

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

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Abstract

We revisit the impact of rising imports from China on within-firm labour productivity growth in the EU. We analyse the period 2003-2016 which covers the recent increase in technology-intensive imports from China. We uncover a changing relationship over time. Higher fractions of Chinese imports in aggregate imports exert an adverse effect on productivity growth in later periods, especially after the financial crisis 2008/09. This mirrors the changing nature of trade with China, reversing the growth-enhancing effect of import-competition. This effect is more pronounced for domestic firms, while multinationals are able to benefit from Chinese imports. Both effects become stronger at higher productivity-growth intensities. The growth-dampening effects particularly strong for firms in low-tech industries and in Southern Europe.

Keywords: import competition, multinational firms, productivity, manufacturing, EU, China

JEL: F14, L20, L60, J24

The impact of import competition from China on firm-level productivity growth in the EU

1. Introduction

The last decades have seen growing trade between developed and emerging economies. Especially firms from China have appeared as competitors to industrialised economies (Athreya and Kapur 2009). As a result, the effects of competition from emerging markets on incumbent firms and markets have become widely debated. A growing literature assesses the effects of import competition from China on regional labour markets and technology in industrialised economies (Autor, Dorn, and Hanson 2013; Autor et al. 2016; Dauth, Findeisen, and Suedekum 2014). Differences between the effects in the US and other economies have become evident suggesting that the US has experienced significantly larger effects on industrial employment than for instance Germany.

This paper revisits the effects import competition from China on the performance of firms in the European Union (EU28). Firm level studies on the impact of import competition on performance are yet rare. Evidence on European firms provided by Bloom et al. (2016) supports a growth-enhancing effect of import competition, as suggested by trade-integration models (Melitz and Ottaviano 2008). However, the period analysed ends before the financial crisis 2008/09 and thus does not cover the emergence of Chinese firms as cost-competitive high-tech exporters (Bloom, Draca, and Van Reenen 2016). This renders a change in the relationship between imports and performance likely (Baldwin 2011).

The EU offers an interesting setting to study the effects of trade, because it is a large economic bloc with centrally negotiated trade agreements and substantial economic diversity

within its boundaries. We use multiple waves of cleaned Bureau van Dijk AMADEUS data to construct a comprehensive dataset that allows us to compute firm performance indicators. We consider imports at the Nace Rev. 2 4-digit level. We regress changes in labour productivity on changes in import intensities for the three-year periods between 2003 and 2016.

We uncover a changing relationship between import- and performance-growth. While in the initial period we find a positive effect, which is in line with Bloom et al., 2016, the effect turned negative over time. In addition, we paint a differentiated picture of the effects of imports on productivity growth. Chinese imports slow down its dynamics in domestic firms. Multinationals are able to dampen the negative effects of competition from China and benefit from Chinese imports at higher growth intensities. Both effects become stronger for faster growing firms. Using a Eurostat taxonomy of technology intensities, we find that the negative effects of the growth of Chinese imports hold for firms assigned to low technology industries. The results for medium high-tech and high-tech industries are more mixed. Moreover, there is geographical variance. Especially firms in “Southern Europe” suffer from import competition. The effect is positive for firms in “Eastern Europe” and statistically insignificant for firms in the “North”.

Our contributions to the literature are twofold:

First, we provide firm-level evidence on the performance for the period 2003-2016 which suggests that the nature of competition has changed. This has theoretical implications. The results for the initial periods of the sample support a growth-enhancing effect of import competition which is in line with the model proposed by Melitz and Ottaviano (2008) that is

supported empirically Bloom et al. (2016). Yet, the effect turns negative in later periods, which suggests a change in the nature of competition driven by changes in value chains due to the unbundling of production stages that facilitates industrialisation (Baldwin 2011) and Chinese industrial policies related to subsidies and R&D. Moreover, we show that this effect is not uniformly distributed across firms. Multiple aspects of heterogeneity moderate the effects of imports from China. The effects differ across sectoral technology intensity, organisational internationalisation, growth intensity or geographic location of the firm.

Second, our findings are relevant for policy makers who seek to adjust the lens of trade and industrial policies. Currently, an economy's competitiveness and firm demography shapes its aggregate capability to benefit from trade with China. Countries with more multinational firms seem to be better equipped to cope with shocks from trade with China. Yet, the changing effect of trade with China potentially has wide policy implications. It shows that adverse effects of import competition can reach firms that are hitherto unaffected by pressures from international competition.

