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The Impact of Import Competition from China on Firm-level Productivity Growth in the EU[1]

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Abstract

We re-examined the impact of rising imports from China on intra-firm productivity growth in the EU over the period 2005-2016. In contrast to previous studies, we find that an increasing share of Chinese imports in total imports slowed down productivity growth over the observation period. This was particularly the case after the 2008/09 financial crisis and was more pronounced for firms with lower productivity growth. On average, the net effect of China's increasing import intensity on productivity growth has been negative for EU firms since 2010. At the beginning of the sample, firms with median growth experienced a modest growth-enhancing effect, which turned slightly negative in the last observation year. The effect was muted for high-growth multinationals, which experienced a productivity growth premium from Chinese import competition at higher growth rates. Compared to the US, the negative impact of Chinese import competition on the performance of EU firms is visible with a time lag.

Keywords: import competition, productivity, manufacturing, EU, China, financial crisis
JEL: D24, F14, L25, L60, J24

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1. Introduction

China's exports to the European Union (EU) have increased significantly since its accession to the World Trade Organization in 2001. Over time they have also grown much more sophisticated and are no longer limited to low-tech, low-wage sectors, as was the case in the 1990s (Athukorala 2009; Ding et al. 2016). In this way, Chinese firms have emerged as direct competitors to firms in advanced economies (Athreye and Kapur 2009).

There is a growing literature assessing the impact of import competition from China on regional labour markets and technology in advanced economies (Autor et al. 2013; Autor et al. 2016; Balsvik et al. 2015; Dauth et al. 2014). Differences between the effects in the United States (US) and other economies have emerged, suggesting that the US has experienced significant negative effects on industrial employment that have not been observed, for example, in Germany or Norway.

Bloom et al. (2016) provided evidence of the productivity-enhancing effects of import competition for firms in the EU, as suggested by trade integration models (Melitz and Ottaviano 2008). However, the period studied by Bloom et al. (2016) ends before the 2008-09 financial crisis. Therefore, it does not capture the rise of Chinese firms as highly cost-competitive exporters in technologically sophisticated industries, which was supported by changes in Chinese economic policy. This suggests that the relationship between imports and performance may also have changed for EU firms.

This paper re-examines the effects of import competition from China on the performance of firms in the EU. The EU provides a compelling context in which to study the effects of trade due to its size as an economic bloc and its centrally negotiated trade agreements, as well as its considerable internal economic diversity. We used a comprehensive dataset of firm-level data combined with highly granular industry-level import data covering the period 2003-2016.

We contribute to the existing literature by showing that the positive relationship between imports and productivity growth reported by Bloom et al. (2016) has changed over time. We observed a positive effect that turns negative in more recent periods. This implies that Chinese imports hampered the productivity dynamics of EU firms over the period covered by the data. However, we also observed heterogeneity in this effect across firm types: multinational firms are better able to mitigate the negative impact of Chinese imports. Moreover, the negative effect is not uniform across the productivity growth distribution. It is stronger for firms with lower and median productivity growth rates.

2. An overview of the literature

The impact of Chinese import competition on industrial employment has been studied first at the regional labour-market level (Acemoglu et al. 2016; Dauth et al. 2014) and later at the firm level for Europe and Japan (Bloom et al. 2016; Yamashita and Yamauchi 2019). Bloom et al. (2016) found that surviving firms competing with Chinese imports became more technology-intensive and more productive through an "escape-entry effect" (Aghion et al. 2009). Firms producing goods and services that are easily substituted by low-cost imports cannot withstand competition and exit. More productive firms in turn escape import competition by innovating and differentiating their products. This leads to higher performance at both the firm and industry levels. At the firm level, resources are reallocated to the most profitable activities, and at the industry level, aggregate performance is enhanced by the exit of less successful firms (Melitz 2003; Melitz and Ottaviano 2008).

In the 1990s and early 2000s, technological imitation was the main strategy pursued by Chinese companies to expand their competence base and enter foreign markets with low-cost products in low-tech industries (Zhang and Zhou 2016). However, Chinese firms have been able to bridge the technology gap in key technology areas (Bergeaud et al. 2022). Over the past two decades, they have entered the market with increasingly technologically advanced products in technology-intensive industries. Thus, while Chinese import competition should have a positive effect on the productivity of domestic firms through the "escape-entry effect", it has been observed that the rapid technological progress of Chinese firms has led to a reduction in more ambitious and riskier R&D activities by competing (domestic) firms. As the returns on investment in innovation decline, firms reduce their technological exploration and focus on technological exploitation (Morandi Stagni et al. 2021). Aghion et al. (2009) referred to this phenomenon as the "discouragement effect".

Evidence from Chile suggests that the "escape-entry" effect occurs only in about 10% of the most productive firms, while import competition has a depressing effect on innovation in most other firms (Cusolito et al. 2023). This, in turn, has a negative impact on productivity growth. Factors such as firm-level technological capabilities or firm size, which help firms cope with the pressure of import competition, mediate the negative effects of the "China shock" (Hombert and Matray 2018; Colatone and Crinò 2014; Mion and Zhu 2013; Fromenteau et al. 2019; Friesenbichler and Reinstaller, 2023; Friesenbichler and Reinstaller, 2022). In an EU setting, both capabilities and economic institutions have also been shown to play a mediating role for the distribution of the economic value generated along the European and global value chains (Kügler, Friesenbichler and Reinstaller, 2023).

The emergence of Chinese firms as cost-competitive and technologically advanced exporters has often been attributed to a combination of factors. A key element is China's industrial development strategy, which has been adapted at different stages of its development. In recent years, the five-year plans have sought to promote technological upgrading and improve the economy's capacity for independent innovation, while earlier stages focused on building an industrial base and establishing a market economy (Jigang 2020).

The Chinese government is actively pursuing industrial leadership and self-sufficiency in strategic industries, focusing on domestic rather than international markets as the foundation of its economy. To capture significant shares of both domestic and international markets, the Chinese government has provided strong support to enterprises in the form of investment funds and subsidies. It is likely that the implementation of the "Second Displacement Strategy" between 2009 and 2016 (Doshi 2021) in particular has changed the nature of competition compared to earlier periods. This initiative was designed to support high-tech industries, such as information technology, robotics, industrial automation, aircraft, new materials, power generation and transmission equipment, pharmaceuticals, and electric vehicles (Naughton et al

2023). In addition, the Made in China 2025 strategy targets ten advanced manufacturing sectors (Li 2018). Public authorities in China have provided direct financial support to Chinese firms to achieve these policy goals through a combination of subsidies, tax breaks, below-market loans and below-market equity. A recent estimate shows that since the introduction of the Government Guidance Funds in 2012, effective public support to government-linked firms has increased from USD 7.9 billion to around USD 418 billion in 2016, reaching USD 850 billion in 2022 (Chimits 2023).

