE-SK-SI-GB-US-PL>



### 4.3 Third Proposition: Firms in Competitive Industries Respond More Sensitive to Competition

#### 4.3.1 Empirical Strategy

When investigating the third proposition, industries have to be classified into leveled and unleveled sectors. Here, I follow Atayde et al. (2021). For every country and year, I compute the average of the average productivity gaps  $\overline{TFP\ gap}_{c,s,t}$  in every country and three-digit NACE industry<sup>44</sup>:  $\overline{TFP\ gap}_{c,t} = \frac{1}{S_{c,t}} \sum_{s_{c,t}=1}^{S_{c,t}} \overline{TFP\ gap}_{c,s,t}$ .<sup>45</sup> Then, for every country and year, I compare the average gap in a given industry with the average gap across industries. In a given country and year, a particular three-digit NACE industry is defined as ‘leveled sector’, if its gap is smaller than the annual country-level average gap:  $neck - and - neck = 1$  if  $\overline{TFP\ gap}_{c,s,t} < \overline{TFP\ gap}_{c,t}$ . If the opposite it true, it is defined as ‘unleveled industry’:  $neck - and - neck = 0$  if  $\overline{TFP\ gap}_{c,s,t} \geq \overline{TFP\ gap}_{c,t}$ .<sup>46</sup> Then, I re-estimate Eq. 3 for each type of industries separately, i.e. one firm-level regression examining the concave relationship for leveled industries and one for the unleveled industries. In other words, I perform one regression for the leveled industries and one regression for the unleveled sectors (Inui et al. 2012).<sup>47</sup>

#### 4.3.2 Results

Table 4 provides the results of the examination of the third proposition. Columns (1) and (3) show the regressions using the first definition of the Lerner index, while columns (2) and (4) display the same for the second definition. Columns (1) and (3) provide the regression results for the leveled industries, whereas columns (2) and (4) show the analogous for unleveled industries.

The conclusions are consistent with Inui et al. (2012) and Aghion et al. (2005). In both specifications, the productivity growth maximising level of market power  $LI^*$  is larger in the leveled than in the unleveled industries. Additionally, the coefficients for the unleveled industries are almost the same as for the entire manufacturing sector.<sup>48</sup> In other words, the productivity growth maximising level of competition in leveled industries is smaller than in unleveled industries, supporting the model by Aghion et al. (2005). In comparison to Inui et al. (2012), the coefficients for the unleveled industries stay significant, favouring the conclusions by Aghion et al. (2005). In the leveled industries, productivity growth maximising Lerner indexes  $LI^*$  equal 0.162 and 0.143. In the unleveled industries, they are 0.093 and 0.142. The relevant inverted values  $1 - LI^*$  for the leveled industries are 0.838 and 0.857. In comparison, the  $1 - LI^*$  by Inui et al. (2012) and Aghion et al. (2005) vary between 0.90 and 0.94. In the

<sup>44</sup> These are used as the dependent variable to assess the second proposition.

<sup>45</sup> For instance, suppose that there are three industries in a given country. Then, the average gap to the frontier in a given country and year are 0.50, 0.30 and 0.80. The country-specific average gap is  $\frac{0.50 + 0.30 + 0.80}{3} = 0.53$ .

<sup>46</sup> Results, however, are robust when using the country-specific median across country-industry-specific average gaps.

<sup>47</sup> The reason is that the critical values used to test for IV relevance can be tabulated for at most three endogenous variables. When involving more than three endogenous variables, IV relevance cannot be evaluated any more.

<sup>48</sup> The results for the entire manufacturing sector are shown in Table 2.

**Table 4** Results of examination of third proposition

	<i>Dependent variable: <math>\Delta \log(TFP)</math></i>			
	Level Lerner index (ROS) (1)	Unlevel Lerner index (ROS) (2)	Level Lerner index (DLW) (3)	Unlevel Lerner index (DLW) (4)
Lerner index <sub>t</sub>	3.546 (2.192)	1.495* (0.827)	0.908 (1.000)	0.908** (0.432)
Squared lerner index <sub>t</sub>	-10.930*** (3.961)	-8.034*** (1.587)	-3.185* (1.661)	-3.202*** (0.695)
Log(real total assets <sub>t-1</sub> )	0.031** (0.014)	0.013* (0.007)	0.023 (0.018)	0.024*** (0.007)
Log(average real wage <sub>t-1</sub> )	-0.224*** (0.027)	-0.223*** (0.016)	-0.175*** (0.045)	-0.212*** (0.016)
Observations	13,671	58,098	7107	32,628
Units	3433	11,683	2186	8002
<i>Underidentification</i>				
Kleibergen-Paap rk LM statistic	36.509	136.256	53.902	421.218
<i>p</i> -value	0.000	0.000	0.000	0.000
<i>Weak identification</i>				
Cragg-Donald Wald F statistic	60.026	386.682	45.267	278.622
Kleibergen-Paap rk Wald F statistic	11.558	42.643	17.373	148.023
Stock-Yogo weak ID test critical values				
10% maximal IV size	13.43	13.43	13.43	13.43
15% maximal IV size	8.18	8.18	8.18	8.18
20% maximal IV size	6.40	6.40	6.40	6.40
25% maximal IV size	5.45	5.45	5.45	5.45
<i>Overidentification test all IVs</i>				
Hansen statistic	2.996	0.411	0.066	1.885
<i>p</i> -value	0.085	0.522	0.797	0.170
<i>Endogeneity</i>				
Endogeneity test	240.891	721.978	19.233	64.317
<i>p</i> -value	0.000	0.000	0.000	0.000
Firm-FE	Yes	Yes	Yes	Yes
Country-year dummies	Yes	Yes	Yes	Yes
Industry-year dummies	Yes	Yes	Yes	Yes
Model type	2SLS-FE	2SLS-FE	2SLS-FE	2SLS-FE