2. A survey of the literature

2.1 Changes in the nature of international competition

There is an ongoing debate about the effects of import competition with China. On the one hand, Melitz-type trade models suggest within-(surviving)firm productivity increases, which is supported empirically by Bloom et al. (2016) using European data up to 2006. On the other hand, a study for the US reports a growth reducing effect of Chinese import competition (Hombert and Matray 2018). Differences in the effects over time may be due to two partly

overlapping developments. First, the nature of the international division of labour could have changed. Second, Chinese industrial policies could have led to an uneven level-playing-field.

Baldwin (2011) argues that the nature of competition has changed, partly due to the availability of ICT rendering knowledge transfer easier. The division of labour has become more granular and international competition occurs at a finer degree of resolution, namely at production stages. Since firms with more sophisticated manufacturing know-how offshored some production stages, they moved their know-how along with the production. Hence, emerging economies like China could initially attract production stages rather than establish entire more complex sectoral structures, which reduced frictions in otherwise time-consuming industrialization processes (Baldwin 2011). This allows Chinese firms to compete on a low wage, high-tech basis.

In addition, the transformation of the Chinese firm base was driven by a proactive state (Mazzucato 2011) implementing a multifaceted range of industrial policies. A pivotal element has been technology imitation, which, especially in more recent years, was coupled with indigenous R&D. The technologies obtained have added to local competence base that eventually enter overseas markets through exports rather than global value chains with international partner firms (G. Zhang and Zhou 2016).

Over and above technology, the Chinese industrial development has been accompanied by subsidies. The promotion of selected firms distorts competition (Barwick, Kalouptsi, and Bin Zahur 2019; Barbieri et al. 2019; Tian 2020). This has affected international markets. For instance, Chinese subsidies led to overcapacities in the steel industries. Chinese producers

gained a competitive advantage at the cost of incumbent producers (Price et al. 2016). In other cases, the combination of technology transfer, imitation (firms could only operate in China when establishing joint ventures that received access to technology) and subsidy policies have undermined competitors of Chinese firms, like in the photovoltaic industry (F. Zhang and Gallagher 2016).

Altogether, this put Chinese firms into a position that allows them to compete internationally on the basis of both low costs and technology. Firms competing with Chinese firms not only face price competition, but also compete with an increasingly sophisticated product portfolio. As a result, imports from China rose sharply after its WTO accession on 11 December 2001 and the export portfolio has undergone rapid technological upgrading. Chinese exports are not confined to low-tech, low-cost sectors as was the case during the first phase of rapid industrial development in the 1990s. Chinese firms compete with firms from high-income countries (Athukorala 2009; Ding, Sun, and Jiang 2015).

2.2 Import competition and economic performance

The intrinsic relationship between competition and economic performance has long been recognised. By and large contributions to the economic growth literature ascribe a growth- and innovation-enhancing effect to product market competition (e.g. Denicolò and Zanchettin 2010). This effect may be reversed at very high levels of competition when there is relatively little incentive for laggard firms to innovate as incremental profits are low. Hence, growth (and innovation) and competition follow an inverted-U relationship. However, econometrically identified tipping points were found at rather high levels of competition (Aghion et al. 2005;

De Bondt and Vandekerckhove 2012; Peneder and Wörter 2014). The growth-decreasing effect can be modest, implying a plateau-shaped equilibrium relationship between competition and growth-driving innovation rather than an inverted-U (Igami and Uetake 2020). With increasing competition product differentiation becomes essential for firm survival. The marginal benefit of vertical differentiation, i.e. differentiation in terms of product quality, increases when low-cost competition increases (Hombert and Matray 2018; Sutton 1991; Zahavi and Lavie 2013). This literature analyses the effects of competition but does not distinguish by its source. National and international competitors are treated equally.

Modern trade theory offers a differentiated micro-level explanation of the impact of import competition on firm level performance (Melitz and Ottaviano 2008). In this perspective, firms producing goods and services which are easily replaced by low-cost imports cannot withstand competition and exit. In contrast, more productive, technologically advanced firms are able to escape import competition by innovation and product differentiation. In this way performance increases through a sorting effect both at the firm and the industry levels. At the firm level, the performance increases as resources are reallocated to more profitable, higher margin activities, whereas at the industry level performance increases through firm exit.