Institutional arrangements in China also disadvantage foreign firms and prevent wages from keeping pace with productivity growth (Barwick et al. 2019; Barbieri et al. 2019; Tian 2020). For instance, it has been argued that Chinese subsidies have led to overproduction in the steel industry, providing Chinese producers with an "unfair" competitive advantage (Price et al. 2016). It has also been argued that the combination of technology transfer, imitation (international firms could only operate in China if they formed joint ventures that were granted access to technology), and subsidy policies (e.g., in the photovoltaic industry) has technologically weakened Chinese firms' competitors (Zhang and Zhou 2016; Zhang and Gallagher 2016).

These developments are reflected in the policy debate. Since it acceded to the World Trade Organization (WTO) in 2001, the Chinese government has faced considerable criticism. As a result, both the European Union and the United States have resisted granting China "market economy" status under the WTO, and this debate is still ongoing. Political scientists have also observed a shift in the Chinese government's strategy following the 2008–09 financial crisis, when it adopted a more assertive economic approach to bolster China's geopolitical standing.

If Chinese firms can enter technologically sophisticated markets with cost advantages due to government support, we should expect the “discouragement” effect postulated by Aghion et al. (2009) to increasingly influence the productivity growth of firms in advanced industrial economies. This effect should be more pronounced for less productive and competitive firms. We re-examined the impact of Chinese import competition on European firms from this perspective, using a comparable sample and econometric approach, over a period that includes the time window of their research and the new phase of Chinese industrial policy starting in 2009.

Our research is related to Bloom et al. (2016). While Bloom et al.’s sample covers a period up to 2007, our data take into account the impact of the 2008–09 financial crisis, which changed the dynamics and structure of global trade (Timmer et al. 2016). We expect that the empirical relationship between import competition and firm performance will change mainly because Chinese exporters have upgraded their technological capabilities while maintaining cost advantages. In addition, the growth slowdown following the 2008–09 financial crisis may have contributed to the negative impact of import competition. In an economic environment with abundant market opportunities, these effects may have been overshadowed by other dynamics.

3. Conjectures

The literature provides evidence for the growth-enhancing effect of import competition, as implied by the Melitz model and empirically supported by Bloom et al. (2016). On the other hand, the unbundling of production from localised knowledge and reduced coordination costs enabled by digitalisation have changed competitive dynamics and eroded Ricardian comparative advantages (Baldwin 2011). As returns on investment in innovation decline, firms reduce their exploration of new technologies and markets and increase their exploitation of existing competitive advantages in specific products and markets (Morandi Stagni et al. 2021). This dynamic is further accelerated by China's industrial policy, which allows Chinese companies to offer low-cost but technologically sophisticated products. As a result, import competition from China may have had a negative impact on firm-level productivity growth in recent years, as the nature of competition has changed over time.

Conjecture I: The impact of increasing import intensity from China on within-firm productivity growth has changed over time. The growth-enhancing effect has turned into a growth-dampening effect.

Firms differ in their capabilities, behaviour, and access to resources, which moderates the effect of import competition. Williamson (1986) was one of the first to point out that multinational firms react differently to import competition than single-country firms because of their international linkages. Multinational firms have better access to resources that allow them to use international trade in their production processes to a greater extent than domestic firms (Navaretti et al. 2004).

Some contributions suggest that this is related to the way these firms organise their value chains. While import competition seems to affect industries with higher levels of routine skills (Lu and Ng 2013), multinational enterprises (MNEs) are also more likely to insource non-routine than routine activities. Costinot et al. (2011) show that industries with low average routineness tend to have higher shares of intra-firm trade. This suggests that MNEs facing import competition can source critical non-routine tasks globally through their network of affiliates. These, in turn, draw on different national capabilities and advantages, allowing MNEs to respond more flexibly to increasing import competition than purely domestic firms. MNEs are also better able to use digital technologies to operate and coordinate large networks of suppliers (Fort 2017). Thus, they may be better positioned to exploit the competitive advantages of the global production system to their advantage through their own subsidiaries and arm's-length suppliers in China and other countries. This leads to our next conjecture:

Conjecture II: Rising import intensity from China has a positive net effect on MNEs' productivity growth.

The literature also discusses the role of firm characteristics in moderating the relationship between international trade and productivity growth. Several authors have found a positive impact of import activity on local productivity growth (Pavcnik 2002; Keller 2000;

Feenstra et al. 2015; Blalock and Veloso 2007; Fernandes 2007; Kasahara and Rodrigue 2008), while others emphasise the role of import diversity (Parsons and Nguyen 2009) or foreign direct investment (Keller and Yeaple 2009). At the firm level, import penetration can trigger productivity growth through technology spillovers due to increased competitive pressure or access to high-quality intermediate goods that allow firms to increase their efficiency. At the sectoral level, these aggregate firm-level effects are complemented by competitive elimination, that is, the exit of the least productive domestic firms within a sector due to increased foreign competition, leading to a reallocation of resources and output from less to more productive firms. Overall, the evidence suggests that higher sectoral import levels are associated with higher firm productivity growth.

These effects are heterogeneous across firms, depending on the relative productivity levels of European incumbents and Chinese exporters, as suggested by Aghion et al. (2009). According to their theory, more productive incumbents try to escape competition by increasing their efforts to improve their performance relative to the Chinese exporters that they perceive as a threat. Less productive incumbents, on the other hand, would be discouraged by competitive entry as it reduces their expected returns on investment in productivity-increasing activities such as innovation. Which effect ultimately prevails depends on the extent to which European incumbents perceive Chinese exporters as a threat and how the relative competitiveness of European firms and Chinese exporters changes over time.

Deviations from this stylised response pattern could be observed if Chinese exporters first enter the lower rungs of industry-specific quality ladders, and then upgrade their exports as they build up capabilities and move into more technologically advanced segments of the European market, as suggested by Sutton and Trefler (2016). In this case, the response of European firms to escape competition may initially be stronger for lower-performing firms operating in less sophisticated segments of the market, as they may perceive the threat from Chinese exporters more strongly than firms further up the quality ladder. However, as Chinese firms improve their capabilities over time, a discouragement effect should set in. Such an effect should be observed for all types of firms, but would be stronger for low performers. Given the heterogeneity of the population of firms studied here, it was not possible a priori to determine which of these effects dominated in the period we studied, as we did not observe the quality segments in which Chinese exporters are active. However, we expected to observe the heterogeneous effects of increasing import intensity from China across the distribution of productivity growth rates of European firms over time.

Conjecture III: The magnitude of the effect of rising import intensity from China on firms' productivity growth varies with firms' productivity growth rates and over time.

4. Estimation approach

To estimate the impact of trade on within-firm productivity performance, we exploited differences in exposure to import penetration across countries and industries over time. The estimation strategy broadly follows previous literature (Bloom et al. 2016; Yamashita and Yamauchi 2019; Ben Yahmed and Dougherty 2017).