*Note:* The table shows the results of the regressions of Eq. 3 that have been separately performed for leveled and unleveled industries. The dependent variable is  $\Delta \log(TFP)$  in all columns. All standard errors, in parenthesis, are clustered at the firm-level. In columns (1) and (2), the variable of interest is the return on sales ('ROS'), while columns (3) and (4) display the results of the regressions introducing the Lerner index derived from the production function ('DLW'). The model type "2SLS-FE" denotes the 2SLS regressions augmented with fixed effects that are used to estimate the equation. Variables of interest are instrumented with their first differences lagged by one period and the number of entrants in a given country, two-digit NACE industry and year  
\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

regression employing the Lerner indexes by De Loecker and Warzynski (2012), the change in the optimising value is as small as in the mentioned studies ( $\sim 1\%$ ). In comparison, in the regression applying the return on sales (as in mentioned studies), the change in the inverted optimising value is larger ( $\sim 5\%$ ). The reasons include the applied methods to obtain efficiency, dependent variables and sampled firms and countries. For instance, these studies analyse all the industries in the given countries. In comparison, my dataset only covers manufacturing sectors which influences the classification of industries, as estimating production functions for service industries is not common in the literature.

## 5 Conclusion

Whether competition spurs or curbs innovation and productivity growth is a crucial issue for Central European manufacturing sectors due to the decline of productivity growth since the financial crisis. Relevant countries may continue liberalisations to foster competition and to support economic development and recovery. Nevertheless, too fierce competition might discourage innovation. I investigate the effects of market power on firm performance not only to provide policy lessons for designing competition policies, but also contribute to the literature by applying an alternative approach to computing Lerner indexes. Therefore, in the first stage, Cobb-Douglas production functions are estimated employing the algorithm by Akerberg et al. (2015), using data on Central European manufacturing firms, from 2009 to 2017. In the second stage, I estimate the non-linear relationship between market concentration and productivity growth, applying fixed effects models and considering endogeneity.

The results show that relationships between competition and productivity growth are indeed concave, supporting the empirical findings and the theoretical model by Aghion et al. (2005). Furthermore, firms in competitive industries respond more strongly to competition, confirming another proposition of the model. Conversely, fiercer competition does not widen the gap to the frontier, supporting the basic oligopoly models. In comparison, productivity growth maximising Lerner indexes are plausibly larger, as relevant countries are either post-communist states that still suffer from strong market barriers, legal monopolies, pervasive roles of the state, and not perfectly-working markets, or belong to the Central European manufacturing core in which the structural shift to service industries have been less pronounced or even reversed. Policy makers should consider the concave relationship between competition and productivity growth when deciding on how much market power to allow. Generally, I recommend to continue liberalising and eliminating market barriers to promote competition in industries with high average market power. To spur innovation in competitive industries, I also suggest to raise research grants that benefit high-tech sectors, to implement tax privileges favouring long-run investments in these firms (e.g. venture capital companies) and to introduce and provide legal frameworks for alternative financing models (e.g. crowd funding).

## Appendix A. The Method by Akerberg/Caves/Frazer

When estimating production functions, much consideration needs to be given to identification problems. First, simultaneity biases arise because of the endogeneity of inputs, i.e. firms with positive productivity shocks demand larger input amounts. Hence, inputs correlate with

unobserved productivity. Second, attrition in the data causes identification problems, because firms with high productivity levels have a higher probability to survive, while firms with low levels of productivity are more likely to exit the market (Levinsohn and Petrin 2003; Olley and Pakes 1996; Marschak and Andrews 1944).

Unlike Olley and Pakes (1996) and Levinsohn and Petrin (2003), Akerberg et al. (2015) allow for a dynamic specification in the choice of labour by claiming that labour also depends on unobserved productivity. In other words, it assumes that labour is chosen prior to other flexible inputs or is dynamic and subject to adjustment costs. Hence, the coefficients of free variables (e.g. labour) cannot be correctly identified in the first stages of Olley and Pakes (1996) and Levinsohn and Petrin (2003). Instead, the coefficients are estimated in the second stage. To get the intuition, imagine a subperiod between periods  $t - 1$  and  $t$ . First, the firm chooses the optimal amount of material. Second, the productivity shock occurs in the subperiod. Third, the amount of labour is purchased. Now, labour is an element of the demand function for material in period  $t$ , which is still invertible as long as  $m$  is strictly increasing in productivity.