This process may come to an end, when the competitive pressure becomes too fierce. If firms are not able to upgrade their portfolio anymore and because competitors are easily able to catch up to or imitate technological advances and innovations the rate of return to R&D and investment will decline. As firms withdraw to an ever-narrower set of competencies which still offer some competitive advantage, investment and productivity will decline as firms

increasingly suffer from price competition. Finally, firms may no longer be economically viable and exit the industry altogether.

2.3 Empirical evidence on import competition and performance

Empirical work has lent support to the theoretical perspective of modern trade theory. Early studies for the United States have linked import competition to productivity increases, especially in highly concentrated markets (MacDonald 1994). Firms exposed to import competition increased their strategic focus. Firms were found to reallocate their resources towards their key portfolio and core competencies, supporting the idea that competition leads to firms concentrating on their most successful products (Bowen and Wiersema 2005).

Bernard, Jensen and Schott (2006) took this line of research an important step forward by explicitly distinguishing the origin of foreign competition. They found that across industries for the US the impact of imports from approximately fifty low-wage countries plant survival and growth were negatively associated with industry exposure to low-wage country imports, and that import competition from low-wage countries was related to within-industry reallocation towards capital-intensive plants.

They have also shown that increasing (international) competition can result in inter-industry adjustments. Plants are more likely to switch industries when exposure to imports from low-wage countries is high. Attempting to escape competition, some firms moved to activities which were less exposed to import competition. These new activities corresponded more closely to the factor endowments of the United States, i.e. the new plants were more skill- and capital-intensive.

2.4 Empirical results for Chinese import competition

With the emergence of China as the principal exporter of industrial goods, the import competition literature has recently shifted its focus on China. The impact of Chinese import competition on industrial employment was first thoroughly discussed at the regional labour-market level (Autor et al. 2016; Dauth, Findeisen, and Suedekum 2014). Relying on the theoretical framework of modern trade theory other studies have studied its firm level impact for the Europe and Japan (Bernard, Redding, and Schott 2011; Bloom, Draca, and Van Reenen 2016; Yamashita and Yamauchi 2019).

Our study is most closely related to the study of Bloom, Draca, and Van Reenen (2016) who have studied the dynamics induced by import competition with China using firm-level data on Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland, and the UK. The paper reports a structural change pattern in which workers shift from low- to high productivity firms. These effects are of the same magnitude, i.e. the aggregate effect on the labour market is balanced. Surviving firms accelerate innovation efforts when exposed to import competition from China. European firms competing against Chinese imports create more patents, become more skill-, R&D- and IT-intensive which increases their productivity, even though prices and profitability decrease. In addition, import competition accelerates the trade-induced selection of more productive firms, which leads to the exit of low-tech firms.

While the findings by Bloom et al (2016) correspond to the Melitz framework, more recent papers come to different conclusions. For instance, Hombert and Matray (2018) report for US data slower sales growth and lower firm-level profitability in response to the increasing

intensity of import-competition. This effect is smaller for firms with larger R&D stocks which are better able to compensate competitive pressure through higher product differentiation. Small firms in the EU were found to be less sensitive to import competition from low-cost countries, while they react strongly to import competition originating from other advanced countries. The opposite holds for large firms. (Colatone and Crinò 2014).

Evidence for Belgian firms shows that Chinese import competition, measured at the industry level, reduces within-firm employment growth and fosters reallocation across firms (Mion and Zhu 2013). Contrary to findings for the US, more capital-intense firms and firms with a lower share of non-production workers were found to be more affected by import competition. These effects are confined to low-tech industries, however. The results also show that import competition from China does not affect firm survival in manufacturing (Mion and Zhu 2013). Moreover, recent research on US firms finds that firms facing competition from China have shifted their expenditures toward investments with a shorter durability (Fromenteau, Schymik, and Tschke 2019). This effect is particularly strong in less productive firms, implying that these suffer from import competition through the capital accumulation channel.

We revisit some of the findings relying on an updated and more comprehensive sample of European firms than the one used by Bloom et al (2016). The main reason for this is that the sample used by these authors stops in 2007. However, the economic crisis of 2008-2009 has had an impact on the dynamics and the structure of global trade (Timmer et al. 2016) and it is to be expected that the observed empirical relations may have changed. The growth slowdown

in the aftermath of the financial crisis 2008/09 may have contributed to bring forward the adverse effects of import competition, which in an economic environment with higher market opportunity may have otherwise been overshadowed by other dynamics. The rich firm sample used in this study allows us to study firms in almost all EU Member States covering the years between 2003 and 2016.