We estimated the specification equation as a log-linear fixed effects model in first differences. Thus, we regressed productivity growth $\left(\Delta \mathrm{LP}_{j,s,c,t}\right)$ on changes in import intensities $(\Delta ImI_{s,c,t})$. The basic productivity growth equation reads:

$$\Delta \mathrm{LP}_{j,s,c,t} = \alpha_{\mathrm{s}} + \alpha_{\mathrm{t}} + \alpha_{\mathrm{c}} + \beta_1 \mathrm{LP}_{j,s,c,2005} + \beta_2 \Delta ImI_{s,c,t} + \beta_3 \Delta \mathrm{CAP}_{j,s,c,t} + e_{j,s,c,t} \qquad \text{(Eq. 1)}$$

where LP denotes the log of labour productivity of firm j in sector s and country c in period t, $\mathrm{LP}_{j,s,c,2005}$ the firm-specific out-of-sample labour productivity level of 2005, $(ImI)_{sct}$ is the import share at the sector-country-year level. CAP_{jsct} is the firm-specific capital intensity, defined as the stock of tangible fixed assets in real terms. α_{c}, α_{t} and α_{s} are country, period, and sector fixed effects; e denotes the error term.[6] We clustered the standard errors at the treatment (i.e., country–industry) level (see Section 7).

We extended this specification to include a time trend over and above the period dummies. This measure is an index variable that takes the value of 1 in 2006, the first year used in our regression analysis, and reaches a maximum of 11 in 2016. This trend is broadly consistent with the technological upgrading of China's export portfolio to the EU. We considered both the trend and the interaction term of the trend with import intensities.

In addition to ordinary least squares (OLS) regressions, we also implemented a two-stage least squares (2SLS) identification strategy because import dynamics may be endogenous.

[6] Singletons which may skew the results are excluded.

Unobserved supply and demand shocks could affect trade and performance, implying that the coefficients suffer from reverse causality. We addressed this issue by using an instrumental variable strategy, following approaches used in the previous literature on Chinese import competition (Autor et al. 2013; Bloom et al. 2016; Dauth et al. 2014). The identification idea is that China's rise in the world economy has been a source of supply shocks to all its trading partners. Using information on China's other trading partners identifies the exogenous component of China's rising competitiveness and removes shocks that are specific to the country, region, or industry.

We calculated the import intensity for a group of extra-EU economies. We used average import intensities of Australia, New Zealand, the United States, Canada, Israel, and Japan. Calculating the mean of the shares avoids bias towards larger countries. The average productivity of the countries is broadly comparable to the average EU productivity and thus captures the size of the shock. Given the differences in competitive positioning, these are countries for which we did not expect significant correlations between demand and supply shocks to firms. Thus, the average import intensities of this group of countries served as an instrument for the Chinese import intensities of EU countries. We tested whether the exclusion restriction is satisfied using a recently proposed procedure that we implemented at the treatment level (D'Haultfœuille et al. 2021).[7] We were not able to reject the null hypothesis that the exclusion restriction is satisfied at the 1% significance level. In the specifications that include

[7] The test could not be performed at the firm level because it was too computationally intensive. Therefore, we averaged the productivity at the country year industry level and computed the test statistics.

interaction terms, we also interacted with the extra-EU import intensities and used these linear combinations as additional instrumental variables.

In the context of China shock analysis, recent papers have critically assessed the use of shift-share instruments (Adão et al. 2019; Goldsmith-Pinkham et al. 2020). Many contributions to this literature rely on shift-share (or Bartik) instruments to identify the effect of import competition on a regional outcome variable. The outcome is regressed on a weighted average of sectoral shocks using regional sectoral shares as weights. These share components of the instrument are assumed to be exogenous to import competition. They are a source of variation that can improve the identification of the effect. However, this approach is not feasible in the firm-level context due to the different structures of the data with respect to the share components. Following Bloom et al. (2016), we relied only on the shift component to identify the effect of changes in import competition on labour productivity growth. The choice of the instrumental variable does not qualitatively affect the within-firm results and ensures a higher degree of comparability of our results with Bloom et al. (2016) contribution.

Finally, we used quantile (least absolute value) regressions to allow the effect of increasing import intensity to vary across the distribution of productivity growth. We estimated the quantiles of the conditional distribution as linear functions of the explanatory variables, including country-fixed effects. We ran simultaneous quantile regressions for the 25th, the 50th and the 75th percentiles. We found different coefficients, indicating that the quantiles of the conditional distribution of labour productivity vary with the independent variables in a way that is not captured by regressing the mean (Koenker and Hallock 2001; Angrist and Pischke 2009).

5. Data and variables

The analysis was based on data from multiple sources. This allowed us to track performance and trade relationships over time, overcoming compatibility issues with multiple classifications. We constructed a unique dataset covering the period from 2003 to 2016 (see Online Appendix for a detailed discussion of the data).

The firm-level indicators were based on AMADEUS, a dataset provided by Bureau van Dijk – A Moody's Analytics Company.[8] We used several ten-year waves of AMADEUS to construct a panel. The first step was to make the waves comparable. Each wave contains an identifier for the firm that is unique within each wave but not unique across waves. We used information on identifier changes provided by Bureau van Dijk to construct unique firm identifiers to control for breaks in records. This dataset was then thoroughly cleaned for duplicate entries due to data updates, outliers, and missing values.

All nominal values were deflated using Eurostat deflators at the available two-digit level of NACE Revision 2 (reference year 2010). NACE is the statistical classification of economic activities in the European Community. This is important because increased competition should lead to lower prices (Auer and Fischer 2010; Weyl 2019). At the industry level, the inflation rate is negatively and significantly correlated with changes in import intensity (ρ: -0.02).

The sample consists of 102,167 enterprises in 25 EU countries (data are missing for Greece, Cyprus, and Lithuania; the United Kingdom is included because it was a member of

[8] See https://www.bvdinfo.com/en-gb/our-products/data/international/amadeus (accessed on 28 July, 2023).

the EU during the analysis period). Only active enterprises were considered. Information on insolvent or bankrupt companies was not used.

5.1 Firm performance

Labour productivity, defined as firm-specific value added divided by the number of employees, is the key performance indicator. The median real labour productivity is EUR 41,777 per person employed. The sample broadly reflects the cross-country distribution of GDP per capita as a measure of productivity in the EU economy.[9]

In 2005, the base year of the sample, the average import intensity was 5.7%. This increased to 8.4% in 2016, the last year of observation. Considering the EU as a bloc, these figures indicate a difference in both levels and dynamics compared to the reference pool of other industrialised countries. The sample mean of the instrumental variable we used in the 2SLS regression was 12.1% in 2005, which increased to 19.5% in 2016.