In the first stage, I run

$$y_{i,t} = \phi_{i,t}(l_{i,t}, k_{i,t}, m_{i,t}, a_{i,t-1}) + \psi_{i,t} \tag{A5}$$

to obtain estimates for the expected output  $\hat{\phi}_{i,t}$  and the productivity shock  $\hat{\psi}_{i,t}$ .  $a$  is the demand shifter that affects the demand for material  $m$ , but does not directly enter the production function as an input. The expected output is

$$\phi_{i,t} = \beta_k \cdot k_{i,t} + \beta_l \cdot l_{i,t} + \beta_m \cdot m_{i,t} + h_t^{-1}(m_{i,t}, k_{i,t}, a_{i,t-1}) \tag{A6}$$

with  $h^{-1}(\cdot)$  being the inverted demand for material (proxy variable). Assuming that the demand for material is strictly monotonically increasing in productivity allows to invert the demand function to obtain productivity as a function of the proxy and state variables. Then, unobserved productivity  $\omega$  is substituted with the inverted function, giving Eq. A6.

In the second stage, estimates for all production function coefficients  $\beta = (\beta_k, \beta_l, \beta_m)$  are calculated by relying on the law of motion of productivity

$$\omega_{i,t} = g_t(\omega_{i,t-1}, a_{i,t-1}) + \xi_{i,t} \tag{A7}$$

using Eq. A8.

$$\omega_{i,t}(\beta) = \phi_{i,t} - \beta_k \cdot k_{i,t} - \beta_l \cdot l_{i,t} - \beta_m \cdot m_{i,t} \tag{A8}$$

Non-parametrically regressing  $\omega(\beta)$  on its lag recovers the innovations to productivity  $\xi$ , required to form moment conditions, used to estimate the coefficients  $\beta$  with GMM. Moment conditions are displayed in Eq. A9. To obtain the standard errors of  $\beta$ , I rely on cluster bootstrapping.

$$\begin{aligned} E[\xi_{i,t} \cdot k_{i,t}] &= 0 \\ E[\xi_{i,t} \cdot l_{i,t-1}] &= 0 \\ E[\xi_{i,t} \cdot m_{i,t-1}] &= 0 \end{aligned} \tag{A9}$$

## Appendix B. The Method by De Loecker and Warzynski

To obtain markups, suppose the following production function.  $Y$  denotes the level of output,  $K$  capital,  $L$  employment,  $M$  material and  $\zeta$  the sum of unobserved productivity and the productivity shock. Again, indices  $i$  and  $t$  represent firms and years.

$$Y_{i,t} = Y_{i,t}(K_{i,t}, L_{i,t}, M_{i,t}, \zeta_{i,t}) \quad (\text{B10})$$

Assuming that active firms minimise costs allows to formulate the associated Lagrangian function with  $r$ ,  $w$ ,  $p_M$  and  $\lambda$  being the interest rate, wage, material price and Lagrange multiplier.

$$\mathcal{L} = r_{i,t} \cdot K_{i,t} + w_{i,t} \cdot L_{i,t} + p_{M,i,t} \cdot M_{i,t} + \lambda_{i,t} \cdot (Y_{i,t} - Y_{i,t}(\cdot)) \quad (\text{B11})$$

The first-order condition for any input free of adjustment costs (in this case material) is described in Eq. B12. Given the cost minimisation problem, the Lagrangian multiplier equals the marginal costs of production  $c$ .

$$\frac{\partial \mathcal{L}}{\partial M_{i,t}} = p_{M,i,t} - \lambda_{i,t} \cdot \frac{\partial Y_{i,t}(\cdot)}{\partial M_{i,t}} = 0 \quad (\text{B12})$$

Rearranging Eq. B12 and multiplying both sides with  $\frac{M_{i,t}}{Y_{i,t}}$  generates Eq. B13 implying that cost minimisation requires the firm to equalise the output elasticity of material with the right-hand side of the equation.

$$\underbrace{\frac{\partial Y_{i,t}}{\partial M_{i,t}} \cdot \frac{M_{i,t}}{Y_{i,t}}}_{\beta_m} = \frac{1}{\lambda_{i,t}} \cdot \frac{p_{M,i,t} \cdot M_{i,t}}{Y_{i,t}} \quad (\text{B13})$$