3. Conjectures

In this period covered by our data, imports from China have not only increased, but also shifted from low- towards in high- and medium-high tech segments. Drawing on the previous literature, we develop a set of conjectures which structure the discussion of the empirical evidence:

The first conjecture departs from the Melitz model, which argues a growth-enhancing effect of import competition that is empirically supported by Bloom et al. (2016). Implementing a straightforward regression warrants negative coefficients for import intensity growth, even though they are statistically insignificant (see column (1) and (2) in Table 1 below). Hence, we first explore why our results differ from Bloom et al. (2016). Following the thought of the changing nature competition (Baldwin 2011), combined with proactive Chinese policies, we assume that increased import competition has led to a growth-dampening effect over time.

Conjecture I: The impact of increasing import intensities from China on within-firm productivity growth has changed over time, turning from initially a growth-enhancing into eventually a growth-decreasing effect.

Next, we consider the observation that the effect of import competition is moderated by several firm characteristics. In our analysis we include information on whether firms are part of a multinational enterprise group, assuming that multinational firms have better access to resources that allow them to benefit from international trade to a greater extent than purely domestic firms (Navaretti, Venables, and Barry 2004).

Conjecture IIa: Multinational firms benefit from trade with China to a greater extent than domestic firms.

Drawing on the firm growth literature (Henrekson and Johansson 2010; Coad and Hölzl 2012), we assume a nonlinear relationship between imports and firm performance. We explore the relationship between growth intensities and the effects of import growth, arguing stronger effects of imports for faster growing firms.

Conjecture IIb: The negative effects of high import growth from China become stronger for firms with higher productivity growth rates.

We jointly interpret the conjecture about the magnitude of the effect across growth intensities and the ability by multinationals to compensate the negative effects. We argue that the moderating effect becomes stronger at higher growth intensities.

Conjecture IIc: The presumed ability of multinational firms to compensate negative effects from high Chinese import growth becomes stronger at higher productivity growth rates.

Firm heterogeneity also relates to firms' technological intensity. The growth literature suggests that more competition leads to more growth for firms at a technology frontier. A growth-reducing effect is expected for firms farther away from the frontier (Acemoglu, Aghion,

and Zilibotti 2004; Ding, Sun, and Jiang 2015). The literature on regional trade shocks has identified employment spillovers in Germany to be particularly strong if triggered by shocks to high-technology industries (Helm 2020). Lacking information about firm-specific technology, we use information about the sectoral technology intensities of the firms' activities. This corresponding to previous evidence finding that firms in low-tech segments are more negatively affected by Chinese imports than firms in high tech sectors (Mion and Zhu 2013).

Conjecture IIIa: Increasing import growth from China has a stronger negative effect in low-tech industries than in high-tech industries.

Another dimension of technological capabilities relates to the geographic environment in which a firm operates, which has been found to be a relevant factor moderating the effects of import competition (Dauth, Findeisen, and Suedekum 2014). We therefore split the sample into three broadly defined country groups: "North" (e.g., Germany, France), "South" (e.g., Spain, Italy) and "CEE" (e.g. Romania, Poland).

Conjecture IIIb: Increasing imports have negative effects on productivity growth in the "South" and positive effects for firms in the "North" and in "CEE".

4. Specification and estimation strategy

To estimate the effects of trade on within firm-level productivity performance, we exploit differences in the import penetration exposure across countries and industries over time. In our estimation strategy we broadly follow previous literature (Bloom, Draca, and Van Reenen 2016; Yamashita and Yamauchi 2019; Ben Yahmed and Dougherty 2017).

We estimate the specification equation as a log-linear unobserved effects model by first differencing to strengthen the causal interpretation of the results. First difference estimators address a possible omitted-variables bias by eliminating time-invariant differences between firms. Hence, we regress productivity growth ($\Delta LP_{j,s,c,t}$) on changes in import ($\Delta ImI_{s,c,t}$) intensities to obtain elasticities for productivity growth. The basic productivity growth equation reads:

$$\Delta LP_{j,s,c,t} = \alpha_0 + \beta_1 \Delta ImI_{s,c,t} + \beta_3 \Delta CAP_{j,s,c,t} + \alpha_s + \alpha_t + \alpha_c + e_{j,s,c,t} \quad (1)$$

where LP denotes a firm j 's labour productivity located in sector s and country c in year t , $(ImI)_{sct}$ is the import share at the sector-country-year level. CAP_{j_sct} 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, and time and sector fixed effects; e denotes the error term.