Labour productivity growth varied across countries, with an annualised pooled average growth rate of 1.6%. Using the full sample, labour productivity growth and import intensity growth were uncorrelated (ρ: 0.00). This labour productivity indicator has been criticised for not accounting for a firm’s capital intensity (Syverson 2011). To address this concern, we included firm-specific fixed asset growth in the estimation of labour productivity growth.

[9] The logarithmic terms of labour productivity and GDP per capita are highly correlated (ρ: 0.95).

5.2 Import intensity

We matched firm-level data with trade data from BACI (Gaulier and Zignago 2010), which is a harmonised trade dataset that includes information on imports. Following previous literature (Bernard et al. 2006; Bloom et al. 2016) we computed a Chinese import intensity indicator based on a value share approach. The measure is based on Chinese imports (IMP_C) and total imports (IMP_{TOT}). Import intensity is then defined as the share of Chinese imports in total imports (IMP_C/IMP_{TOT}) for a given country, year, and NACE Revision 2, 4-digit industry.[10]

This allowed us to illustrate the relationship between labour productivity growth and Chinese import intensity. We split the sample into industries that did not import from China, the non-treated group, and industries that reported imports from China, the treated group. In the treatment group, the average import intensity increased from 6.1% in 2004 to 11.7% in 2016. This corresponds to an average annual increase of approximately 0.5 percentage points. There are also differences in productivity growth rates. Firms in the non-treated group grew at an average rate of 2.2%, while firms in the treated group grew at 1.8%.

Beyond the non-treated firms (i), we further differentiated the treated group by the intensity growth of the treatment: (ii) industries with Chinese import intensity growth below the 25th percentile, (iii) industries between the 25th and 75th percentile, and (iv) industries above the 75th percentile. The following figure shows the average annual change in productivity

[10] We recoded trade data available in the Harmonized System (HS) classification, a standardised numerical method for classifying traded products, to match the industry classification used in AMADEUS (NACE Rev. 2, 4-digit level). The 6-digit hs92 data are converted to hs02, for which a NACE Rev. 1 correspondence table is available, which can be transformed to NACE Rev. 2 at the 4-digit level (see Online Appendix).

between 2004 and 2016. In the later years of the sample, the group of non-treated firms had higher productivity growth. Productivity growth tends to be lower the more intensive the treatment is.

Figure 1 about here

5.3 Multinational enterprises

We also used information on the ownership structure of a firm. We define a dummy variable that takes the value of one if a firm belongs to a multinational enterprise group and zero otherwise. Differentiating between MNEs and domestic firms is necessary because they have access to different networks and factors of production (Navaretti et al. 2004).

Of the firms in the sample, 23.4% are multinationals, which are different from domestic companies. Their average labour productivity (EUR 55,730) is significantly higher than the average of domestic firms (EUR 38,561; real terms, reference year 2010). Differences in performance can also be observed in growth intensity. The average domestic firm grew in labour productivity by 1.0% per year. The average growth rate of multinationals was 1.4% (p-value: 0.000).

The industries to which multinational enterprises are more likely to be assigned face slightly more import competition from China (7.5% for domestic enterprises and 7.6% for multinational enterprises; the difference is statistically significant, p-value: 0.000). Industries in which multinationals are active also experienced slightly higher growth in Chinese imports (0.32%) than domestic firms (0.28%).

6. Results

We tested the above hypotheses in a series of regressions of labour productivity growth on changes in trade intensity measured at the industry level (Table 1). We implemented 2SLS specifications, supported by post-estimation tests, to account for possible endogeneity. The Kleibergen-Paap rank Lagrange multiplier statistic was highly significant in all specifications, and the Kleibergen-Paap rank Wald F statistic exceeded the critical values of the 10% maximum instrumental variable size, as proposed by Stock and Yogo (2002). The equations are identified exactly (see Table 2 and Table A1-A3 and Figure A1-A3 in the Online Appendix).

Table 1 about here

In the baseline specification shown in Table 1, columns (1) and (2), we found a positive effect of import intensity growth on labour productivity growth. The OLS coefficient (1) was only weakly significant, and the coefficient of the 2SLS estimation (2) was insignificant.

To test Conjecture I, that there is a time-varying, initially positive, and eventually negative effect of changes in import intensity on productivity growth, we included a time index variable and its interaction with changes in import competition (Δ IMI*Trend) over and above the time fixed effects (see columns (3) and (4)).

We found positive and significant coefficients on changes in import competition. This indicates that there is a positive base effect of increased import competition from China on domestic productivity growth, supporting Bloom et al.'s (2016) findings. However, the coefficient of the interaction term of changes in import intensity with the time trend is significantly negative, indicating that the positive baseline effect of increasing import intensity on firms' productivity growth has decreased over the years. When we used the average value of import intensity growth and set the coefficients of regressions (3) and (4), we saw that the net effect becomes negative from 2014 in both the IV estimate and the OLS regression.

In addition, we considered macroeconomic developments and implement specifications based on a dummy variable that takes the value of one for the period following the 2008–09 financial crisis and zero otherwise (columns (5) and (6)). The coefficients on the crisis, and the interaction of the crisis dummy with import intensity growth, are negative and significant. Again, when we included the average annual growth rates of import intensity, we found that the net effect of changes in China's import competition was positive before the financial crisis but became negative thereafter. Thus, the results support Conjecture I.

The second conjecture is that MNEs can offset the negative effects of Chinese import competition. Therefore, we introduced firm characteristics that captured the heterogeneous responses of firms. We included a time-invariant binary variable measuring whether a firm belongs to a multinational group, as well as an interaction term of this dummy with changes in Chinese import intensities (Table 1, columns (7) and (8)). The coefficient measuring whether a firm is part of a multinational enterprise group was positive and statistically significant. The coefficient of import intensity growth became insignificant in both regressions. The interaction terms of being a multinational with import intensity growth showed a positive and significant coefficient in the OLS regression. However, this coefficient became negative and insignificant in the 2SLS regression.

In specifications (9) and (10), we asked whether the time-varying effect of changes in Chinese import competition on productivity growth differed for multinational firms compared to domestic firms. We extended specifications (3) and (4) to include the MNE dummy and a triple interaction term (Δ IMI*Trend*MNE). In both OLS and IV regressions, the estimated coefficients for import intensity growth and its interaction with the time trend were quite stable compared to specifications (3) and (4) of Table 1, indicating a positive base effect that declined over time and became negative in the later years of our sample. In contrast, the coefficient of the triple interaction with the MNE dummy was significantly positive in the OLS regression, indicating the dampening effect of being a multinational firm. Using the average growth of import competition and considering the coefficients of regression (9), we found that the net effect of changes in Chinese import competition on the productivity growth of domestic firms became negative in 2011 but remained positive for multinational firms throughout the observation period. In the 2SLS, the coefficient of the triple interaction of changing import intensity, time, and being a multinational was not statistically significant.