Next, the expression for the price–cost margin  $\mu_{i,t} = \frac{p_{Y,i,t}}{\lambda_{i,t}}$ , which is robust to various static price setting models and does not require any assumptions on the particular form of price competition between firms, is plugged in into Eq. B13. Nevertheless, this assumes that companies set prices every period ruling out dynamics in pricing. In comparison, a full profit maximisation problem may also be considered. Nonetheless, cost minimisation problems are part of profit maximisation problems and, therefore, suffice to derive price–cost margins. Furthermore, profit maximisation requires to introduce additional assumptions (e.g. type of competition) substantially raising complexity (Koppenberg and Hirsch 2021; Basu 2019; De Loecker and Warzynski 2012). Now, the output elasticity of material equals the price–cost margin times the share of nominal material expenditures in nominal revenue  $\theta$  computable from the data. As in De Loecker and Warzynski (2012), I correct  $\theta$  for fluctuations stemming from variations in output unrelated to variables impacting input demand by multiplying it with the exponentiated productivity shock from the first stage  $e^{\psi_{i,t}}$ .

$$\beta_m = \mu_{i,t} \cdot \underbrace{\frac{p_{M,i,t} \cdot M_{i,t}}{p_{Y,i,t} \cdot Y_{i,t}}}_{\theta_{i,t}} \quad (\text{B14})$$

Table 5 Results of production function estimation for Austria

Industry	Labour (1)	Capital (2)	Material (3)	Number observations (4)	Number firms (5)	p-Value CRS (6)	Attrition (7)
C10 food products	0.394*** (0.000)	0.036*** (0.000)	0.566*** (0.000)	270	79	0.00	Yes
C11 beverages	NA	NA	NA	38	12	NA	No
C13 textiles	0.245** (0.100)	0.062** (0.031)	0.662** (0.276)	67	21	0.92	Yes
C14 wearing apparel	NA	NA	NA	16	8	NA	No
C15 leather	NA	NA	NA	21	6	NA	No
C16 wood products	0.383*** (0.000)	0.160*** (0.000)	0.443*** (0.000)	140	41	0.00	No
C17 paper and pulp products	0.196*** (0.000)	0.045*** (0.000)	0.805*** (0.000)	106	27	0.00	No
C18 printing and recorded media	0.618*** (0.206)	-0.382* (0.215)	0.681*** (0.213)	73	23	0.84	No
C20 chemicals and chemical products	0.454 (0.397)	0.032 (0.076)	0.298 (0.572)	161	49	0.82	No
C21 pharmaceutical products	0.255*** (0.077)	0.019 (0.019)	0.804*** (0.246)	66	20	0.81	Yes
C22 rubber and plastics products	0.262*** (0.000)	0.038*** (0.000)	0.673*** (0.000)	152	48	0.00	No
C23 other non-metallic mineral products	0.206 (0.171)	0.054 (0.058)	0.694 (0.572)	170	50	1.00	Yes

Table 5 continued

Industry	Labour (1)	Capital (2)	Material (3)	Number observations (4)	Number firms (5)	p-Value CRS (6)	Attrition (7)
C24 basic metals	0.263*** (0.082)	0.082*** (0.025)	0.621*** (0.193)	215	57	0.92	Yes
C25 fabricated metal products	0.552*** (0.044)	-0.006 (0.016)	0.453*** (0.037)	314	96	1.00	Yes
C26 computer, electronic, optical products	2.548*** (0.692)	-0.169** (0.083)	0.250*** (0.033)	165	53	0.04	Yes
C27 electrical equipment	0.221*** (0.012)	0.036 (0.024)	0.691*** (0.005)	126	36	0.10	Yes
C28 machinery	0.405*** (0.020)	-0.011 (0.077)	0.595*** (0.057)	403	119	0.75	Yes
C29 motor vehicles, trailers, semi-trailers	0.411 (0.498)	0.017 (0.020)	0.606 (0.728)	111	34	1.00	No
C30 other transport equipment	NA	NA	NA	24	8	NA	No
C31 furniture	0.351** (0.138)	-0.014 (0.010)	0.640** (0.252)	41	12	1.00	Yes
C32 other manufacturing	0.636 (0.953)	-0.016 (0.140)	0.397 (0.742)	46	18	1.00	Yes
C33 repair, installation	0.793*** (0.191)	0.087** (0.042)	0.273*** (0.105)	44	15	0.45	No

Note: All elasticities are cluster bootstrapped at the firm-level. Firms with negative or zero output and input amounts are automatically dropped by using logged variables  
\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$