Following the literature, in addition to OLS regressions we implement a 2SLS-identification strategy with robust standard errors since productivity growth may be endogenous with import dynamics. There may be unobserved supply and demand shocks affecting trade and performance, which implies that the coefficients may suffer from reverse causality. We address this issue by using an instrumental variable strategy following approaches used in the previous literature on Chinese import competition (Autor, Dorn, and Hanson 2013; Bloom, Draca, and Van Reenen 2016; Dauth, Findeisen, and Suedekum 2014).

We compute the import intensity for a group of extra-EU economies. The countries' wealth is largely comparable with average EU Member State and capture the size of the shock, which is why developing countries are excluded. At the same time the countries in the

identification group do not share the same shocks as the countries under consideration. We use the mean values of the import intensities of Australia, New Zealand, USA, Canada, Israel and Japan. Computing the mean of shares avoids bias towards larger countries. Given the differences in the competitive positioning, these are countries for which we do not expect significant correlations between demand and supply shocks with the firms in our sample. The idea is that the rise of China in the world economy induced supply shocks for all trading partners. Using information for these countries identifies the exogenous component of rising competitiveness of China and purges shocks that are specific to the country, region or industry.

Eventually, we use quantile (least-absolute-value) regressions with bootstrapped standard errors (100 replications) to allow the effect of increasing import intensities to differ across the productivity growth distribution. We estimate the quantiles of the conditional distribution as linear functions of the explanatory variables, including time and country fixed effects. We implement a simultaneous quantile regression for the 25%-, the 50%- and the 75%-percentiles. We uncover varying coefficients, which indicates that the data are heteroskedastic, which regressions to the mean cannot capture. Since quantile regression are perceived as a way to reduce large outliers, these specifications draw on the full sample, i.e. the outliers, defined as the top and bottom 1% of the distribution of the dependent variable, are considered (Koenker and Hallock 2001; Angrist and Pischke 2008).

5. Data and variables

Our analysis draws on a wealth of data from multiple sources to be able to depict performance and trade relationships over time and thereby overcome compatibility issues of

multiple classifications. We create a unique dataset and provide an extensive discussion of the construction of the indicators used in “Annex B: Robustness checks”.

The firm level indicators are based on AMADEUS, a dataset provided by the Bureau van Dijk.¹ We use multiple ten-year waves of AMADEUS data to generate a panel of firms. In a first step, the survey waves had to be made comparable. Each release contains a firm identifier, which is unique within each release but not across releases. Drawing on information on identifier changes provided by Bureau van Dijk, we construct unique firm identifiers to control for breaks in the records. This dataset was then thoroughly cleaned with respect to duplicate entries due to data updates, outliers, missing values etc.

All nominal values were deflated using Eurostat deflators at the most granular, Nace Rev. 2 digit-level available. This is important since fiercer competition should exert a price-decreasing effect (Auer and Fischer 2010; Weyl 2019). The sectoral inflation rate is negatively and significantly correlated with changes in import intensities (ρ : -0.02).

5.1 Firm performance

The key outcome performance variable is labour productivity, defined as the firm specific value added divided by the number of employees. This indicator has been criticised because it does not consider a firm’s capital intensity. To address this concern, we include the firm-specific fixed asset growth in the labour productivity growth estimations (Syverson 2011).

In addition, we define a measure of a firm’s lagged distance to the industry-specific labour productivity frontier firm in percent. Higher values therefore indicate a greater distance

¹ See <https://www.bvdinfo.com/en-gb/our-products/data/international/amadeus> (accessed on 18th February 2020).

to the frontier and a bigger catching-up potential, while the frontier firm receives a value of zero. The threshold for frontier firms is defined as the productivity level at the 95%-percentile at the Nace Rev. 2 3-digit level for each period of observation. The choice of the industry-level was motivated by the need to obtain a sufficient number of observations while defining the industry at a level as granular as possible. In the regression analysis we use the distance indicator in logarithmic terms.

5.2 Multinational enterprises

Moreover, we use information about a firm's ownership structure. We define a dummy variable taking on the value of one if a firm is part of a multinational group, and zero otherwise. Since AMADEUS only covers European firms, we used an opportunity to access global ownership information from Bureau van Dijk's ORBIS database.² Differentiation between firms belonging to a multinational enterprise group and domestic firms is necessary because of the different networks and production factors which they can access (Navaretti, Venables, and Barry 2004).