Finally, we ran a quantile regression for three separate quantiles to test whether the coefficients of the time trend and its interaction terms with import intensity growth and the MNE dummy varied along the growth distribution. In this way, we tested Conjecture III, which states that the magnitude of the effect of increasing import competition from China varies with the productivity growth rate of domestic and multinational firms over time. Columns (11) to (13) of Table 1 show the positive coefficients of changes in import intensity. The positive base effect of Chinese import growth on productivity growth was more pronounced for low-growth firms than for high-growth firms. The difference between the 25th and the 75th percentile was statistically highly significant (p-value: 0.000). However, these positive effects diminished over time. This dampening effect was also more pronounced for domestic firms with lower productivity growth rates than for high-growth firms. Again, the difference between the 25th and the 75th percentile was statistically highly significant. The effects for the 50th and the 75th percentile were mostly identical. Assuming the average growth of import competition for firms in the 25th percentile, the net effect of increasing import intensity from China was negative for low-growth domestic firms starting in 2010. On average, firms growing in the 75th percentile experienced a growth-dampening net effect one year later in 2011. Hence, Chinese exporters have become a more credible threat to firms with lower productivity growth. This suggests that, over time, a discouragement effect has set in, reducing labour productivity growth. This effect was less pronounced for European firms with higher productivity growth rates.

How did multinationals compare? The coefficients of MNE affiliation were significantly positive in all three quantile regressions. They increased with higher productivity growth percentiles. Thus, multinationals have a growth premium that is particularly pronounced at higher growth rates. We also interacted the MNE dummy variable with the time trend and the change in import competition from China (Δ IMI*Trend*MNE). The coefficient of the triple interaction effect was significantly different from zero only for firms in the 75th percentile. MNEs in the 75th productivity growth percentile were able to offset the growth-dampening effect experienced by other firms over time. The net effect of increasing Chinese import intensity for high-growth MNEs was positive (though declining) throughout the period. MNEs with lower growth rates (25th or 50th percentile) did not differ from their domestic counterparts in terms of the impact of increasing Chinese import intensity.

Next, we used the average annual increase in Chinese import intensities to quantify the size of the effect. In 2005, the results suggest a growth-enhancing effect of rising Chinese import intensity. At the 25th percentile for domestic firms, the effect was 0.04 percentage points. The effect was slightly lower at 0.02 percentage points at both the median and 75th percentile.

In 2011, the median year of the sample, the growth-reducing effect was -0.03 percentage points at the 25th percentile for domestic firms, and -0.02 percentage points at the 50th and 75th percentiles. Multinationals growing at the 75th percentile offset the negative growth effect by 0.03 percentage points, so that the net effect was slightly positive (0.01 percentage points).

In 2016, we found a small but statistically significant effect of -0.08 percentage points on productivity growth at the 25th percentile for domestic firms. The effect at the 50th and the 75th percentiles was -0.06 percentage points. This effect was partly offset by an increase of 0.05 percentage points for multinationals growing at the 75th percentile. Therefore, the net effect for multinationals in 2016 was -0.01 percentage points.

MNEs experienced a productivity growth premium. While statistically significant, it was small at the 25th percentile (0.3 percentage points), but increased in size at the 50th percentile (0.8 percentage points) and the 75th (2.8 percentage points) percentiles.

The control variables performed as expected. The coefficients on capital stock growth remained significantly positive, and the coefficient on the out-of-sample level of productivity was negative in all regressions. The unreported country, time, and industry dummies were mostly significant.

7. Discussion

The view has long been that imports from China will have a positive impact on specialisation and productivity growth of firms and industries. This is empirically supported by European data before the 2008–09 financial crisis (Bloom et al. 2016). However, recent evidence shows that after the financial crisis Chinese firms have increasingly entered market segments previously served by firms from industrialised economies (Autor et al. 2013). China's industrial policies have enabled Chinese firms to compete on both price and quality.

This led us to the first conjecture: imports from China initially had a positive effect on intra-firm productivity growth, which diminished over time and eventually turned negative. The regression analysis strongly supported this conjecture. We found a growth-enhancing net effect of increasing import intensity from China especially in the years before the financial crisis. This suggests that in the EU increased import competition initially induced productivity growth at the firm level. However, there was a reversal of the net effect, which became negative over time. This is in contrast to the US, where the negative effect of Chinese import competition plateaued after 2010 (Autor et al. 2021). EU firms appear to have been able to avoid the negative effects of competition from China for a more extended period. This may be due to differing industrial structures. However, the evidence suggests that Chinese firms have increasingly been able to strengthen their competitive position in markets where EU firms are specialised.

This effect of import intensity growth on productivity growth was not evenly distributed. Firm heterogeneity moderates the effect of import competition from China (Mion and Zhu 2013; Fromenteau et al. 2019). Multinational firms may be better able to take advantage of international trade opportunities. We showed that being a multinational is generally associated with higher productivity growth. In addition, our results indicated that multinationals experience a smaller negative effect from rising imports from China. This suggests that the composition of the firm population in terms of multinational and domestic firms shapes the ability to cope with increasing imports from China at the aggregate level. The magnitude of the dampening effects also depends on the performance of the firms in terms of their labour productivity growth rates. This was shown in the quantile regressions. We found a positive net effect of increasing import intensity from China on productivity growth for high-growth MNEs over the entire observation period. Our main finding of a changing and increasingly dampening net effect of increasing Chinese import intensity on firm-level productivity growth over time was confirmed. However, the magnitude of these effects is generally small. This suggests that the actual economic impact of these effects was generally limited.

The results, therefore, support the perspective outlined in the literature review that the impact of import competition with Chinese firms on firm-level performance has changed over the period studied in this paper. Our results contribute to the debate on trade policy and the impact of Chinese industrial policies, such as the competition-distorting use of subsidies, intellectual property rights, and market regulations. This is relevant, as the competitive pressure from China is expected to have further increased with “Made in China 2025”, China’s industrial strategy (Li 2018), which aims not only to further upgrade the Chinese economy technologically, but also to achieve independence from foreign suppliers in “core products” such as semiconductors, aerospace, information technology, or biotechnology. With policy changes in the aftermath of the COVID-19 pandemic both in the US and the EU, the results reported in this paper may be subject to changes again. These measures, such as the Inflation Reduction Act that became effective in 2022 or the Green Deal Industrial Plan currently under implementation in the EU, aim to protect domestic firms from Chinese competitors in certain strategic industries. It is not yet possible to take these developments into account.

From a methodological standpoint, our results come with some limitations. Like other studies on Chinese import competition, we estimated partial equilibrium models. Thus, we were not able to capture the full economic or welfare effects of trade, as suggested, for example, by Caliendo et al. (2019) for the US. Following a similar general equilibrium approach, Fischer et al. (2021) questioned the identification strategy proposed by Autor et al. (2013). The authors used a method that isolates the China-specific supply shocks from the sectoral shocks that are common to all exporters, thereby correcting for the identification of supply-induced export growth at the sectoral level. The results were strengthened in the general equilibrium estimations, while the partial equilibrium results were hardly affected. This instrumentation approach requires demand elasticities, which are not available for the currently used data at the NACE Revision 2, 4-digit level.