**Table 6** Results of production function estimation for Czech Republic

Industry	Labour (1)	Capital (2)	Material (3)	Number observations (4)	Number firms (5)	p-Value CRS (6)	Attrition (7)
C10 food products	0.112*** (0.000)	0.090*** (0.000)	0.763*** (0.000)	4153	679	0.00	Yes
C11 beverages	0.165*** (0.015)	0.112** (0.049)	0.788*** (0.021)	756	123	0.02	Yes
C13 textiles	0.317*** (0.000)	0.118*** (0.000)	0.525*** (0.000)	1058	174	0.00	Yes
C14 wearing apparel	0.311*** (0.048)	0.041 (0.029)	0.621*** (0.096)	689	125	0.86	Yes
C15 leather	0.440*** (0.005)	0.071** (0.033)	0.499*** (0.010)	228	39	0.58	Yes
C16 wood products	0.219*** (0.004)	0.070*** (0.016)	0.671*** (0.004)	2042	337	0.00	Yes
C17 paper and pulp products	0.230*** (0.002)	0.040*** (0.014)	0.752*** (0.008)	991	159	0.00	Yes
C18 printing and recorded media	0.372*** (0.010)	0.030 (0.024)	0.516*** (0.009)	1132	180	0.00	Yes
C20 chemicals and chemical products	0.191*** (0.000)	0.153*** (0.000)	0.599*** (0.000)	1451	211	0.00	Yes
C21 pharmaceutical products	0.196*** (0.011)	0.097*** (0.034)	0.725*** (0.014)	303	42	0.45	No
C22 rubber and plastics products	0.282*** (0.000)	0.053*** (0.000)	0.673*** (0.000)	4264	646	0.00	Yes
C23 other non-metallic mineral products	0.215*** (0.012)	0.072*** (0.019)	0.717*** (0.009)	2217	342	0.89	Yes

Table 6 continued

Industry	Labour (1)	Capital (2)	Material (3)	Number observations (4)	Number firms (5)	p-Value CRS (6)	Attrition (7)
C24 basic metals	0.242*** (0.010)	0.048* (0.025)	0.685*** (0.004)	1099	173	0.19	Yes
C25 fabricated metal products	0.296*** (0.000)	0.074*** (0.000)	0.583*** (0.000)	10,249	1683	0.00	Yes
C26 computer, electronic, optical products	0.343*** (0.004)	0.050*** (0.012)	0.610*** (0.006)	1506	232	0.11	Yes
C27 electrical equipment	0.354*** (0.004)	0.053*** (0.020)	0.555*** (0.005)	3160	492	0.00	Yes
C28 machinery	0.284*** (0.003)	0.048*** (0.010)	0.645*** (0.006)	6218	940	0.00	Yes
C29 motor vehicles, trailers, semi-trailers	0.350*** (0.000)	0.040*** (0.000)	0.625*** (0.000)	2337	357	0.00	Yes
C30 other transport equipment	0.256*** (0.015)	0.006 (0.047)	0.695*** (0.010)	636	95	0.09	Yes
C31 furniture	0.177*** (0.023)	0.058 (0.038)	0.726*** (0.047)	1326	219	0.13	Yes
C32 other manufacturing	0.315*** (0.013)	0.074** (0.031)	0.582*** (0.015)	1289	216	0.12	Yes
C33 repair, installation	0.431*** (0.010)	0.014 (0.021)	0.527*** (0.008)	2896	486	0.00	Yes

Note: All elasticities are cluster bootstrapped at the firm-level. Firms with negative or zero output and input amounts are automatically dropped by using logged variables  
\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

Table 7 Results of production function estimation for Hungary

Industry	Labour (1)	Capital (2)	Material (3)	Number observations (4)	Number firms (5)	p-Value CRS (6)	Attrition (7)
C10 food products	0.190*** (0.010)	0.030 (0.067)	0.666*** (0.032)	2269	369	0.00	Yes
C11 beverages	0.397*** (0.014)	0.040 (0.084)	0.636*** (0.027)	465	78	0.11	Yes
C13 textiles	0.362*** (0.014)	0.087*** (0.018)	0.551*** (0.011)	234	43	1.00	Yes
C14 wearing apparel	0.391*** (0.010)	0.077** (0.039)	0.340*** (0.034)	261	43	0.00	Yes
C15 leather	0.299*** (0.012)	0.104 (0.082)	0.529*** (0.037)	143	22	0.07	Yes
C16 wood products	0.232* (0.139)	-0.018 (0.042)	0.725** (0.352)	349	64	0.89	Yes
C17 paper and pulp products	0.268*** (0.019)	0.228*** (0.039)	0.435*** (0.008)	371	56	0.00	Yes
C18 printing and recorded media	0.116*** (0.026)	0.150*** (0.034)	0.306*** (0.069)	324	54	0.00	Yes
C20 chemicals and chemical products	0.149*** (0.014)	0.110*** (0.032)	0.701*** (0.017)	493	83	0.23	Yes
C21 pharmaceutical products	0.751*** (0.083)	0.175*** (0.026)	2.109*** (0.144)	207	31	0.00	Yes
C22 rubber and plastics products	0.206*** (0.000)	0.129*** (0.000)	0.638*** (0.000)	1308	209	0.00	Yes
C23 other non-metallic mineral products	0.256*** (0.031)	0.031 (0.097)	0.693*** (0.099)	785	117	0.92	Yes