5.3 Import intensity

We matched the firm-level data with trade data obtained from BACI, which is a harmonised trade data set containing information on imports. We follow previous literature (Bernard, Jensen, and Schott 2006; Bloom, Draca, and Van Reenen 2016) and compute a Chinese import intensity indicator which is based on a value-share approach. The measure

² We define being a multinational firm as a time invariant characteristic. For further information about the data see <https://www.bvdinfo.com/en-us/our-products/data/international/orbis> (accessed on 5th August 2020).

draws on Chinese imports (IMP_C) and total imports (IMP_{TOT}). Import intensity is then defined as the share of Chinese in total imports (IMP_C/IMP_{TOT}) in a given country, year and Nace Rev. 2, 4-digit industry.

Matching trade data with industry affiliations to which firms in AMADEUS are assigned was challenging, because BACI is a product-based and not an industry classification. To match trade data with the industry classification used in AMADEUS (Nace Rev. 2., 4-digit), we recode hs92 6-digit data to hs02, for which a Nace Rev. 1 correspondence table is available, which again can be transformed into Nace Rev. 2 data at the four-digit level (see Annex).

5.4 Outliers and control variables

Our target variable is labour productivity, which may suffer from outliers possibly biasing the results. We therefore exclude the top and bottom 1%-percentile of the observed firm productivity growth distribution. Imports from China are measured at the Nace Rev. 2 4-digit level and may also be subject to outliers. Due to the disaggregated perspective, imports, especially in smaller countries, are volatile across years. To smooth the data, we use five three-year periods (2003-2005, 2006-2008, 2009-2011, 2012-2014 and from 2015 onwards).

We include three-year period dummies to capture sample-wide time effects. Since productivity developments may hinge on unobserved country and sector characteristics, we control for country and sector fixed effects.

China became the world's largest exporter of goods, and its portfolio has substituted goods of other emerging economies like India or Singapore (Pham et al. 2017). It is possible that the effects of multinationals change when firm-specific catching-up processes are included

in the regression (Acemoglu, Aghion, and Zilibotti 2004). We therefore add the time-varying, firm-specific distance-to-the-frontier variable in the full specification to test if the results hold if catching-up mechanisms are considered.

6. Descriptive results

The data allows us to paint a descriptive picture along the lines of the previously posed conjectures. The total sample consists of 375,041 firms in twenty-five EU countries (data for Greece, Cyprus and Lithuania are missing; the UK is included, because it was an EU Member State in the period analysed). Only active firms were considered. Information on insolvent or bankrupt firms was not used.

6.1 Labour productivity and import intensities

The mean of labour productivity in real terms amounts to 42.4k Euros (reference year 2010). The firms with the highest median labour productivity are found in the Austria (EUR 73.6k), the Netherlands (71.8k) and Luxembourg (69.8k), while the lowest average productivity levels are in Bulgaria (4.5), Romania (5.5k), and Hungary (11.2k). Hence the sample broadly mirrors the cross-country distribution of GDP per capita as an economy-wide productivity measure.

In the first period observed (2003-2005), the sample wide import intensity was on average at 4.8%. It rose to 7.5% in the last period observed (2015-2017). When considering the EU as a bloc, these figures indicate a difference in both levels and dynamics in comparison to the reference pool of other industrialised countries. The sample mean of the instrumental variable that we use in the 2SLS regression was in the first period 11.2% and increased by the

last period to 17.4%. Hence, the global exposure to Chinese import competition was higher in the first period of our study than the exposure of European at the end of the period analysed.

Then again, the mean import intensities vary vastly across countries. Particularly high shares are observable for the industries in the United Kingdom (11.7%), Italy (8.6%) and Poland (7.9%). The countries with the lowest import intensities from China are Hungary (2.4%), Latvia (2.8%) and Austria (3.2%). Labour productivity levels and import intensities are weakly correlated (ρ : 0.03, p -value <0.01). Chinese imports have expanded markedly in the United Kingdom (1.11%), Slovenia (1.08%), Malta (1.00%) and Spain (0.93%). The mean import intensities have decreased in Bulgaria (-0.34%), Romania (-0.16) and Croatia (-0.10%).