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Tables and Figures

Table 1: Impact of changes in import intensities on labour productivity growth

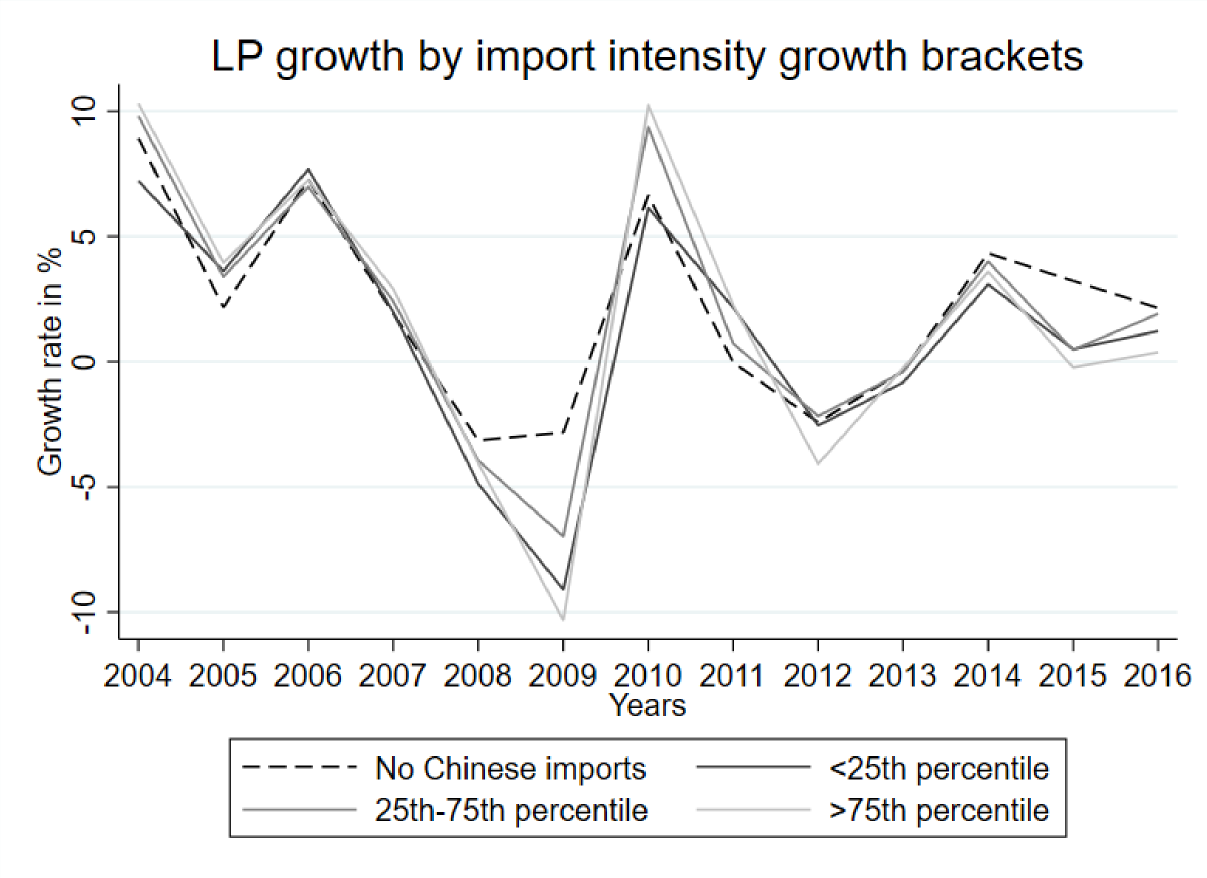
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Baseline		**Trend**		**Financial Crisis**		**MNE**		**Trend*MNE**		**25th perc.**	**50 th perc.**	**75 th perc.**
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	QUANT	QUANT	QUANT
Δ IMI	0.056*	0.128	0.327***	0.723**	0.275***	0.692***	0.029	0.129	0.332***	0.718**	0.244***	0.141***	0.145***
	(0.029)	(0.134)	(0.082)	(0.331)	(0.062)	(0.201)	(0.030)	(0.138)	(0.082)	(0.331)	(0.028)	(0.020)	(0.028)
Trend			-0.005***	0.005					-0.005***	0.005	-0.003***	-0.005***	-0.007***
			(0.000)	(0.004)					(0.000)	(0.004)	(0.000)	(0.000)	(0.000)
Crisis					-0.009***	-0.007***							
					(0.002)	(0.002)							
MNE							0.018***	0.018***	0.018***	0.019***	0.003***	0.009***	0.018***
							(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Δ IMI * Trend			-0.033***	-0.065*					-0.037***	-0.062*	-0.037***	-0.025***	-0.024***
			(0.009)	(0.034)					(0.009)	(0.034)	(0.005)	(0.003)	(0.005)
Δ IMI * Crisis					-0.185**	-0.628***							
					(0.073)	(0.223)							
Δ IMI * MNE							0.127**	-0.022					
							(0.049)	(0.209)					
Δ IMI * Trend * MNE									0.015***	-0.015	0.007	0.005	0.013**
									(0.006)	(0.023)	(0.005)	(0.004)	(0.005)
Δ Capital	0.031***	0.031***	0.031***	0.031***	0.032***	0.032***	0.032***	0.032***	0.032***	0.031***	0.024***	0.028***	0.029***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
LP, base	-0.066***	-0.066***	-0.066***	-0.066***	-0.065***	-0.065***	-0.067***	-0.067***	-0.067***	-0.067***	-0.047***	-0.032***	-0.031***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Fixed effects	Y	Y	Y	Y	N	N	Y	Y	Y	Y	Y	Y	Y
Observations	889,027	889,027	889,027	889,027	889,027	889,027	888,453	888,453	888,453	888,453	888,453	888,453	888,453
R^2	0.021	0.01	0.021	0.011	0.012	0.01	0.022	0.01	0.022	0.011	0.0231	0.0131	0.0211

Note: This table reports the regression results of the impact of changes in import intensity on productivity growth. Growth rates in log differences are denoted by Δ. Constants are not reported. All specifications include country, sector, and year-fixed effects. In the first stage, the F-statistics of the instruments are above 10 in all specifications. All 2SLS specifications were identified exactly. The Wald test statistics for the joint significance of the interaction effects are highly significant (p-value<0.01). Standard errors are in parentheses in specifications (1)–(10) and clustered at the treatment level. *** p-value<0.01, ** p-value < 0.05, * p-value < 0.1.