Table 7 continued

Industry	Labour (1)	Capital (2)	Material (3)	Number observations (4)	Number firms (5)	p-Value CRS (6)	Attrition (7)
C24 basic metals	0.216*** (0.017)	0.126*** (0.012)	0.633*** (0.007)	326	52	0.03	Yes
C25 fabricated metal products	0.454*** (0.000)	-0.015*** (0.000)	0.492*** (0.000)	2680	430	0.00	Yes
C26 computer, electronic, optical products	0.485*** (0.074)	0.003 (0.019)	0.582*** (0.100)	748	107	0.68	Yes
C27 electrical equipment	0.283*** (0.000)	0.060*** (0.000)	0.614*** (0.000)	665	99	0.00	Yes
C28 machinery	0.288*** (0.003)	0.022** (0.011)	0.628*** (0.006)	1377	215	0.00	Yes
C29 motor vehicles, trailers, semi-trailers	0.351*** (0.009)	0.125*** (0.012)	0.561*** (0.002)	875	130	0.00	Yes
C30 other transport equipment	0.277*** (0.082)	0.047 (0.034)	0.693*** (0.204)	127	19	1.00	No
C31 furniture	0.286 (0.448)	0.052 (0.082)	0.623 (0.975)	316	50	1.00	Yes
C32 other manufacturing	0.396*** (0.030)	0.115** (0.055)	0.519*** (0.027)	354	63	0.72	Yes
C33 repair, installation	0.511 (0.426)	-0.097 (0.167)	0.550 (0.514)	279	50	1.00	Yes

Note: All elasticities are cluster bootstrapped at the firm-level. Firms with negative or zero output and input amounts are automatically dropped by using logged variables  
\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

**Table 8** Results of production function estimation for Slovakia

Industry	Labour (1)	Capital (2)	Material (3)	Number observations (4)	Number firms (5)	<i>p</i> -Value CRS (6)	Attrition (7)
C10 food products	0.164*** (0.008)	0.033 (0.034)	0.778*** (0.015)	2058	385	0.06	Yes
C11 beverages	0.197*** (0.014)	0.054* (0.030)	0.818*** (0.029)	445	74	0.11	Yes
C13 textiles	0.288*** (0.005)	0.090*** (0.023)	0.540*** (0.008)	435	77	0.00	Yes
C14 wearing apparel	0.396*** (0.063)	0.038 (0.033)	0.474*** (0.042)	762	140	0.28	Yes
C15 leather	0.463*** (0.016)	0.030 (0.033)	0.485*** (0.014)	308	53	0.54	Yes
C16 wood products	0.115*** (0.011)	0.030 (0.037)	0.673*** (0.013)	1473	262	0.00	Yes
C17 paper and pulp products	0.026 (0.083)	0.151*** (0.043)	0.727*** (0.026)	345	55	0.05	No
C18 printing and recorded media	0.139*** (0.040)	0.157** (0.066)	0.580*** (0.013)	473	79	0.00	Yes
C20 chemicals and chemical products	0.104 (0.083)	0.186*** (0.042)	0.637 (0.414)	384	70	0.89	No
C21 pharmaceutical products	NA	NA	NA	86	13	NA	No
C22 rubber and plastics products	0.164*** (0.009)	0.035 (0.022)	0.812*** (0.009)	1754	287	0.56	Yes
C23 other non-metallic mineral products	0.095*** (0.014)	0.038 (0.045)	0.787*** (0.018)	986	166	0.03	Yes

Table 8 continued

Industry	Labour (1)	Capital (2)	Material (3)	Number observations (4)	Number firms (5)	p-Value CRS (6)	Attrition (7)
C24 basic metals	0.131*** (0.019)	0.034 (0.059)	0.761*** (0.042)	377	59	0.02	No
C25 fabricated metal products	0.200*** (0.008)	-0.005 (0.013)	0.570*** (0.015)	4875	863	0.00	Yes
C26 computer, electronic, optical products	0.158*** (0.034)	-0.055 (0.041)	0.768*** (0.061)	571	103	0.01	Yes
C27 electrical equipment	0.337*** (0.007)	0.047*** (0.013)	0.548*** (0.003)	1056	168	0.00	Yes
C28 machinery	0.221*** (0.009)	0.076*** (0.018)	0.634*** (0.014)	1770	292	0.00	Yes
C29 motor vehicles, trailers, semi-trailers	0.340*** (0.026)	0.130*** (0.047)	0.661*** (0.020)	757	126	0.00	No
C30 other transport equipment	0.276*** (0.118)	0.014 (0.051)	0.674*** (0.023)	142	23	0.62	Yes
C31 furniture	0.162 (0.328)	0.032 (0.298)	0.681 (1.617)	781	132	1.00	Yes
C32 other manufacturing	0.257*** (0.013)	0.025 (0.032)	0.632*** (0.008)	383	65	0.00	No
C33 repair, installation	0.372*** (0.022)	0.007 (0.030)	0.526*** (0.014)	1238	202	0.01	Yes

Note: All elasticities are cluster bootstrapped at the firm-level. Firms with negative or zero output and input amounts are automatically dropped by using logged variables  
\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