6.2 Productivity growth

Labour productivity growth varies across countries, with an annualised pooled mean growth rate of 1.3%. The highest annual productivity growth rates are on average observable in Poland (4.2%), Romania (3.8%), Estonia (3.9%). On average, the lowest growth rates of the firms in the sample are found in Ireland (-2.4%), the Netherlands (-1.0%) and Austria (0.1%). Labour productivity growth and the growth of import intensities are uncorrelated (ρ :0.00, p -value >0.1).

The mean growth rates of firms in New Member States in Central and Eastern Europe tend to be larger than in Old Member States. Thus, productivity growth should be interpreted against the backdrop of catching-up dynamics. We therefore define a sectoral distance-to-the-frontier. The measures show that overall productivity performance is achieved by firms that – at least partly – differ in their relative sector-specific performance. The measure

of the distance to the sectoral productivity frontier, a relative competitiveness measure, is highly and positively correlated with productivity growth ($\rho:0.18$).

The sample is more mixed when it comes to the mean distance to the productivity frontier. The countries with the lowest mean of the distance indicators are Malta (2.9%), Latvia (3.3%) and the Netherlands (7.6%), whereas the countries with the highest distance are Romania (87.2%), Croatia (80.1%) and Bulgaria (72.4%). The growth of import intensities is weakly and negatively ($\rho: -0.03$, $p\text{-value}<0.01$) correlated with the distance to the productivity frontier. This shows a slight tendency of Chinese imports targeting more productive markets.

6.3 Multinational enterprises

15.7% of the firms in the sample are multinational enterprises. They differ from domestic firms in the key variables. At 109.9k Euros, their mean labour productivity is significantly higher than the mean of domestic firms (57.3k Euros; real terms, reference year 2010). Differences in performance are also observable in growth intensities. The mean domestic annualised firm grows in labour productivity 1.3%. The mean growth rate of multinationals is at 1.7% significantly higher. These differences become visible across the distribution of growth rates. While there are no ostensible differences in lower growth intensities, the gap between multinationals and domestic firms widens, especially for firms growing faster than the median growth rate of 2.7%.

The Industries to which multinationals are assigned face slightly more import competition from China (7.5% for domestic firms and 7.6% for multinationals; the difference

is statistically significant, p-value: 0.015). Industries in which multinationals are active also experienced a slightly higher growth in Chinese imports (0.9%) than domestic firms (0.8%).

6.4 Technology intensity and sector evidence

Since data on firm-specific capabilities and technologies are largely missing, we apply a classification provided by Eurostat that splits sectors by their technology intensity.³ Similar taxonomies have been applied in previous studies about competitiveness and trade (Birch, MacKinnon, and Cumbers 2010; Pham et al. 2017). Four classes are defined:

- high-technology (e.g., ICT and pharma),
- medium-high-technology (e.g., chemicals or machinery and equipment),
- medium-low-technology (e.g., basic metals or rubber and plastic products) and
- low-technology (e.g., textiles or furniture).

The developments of Chinese import intensities showed remarkable different developments over time. In the first period (2003-2006) of the sample, imports from China accounted for 5.4% in low-tech industries and increased slightly to 6.8% in the last observed period. Medium-low tech industries increased their import penetration ratios from 3.8% to 7.2% and medium-high tech industries from 6.6% to 11.6%. The increase in imports was most pronounced in high-tech industries with Chinese import intensities rising from 6.6% to 14.8%. This shows that China is predominantly a medium-high and high-tech exporting country. The increase in imports from China was most pronounced in high-tech industries

³ See https://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:High-tech_classification_of_manufacturing_industries (accessed on 24th January 2021).

This picture from sector taxonomies are reflected at the more granular Nace Rev. 2, 2-digit industry-level. We study the mean import intensity growth in a pooled sample. The industries with the most dynamic expansion of Chinese import intensities were the Manufacture of computer, electronic and optical products (2.1%) and the Manufacture of electrical equipment (2.5%) and the Manufacture of machinery and equipment n.e.c. (1.1%). The industries with the lowest import intensity growth were the Manufacture of tobacco products (-0.4%) and the Manufacture of leather and related products (-0.18%).

7. Regression results

We test the conjectures posed above in a series of regressions of labour productivity growth on changes in trade intensities measured at the Nace Rev. 2 4-digit industry level. In our basic specification shown in Table 1, columns (1) and (2), we find a negative effect of import intensity growth on labour productivity growth. The coefficients are statistically insignificant, however.