Table 2: First stage F-statistics of excluded instruments

	Baseline		Δ IMI * Trend		Δ IMI * Crisis		Δ IMI * MNE		Δ IMI * Trend * MNE	
	Test value	p-value	Test value	p-value	Test value	p-value	Test value	p-value	Test value	p-value
1st stage F-statistic of excl. instruments: Δ Import intensity	F(1,4013): 71.43	0.000	F(2,4013): 37.36	0.000	F(2,4013): 54.55	0.000	F(2,4013): 46.16	0.000	F(3,4013): 32.22	0.000
1st stage F-statistic of excl. instruments: Δ Import intensity*Trend			F(2,4013): 37.71	0.000					F(3,4013): 30.47	0.000
1st stage F-statistic of excl. instruments: Δ Import intensity*Crisis					F(2,4013): 64.62	0.000				
1st stage F-statistic of excl. instruments: Δ Import intensity*MNE							F(2,4013): 64.86	0.000		
1st stage F-statistic of excl. instruments: Δ Import intensity*Trend * MNE									F(3,4013): 73.52	0.000

Figure 1: Labour productivity growth by Chinese import intensity growth brackets



Note: The graph splits the sample into firms in industries (i) without Chinese imports, (ii) with Chinese import intensities below the 25th percentile, (iii) industries between the 25th and 75th percentile, and (iv) industries above the 75th percentile. Productivity growth tends to be lower in the later years of the sample when the treatment intensity is higher.

Online Appendix

First stage results

Table A3: Labor productivity growth and changes of Chinese trade intensities, IV regressions incl. first stages

	Baseline		**Trend**			**Crisis**		
	Δ IMI	2nd Stage	Δ IMI	Δ IMI * Trend	2nd Stage	Δ IMI	Δ IMI * Crisis	2nd Stage
Δ IMI		0.13			0.72**			0.69***
		(0.134)			(0.331)			(0.201)
Trend			-.00***	-.00***	-0.00***			
			(0.0001)	(0.0001)	(0.000)			
Crisis						-0.00	0.00***	-0.01***
						(0.0000)	(0.001)	(0.002)
Δ IMI * Trend					-0.07*			
					(0.034)			
Δ IMI * Crisis								-0.63***
								(0.223)
Δ IV	0.18***		0.27***	-0.11		0.32***	-0.02***	
	(0.0208)		(0.0404)	(0.2928)		(0.0328)	(0.0041)	
Δ IV * Trend			-0.01***	0.18***				
			(0.0034)	(0.0332)				
Δ IV * Crisis						-0.15***	0.19***	
						(0.0289)	(0.0191)	
Δ Capital	0.00	0.03***	0.00	0.00	0.03***	0.00	0.00	0.03***
	(0.0002)	(0.003)	(0.0002)	(0.0011)	(0.003)	(0.0002)	(0.0000)	(0.003)
LP, base	-0.00	-0.07***	-0.00	0.00	-0.07***	-0.00	0.00	-0.07***
	(0.0000)	(0.001)	(0.0001)	(0.0005)	(0.001)	(0.0000)	(0.0000)	(0.001)
Period-FE	Y	Y	Y	Y	Y	N	N	N
Sector-FE	Y	Y	Y	Y	Y	Y	Y	Y
Country-FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	889,027	889,027	889,027	889,028	889,029	889,030	889,031	889,032

Note: This table reports the first- and second-stage regression results of the impact of changes in import competition on productivity growth. Growth rates (denoted by Δ) are measured in logarithmic terms. All 2SLS specifications are exactly identified. The Wald test statistics for joint significance of the interaction effects are highly significant (p-value<0.01). Standard errors clustered at the treatment (industry) level in parentheses, N=889,027, *** p-value<0.01, ** p-value <0.05, * p-value <0.1.

Table A4: Labor productivity growth and changes of Chinese trade intensities, IV regressions incl. first stages (cont'd)

	MNE			**Trend*MNE**			
	Δ IMI	Δ IMI * MNE	2^{nd} Stage	Δ IMI	Δ IMI * MNE	Δ IMI * MNE ∗ Trend	2^{nd} Stage
Δ IMI			0.13				0.72**
			(0.138)				(0.331)
Trend				-0.00***	-0.00***	-0.00***	-0.01***
				(0.000)	(0.001)	(0.000)	(0.000)
MNE	-0.00	0.00***	0.02***	-0.00	-0.00	0.01***	0.02***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)
Δ IMI * Trend							-0.06*
							(0.034)
Δ IMI * MNE			-0.02				
			(0.209)				
Δ IMI * Trend * MNE							-0.02
							(0.023)
Δ IV	0.18***	-0.00***		0.27***	-0.11	0.11	
	(0.023)	(0.001)		(0.040)	(0.291)	(0.079)	
Δ IV * Trend				-0.01***	0.18***	-0.01	
				(0.003)	(0.034)	(0.008)	
Δ IV * MNE	-0.00	0.19***					
	(0.017)	(0.017)					
Δ IV * MNE ∗ Trend				-0.00	-0.00	0.18***	
				(0.002)	(0.017)	(0.017)	
Δ Capital	0.00	0.00	0.03***	0.00	0.00	-0.00	0.03***
	(0.000)	(0.000)	(0.003)	(0.000)	(0.001)	(0.000)	(0.003)
LP, base	-0.00	-0.00**	-0.07***	-0.00	0.00	-0.00	-0.07***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Period, Sector, Country FE	Y	Y	Y	Y	Y	Y	Y

Note: This table reports the results of the first and second stage regressions of the impact of changes in import competition on productivity growth. Growth rates (denoted by Δ) are measured in logarithmic terms. All 2SLS specifications are exactly identified. The Wald test statistics for joint significance of the interaction effects are highly significant (p-value<0.01). Standard errors clustered at the treatment (industry) level in parentheses. N=888,453, *** p-value<0.01, ** p-value <0.05, * p-value <0.1.

Table A5: Specification tests

	Baseline		**Interaction with Trend**		**Interaction with Crisis**		**Interaction with MNE**		**Interaction with MNE and Trend**	
	Test value	p-value	Test value	p-value	Test value	p-value	Test value	p-value	Test value	p-value
1st stage F-statistic of excl. instruments: Δ Import intensity	F(1,4013): 71.43	0.000	F(2,4013): 37.36	0.000	F(2,4013): 54.55	0.000	F(2,4013): 46.16	0.000	F(3,4013): 32.22	0.000
1st stage F-statistic of excl. instruments: Δ Import intensity*Trend			F(2,4013): 37.71	0.000					F(3,4013): 30.47	0.000
1st stage F-statistic of excl. instruments: Δ Import intensity*Crisis					F(2,4013): 64.62	0.000				
1st stage F-statistic of excl. instruments: Δ Import intensity*MNE							F(2,4013): 64.86	0.000		
1st stage F-statistic of excl. instruments: Δ Import intensity*Trend * MNE									F(3,4013): 73.52	0.000
Kleiberger-Paap rank LM statistic	55.724	0.000	62.77	0.000	64.65	0.000	54.24	0.000	61.11	0.000
Kleibergen-Paap rank Wald F statistic	71.434		47.53		58.79		33.41		29.69	
Stock-Yogo weak ID test critical values: 10% maximal IV size	16.38		7.03		7.03		7.03		5.44	
Endogeneity test of endogenous regressors		0.592		0.327		0.3414	0.61			0.337

The dataset

AMADEUS data

The AMADEUS database is a product of Bureau van Dijk for company information and contains 21 million companies across Europe.[1] The data provide a rich source of financial information and company characteristics (e.g., sector, location, ownership and governance structures). The data is provided in several annual releases.