**Table 9** Results of production function estimation for Slovenia

Industry	Labour (1)	Capital (2)	Material (3)	Number observations (4)	Number firms (5)	p-Value CRS (6)	Attrition (7)
C10 food products	0.275*** (0.000)	0.015*** (0.000)	0.671*** (0.000)	915	143	0.00	Yes
C11 beverages	0.285*** (0.017)	0.088** (0.036)	0.693*** (0.027)	104	16	0.00	No
C13 textiles	0.215*** (0.000)	0.228*** (0.000)	0.447*** (0.000)	294	42	0.00	No
C14 wearing apparel	0.520* (0.307)	0.033 (0.023)	0.509* (0.299)	183	28	0.92	No
C15 leather	0.372*** (0.005)	0.053*** (0.010)	0.443*** (0.013)	115	15	0.00	Yes
C16 wood products	0.359* (0.213)	0.002* (0.001)	0.525* (0.311)	983	152	0.82	Yes
C17 paper and pulp products	0.150*** (0.014)	0.077*** (0.026)	0.741*** (0.009)	267	38	0.04	Yes
C18 printing and recorded media	0.307*** (0.009)	0.092** (0.042)	0.406*** (0.022)	441	67	0.00	No
C20 chemicals and chemical products	0.267*** (0.009)	0.043** (0.019)	0.708*** (0.013)	443	60	0.11	No
C21 pharmaceutical products	NA	NA	NA	44	6	NA	No
C22 rubber and plastics products	0.379*** (0.002)	0.067*** (0.008)	0.474*** (0.004)	1410	213	0.00	Yes
C23 other non-metallic mineral products	0.300*** (0.131)	0.176** (0.086)	0.466** (0.216)	525	76	0.89	Yes



Table 9 continued

Industry	Labour (1)	Capital (2)	Material (3)	Number observations (4)	Number firms (5)	p-Value CRS (6)	Attrition (7)
C24 basic metals	0.300*** (0.095)	0.063 (0.070)	0.588*** (0.188)	320	44	0.84	Yes
C25 fabricated metal products	0.487*** (0.000)	0.012*** (0.000)	0.382*** (0.000)	3406	522	0.00	Yes
C26 computer, electronic, optical products	0.273*** (0.005)	0.094*** (0.017)	0.495*** (0.002)	572	78	0.00	Yes
C27 electrical equipment	0.348 (0.242)	0.081 (0.057)	0.500 (0.348)	641	92	0.92	No
C28 machinery	0.316*** (0.002)	0.030*** (0.006)	0.585*** (0.003)	1463	202	0.00	Yes
C29 motor vehicles, trailers, semi-trailers	0.324*** (0.001)	0.033*** (0.003)	0.596*** (0.007)	343	51	0.00	No
C30 other transport equipment	NA NA	NA NA	NA NA	85	14	NA	No
C31 furniture	0.301*** (0.000)	0.006*** (0.000)	0.535*** (0.000)	621	91	0.00	Yes
C32 other manufacturing	0.420** (0.185)	0.019 (0.011)	0.458** (0.204)	291	41	0.79	No
C33 repair, installation	0.583*** (0.009)	0.019 (0.032)	0.296*** (0.009)	561	104	0.00	Yes

Note: All elasticities are cluster bootstrapped at the firm-level. Firms with negative or zero output and input amounts are automatically dropped by using logged variables  
\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

Last, solving for the price–cost margin and plugging the resulting identity into the equation of the Lerner index  $LI$  gives

$$\begin{aligned}
 LI_{i,t} &= \frac{p_{Y,i,t} - c_{i,t}}{p_{Y,i,t}} \\
 &= 1 - \frac{c_{i,t}}{p_{Y,i,t}} \\
 &= 1 - \frac{1}{\mu_{i,t}}
 \end{aligned}
 \tag{B15}$$

## Appendix C. Estimates of the First Stage

**Table 10** Results of examination of first proposition using country-industry-level measures of market concentration

	<i>Dependent variable: <math>\Delta \log(TFP)</math></i>				
	HHI (1)	CR4 (2)	Theil's L (3)	Theil's S (4)	Theil's T (5)
HHI <sub><i>t</i></sub>	0.188* (0.105)				
Squared HHI <sub><i>t</i></sub>	−0.079 (0.140)				
CR4 <sub><i>t</i></sub>		0.161* (0.092)			
Squared CR4 <sub><i>t</i></sub>		−0.083 (0.090)			
Theil's L <sub><i>t</i></sub>			0.433** (0.169)		
Squared Theil's L <sub><i>t</i></sub>			−0.095* (0.052)		
Theil's S <sub><i>t</i></sub>				0.538*** (0.163)	
Squared Theil's S <sub><i>t</i></sub>				−0.156** (0.063)	
Theil's T <sub><i>t</i></sub>					0.777*** (0.271)
Squared Theil's T <sub><i>t</i></sub>					−0.328** (0.156)
Log(real total assets <sub><i>t</i>−1</sub> )	0.019*** (0.003)	0.019*** (0.003)	0.020*** (0.003)	0.020*** (0.003)	0.019*** (0.003)
Log(average real wage <sub><i>t</i>−1</sub> )	−0.204*** (0.007)	−0.204*** (0.007)	−0.205*** (0.007)	−0.205*** (0.007)	−0.204*** (0.007)