Using multiple releases:

To obtain a large sample starting in 2004, we use biennial releases from 2012 to 2018 (i.e., 2018, 2016, 2014, and 2012). Appending releases poses a number of data consistency challenges. First, each release uniquely characterizes a firm over time using a Bureau van Dijk identifier. However, these identifiers can change over time for the same firm, so the identifier is not unique across AMADEUS releases. Therefore, appending firms using uncleaned identifiers would lead to biased results. We generate harmonized identifiers using information on identifier changes provided by Bureau van Dijk (see http://idchanges.bvdinfo.com/, accessed on April 18, 2023) and therefore create a consistent panel of firms using multiple releases. Second, later releases provide more recent data. Therefore, some firms may have different values for the same variable in the same year. If there are duplicates, we use the most frequent observation, assuming that the most recent information is the most accurate. If the most recent information is missing, we use the average of all other observations.

Data cleaning:

[1] See http://idchanges.bvdinfo.com/ (accessed on July 28, 2021).

The dataset contained raw data which required further cleaning before it could be used econometrically:

- The financial figures of companies are derived from balance sheet data, which may use fiscal years. We have used the calendar year as a reference point and therefore assign deviating information to a given year. Firms whose financial year ends before June were assigned to the previous year.
- Monetary values were deflated using Eurostat deflators at the NACE Rev. 2, 2-digit level. Deflators for total manufacturing were used when deflators were missing at the industry level. As deflators for Malta were not available, deflators for Italy were used instead.
- Negative values of the variables turnover, persons employed, material costs and persons employed were replaced by missing values.
- The dataset contains information on the value added of an enterprise. If this information was missing, we created a variable for value added, defined as the sum of operating profit and the cost of employees.
- Bureau van Dijk provides information on the activity status of the firm. The variable can take the following forms Active, Active (dormant), Active (bankruptcy), Dissolved, Dissolved (liquidation), Dissolved (merger or acquisition), Inactive (not specified), Unknown. We restrict the sample to active firms only.

- We restrict the definition of capital stock to tangible assets only. AMADEUS also provides information on intangible assets. However, these include goodwill and therefore do not exclusively measure a firm's knowledge stock with respect to its assets.
- We limit the analysis to EU member states in 2016, the most recent year available. We could not include firms in Greece, Lithuania and Cyprus due to missing information on value added. In addition, we had to exclude firms in Luxembourg and Malta due to small sample sizes in some specifications.

Olley-Pakes productivity estimators

The Olley-Pakes estimators require information on investment, which is not available in the data. We therefore construct a proxy variable for investment, which is defined as the deflated value of tangible assets in period (t) minus the value in the previous period (t-1) plus depreciation.

Entry and exit information is not taken into account. Although the AMADEUS data provide an interesting sample for studying firm performance across countries and industries, they do not provide a complete representation of firms in a given (domestic) sector, which makes it difficult to calculate the market shares that underlie the idea of including firm entry and exit. In addition, international competition poses a further challenge to the definition of relevant markets.

The data were not winsorized as in Bloom, Draca, and Van Reenen (2016), but the top and bottom 1%-percentile observations of the productivity variables were excluded as outliers.

BACI data

This analysis requires information on imports and exports, which we obtain from the BACI database. BACI provides harmonized COMTRADE data. A typical record contains the exports of a given commodity between two countries in a given year in terms of value (US dollars), weight, and supplementary quantity (number of the supplied commodities).

COMTRADE provides two sets of series for a given trade flow when both trading partners report the transaction to the UN. Exports are generally reported on a free on board (FOB) basis, while the corresponding imports from the trading partner are reported including the cost of insurance and freight (CIF). While the two series should be identical for a given product and year (except for the CIF positions), in practice these data often prove to be inconsistent. (Gaulier and Zignago 2010). BACI ensures the consistency of bilateral trade flows reported by the exporting and importing countries. It uses mirror flows to fill in missing reports. It also estimates proxies for the correct CIF costs, which are then used to make import and export series consistent between trading partners. Trade data for Luxembourg were missing; trade data for Belgium were used for enterprises located in Luxembourg.

Matching trade and industry classifications

Matching trade with industry information is a common problem in trade research because different classifications are used and the classifications themselves change over time to reflect technological and structural developments reflected in economic activities. Correspondence tables are only available for certain versions, if at all. BACI trade data are available at the product level using the Harmonized System codes. In order to obtain sufficient time coverage, the 1992 classification (hs92, 6-digit level) is used. This system differs from the industry classification (NACE Rev. 2., 4-digit level) used in the data set at the enterprise level. Correspondence tables are used to match the activity to the industry classification. However, these are not available for hs92, so we recode hs92 to hs02, a later classification. This allows us to match the hs02 codes to NACE Rev1, an older industrial classification. Since the classification is available at a granular 4-digit level, we are able to recode the data from NACE Rev. 1 to NACE Rev. 2, which is used in the firm-level dataset. The conversion process resulted in some 4-digit classes being split into several other classes. We have distributed these values evenly across the classes.

We use harmonized trade data from the BACI database to construct measures of import competition. The database is based on the United Nations' COMTRADE database, which contains detailed import and export data reported by the statistical agencies of nearly 200 countries from 1962 to the most recent year. The database reconciles the exporter's and importer's declarations to the United Nations. The reported data are inconsistent for a number of reasons. For example, imports are reported CIF (cost, insurance and freight) while exports are reported FOB (free on board), different product classifications may apply, or the final destination is uncertain.[2] The data is adjusted for distortions due to CIF and FOB. The reliability of the reported data is also taken into account.

[2] See Gaulier and Zignago 2010 and http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=37 (retrieved on February 10, 2021).

Matching trade with industry information is a common problem in trade research because different classifications are used and the classifications themselves change over time to reflect technological and structural developments reflected in economic activities. Correspondence tables are only available for certain versions, if at all. BACI trade data are available at the product level using the Harmonized System codes. In order to obtain sufficient time coverage, the 1992 classification (hs92, 6-digit level) is used. This system differs from the industry classification (NACE Rev. 2., 4-digit level) used in the data set at the enterprise level.

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