**Table 10** continued

	<i>Dependent variable: <math>\Delta \log(TFP)</math></i>				
	HHI (1)	CR4 (2)	Theil's L (3)	Theil's S (4)	Theil's T (5)
Observations	82,292	82,292	81,142	81,142	81,142
Units	15,739	15,739	14,589	14,589	14,589
<i>Underidentification</i>					
Kleibergen-Paap rk LM statistic			46.887	47.022	41.976
p-value			0.000	0.000	0.000
<i>Weak identification</i>					
Cragg-Donald Wald F statistic			286.509	275.737	77.781
Kleibergen-Paap rk Wald F statistic			23.206	37.482	15.670
Stock-Yogo weak ID test critical values					
10% maximal IV size			13.43	13.43	13.43
15% maximal IV size			8.18	8.18	8.18
20% maximal IV size			6.40	6.40	6.40
25% maximal IV size			5.45	5.45	5.45
<i>Overidentification test all IVs</i>					
Hansen statistic			1.321	1.008	2.941
p-value			0.250	0.315	0.115
<i>Endogeneity</i>					
Endogeneity test			11.006	13.849	14.887
p-value			0.004	0.001	0.001
Firm-FE	Yes	Yes	Yes	Yes	Yes
Country-year dummies	Yes	Yes	Yes	Yes	Yes
Industry-year dummies	Yes	Yes	Yes	Yes	Yes
Model type	FE	FE	2SLS-FE	2SLS-FE	2SLS-FE

*Note:* The table shows the results of the regressions of Eq. 3. The dependent variable is  $\Delta \log(TFP)$  in all columns. All standard errors, in parenthesis, are clustered at the firm-level. In column (1), the variable of interest is the Herfindahl-Hirschman Index ('HHI'), in column (2) the CR4, in column (3) Theil's L, in column (4) Theil's S and in column (5) Theil's T. The model type "FE" denotes fixed effects regressions, while "2SLS-FE" means that 2SLS regressions are augmented with fixed effects. If the endogeneity tests suggest that the variables of interest are exogenous, then the results of the simple fixed effects estimations are shown. If they propose endogeneity, then the results of the 2SLS regressions augmented with fixed effects are displayed. In columns (3)–(5), variables of interest are instrumented with their first differences lagged by one period and the logged number of entrants in a given country, two-digit NACE industry and year

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

## Appendix D. Estimates of Country-Industry-Level Measures of Concentration

The first country-industry-level of measure used is the HHI, being the sum of squared market shares calculated from the firm-level real operating revenues, *OPRE*. It varies between zero (perfect competition) and one (monopoly). In comparison, the CR4 is the sum of the market shares of the four largest firms. Last, Theil's L, S and T indexes, also being calculated from the firm-level real operating revenues, vary between zero and infinity. The larger the value, the more concentrated is the market. Due to their formulas, their coefficients cannot

be interpreted in a meaningful way (Atayde et al. 2021; Opoku et al. 2020; Lu and Yu 2015; Inui et al. 2012). In Eq. 4, showing each measure's formula,  $N$  denotes the number of firms by country, three-digit NACE industry and year and  $\overline{OPRE}$  the average operating revenue varying at the same level.

$$\begin{aligned}
 HHI_{c,s,t} &= \sum_{i=1}^{N_{c,s,t}} \frac{OPRE_{i,t}}{\sum_{i=1}^{N_{c,s,t}} OPRE_{i,t}} \\
 CRA_{c,s,t} &= \sum_{i=1}^4 \max_{\{4\}} \frac{OPRE_{i,t}}{\sum_{i=1}^{N_{c,s,t}} OPRE_{i,t}} \\
 Theil's L_{c,s,t} &= \frac{1}{N_{c,s,t}} \cdot \sum_{i=1}^{N_{c,s,t}} \log \left( \frac{\overline{OPRE}_{c,s,t}}{OPRE_{i,t}} \right) \\
 Theil's S_{c,s,t} &= \sum_{i=1}^{N_{c,s,t}} \left\{ \frac{OPRE_{i,t}}{N_{c,s,t} \cdot \overline{OPRE}_{c,s,t}} \cdot \log \left( \frac{N_{c,s,t} \cdot \overline{OPRE}_{c,s,t}}{OPRE_{i,t}} \right) \right\} \\
 Theil's T_{c,s,t} &= \frac{1}{N_{c,s,t}} \cdot \sum_{i=1}^{N_{c,s,t}} \frac{OPRE_{i,t}}{\overline{OPRE}_{c,s,t}} \cdot \log \left( \frac{OPRE_{i,t}}{\overline{OPRE}_{c,s,t}} \right)
 \end{aligned} \tag{D16}$$

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## Declarations

**Conflict of interest** The author declares no competing interests.

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