To test *Conjecture I*, stating that there are time varying coefficients that capture initially positive and eventually negative effect we include an index variable for the five periods that we interact with the changes in import competition ($\Delta \text{Import} * \text{Period}$) over and above the individual time dummies. We find a positive and significant coefficient for changes in import competition. This indicates that there was a positive effect in the first period of our sample, which overlaps with the period studied by Bloom et al. (2016). However, the interaction term is negative and significant. Multiplying the term with the period variable shows that the

aggregate effect turned negative after the financial crisis 2008/09 (Table 1, columns (3) and (4)). Thus, our results provide evidence for *Conjecture I*.

Table 1 about here

Next, we test the *Conjecture IIa* which states that multinationals cope better with imports from China. Hence, we introduce firm characteristics that capture the heterogeneous reactions of firms. We include a time-invariant dummy variable measuring if a firm is part of a multinational enterprise group and interaction of multinationals with changes in import intensities (Table 1, columns (5) and (6)). The coefficient measuring if a firm is part of a multinational is statistically insignificant. Yet, the interaction terms of being a multinational with import intensity growth show positive coefficients in both the OLS and the 2SLS specification. The negative effect of changes in import intensities is dampened.

Next, we implement quantile regressions for nine quantiles separately to test whether the negative effects obtained from the OLS and 2SLS regressions are uniform across the growth distribution. We thereby test *Conjecture IIb*, which states that the negative effects become stronger at higher growth-intensities. Columns (7) to (9) of Table 1 show that the adverse effect of Chinese imports varies across the productivity-growth distribution. While the coefficient at the 25%-percentile is statistically insignificant, it turns negative and significant at the 50%-percentile. The negative effect gains in magnitude at higher growth intensities, which is

why we support the conjecture that negative effects of trade become stronger at higher productivity-growth intensities.

Conjecture IIc suggests that the ability of multinational firms to compensate adverse effects from Chinese imports becomes stronger at higher growth intensities. To test this conjecture, we jointly interpret both the coefficient for being a multinational and the coefficient of the interaction effect of the multinational dummy with import intensity growth (Table 1).

The coefficients for being part of a multinational group are significantly positive for all three quantile regressions and increase with higher productivity growth rates. Thus, being part of a multinational positively affects productivity growth. This growth premium is particularly pronounced when multinationals perform well.

The coefficients of the interaction effects are positive and significant in these specifications. They gain in magnitude with increasing productivity growth. Hence, faster growing multinationals are not only better able to dampen the adverse effects of import competition, they also gain from import growth from China.

Eventually, we test whether there are differences across technology intensities (*Conjecture IIIa*). We assign firms to the Eurostat taxonomy using Nace Rev. 2 industry information and run the regression for each level of technology intensity separately. Table 2 shows the results of the 2SLS specifications controlling for endogeneity for low- technology industries (column (1)), medium-low technology (2), medium-high technology (3) and high-technology industries (4). We find significantly negative coefficients of imports from China in low-tech industries. The results for firms in medium-low and medium-high technology

industries are insignificant. The effect is negative and weakly significant for firms assigned to the high-tech sector.

Table 2 about here

The control variables perform as expected. The dummy variables are jointly significant, and the coefficients of the growth of the capital stocks remain significantly positive in all regressions. The adverse effects of increasing import intensities from China are robust to the inclusion of the lagged distance to the frontier variable in logarithmic levels. The coefficients of the distance variable are positive and reflects catching-up mechanisms.

Eventually, we run the regressions for country groups to test Conjecture IIIb, stating that there is a growth-enhancing effect of import competition for firms in the country group “North” or “CEE” and a negative effect for firms in the “South”. The regression results reveal a positive coefficient for increasing import intensities for firms in Central and Eastern Europe. Firms in Southern European countries face adverse effects from competition. The results for firms in Northern Europe are statistically insignificant, even though the coefficient is positive.

Table 4 about here

8. Discussion

Trade with China has changed significantly over the period analysed. China's export portfolio increasingly shifted towards high-tech goods like ICT. In addition, Chinese industrial policies have enabled Chinese firms to compete both on a price and technological basis. This is supported by trade statistics which reveal that especially high-tech imports from China have increased substantially, especially after the financial crisis of 2008/09. This led us to the first conjecture presuming that imports from China initially had a positive effect on within-firm productivity growth, which decreased over time and eventually turned negative. This conjecture is strongly supported by our regression analysis. Increases in trade with China exerts a negative effect on productivity-growth in later periods in our sample.

Even though trade theory tends to highlight the benefits of trade (Feenstra 2015; Fujita et al. 1999), it does not deny that such a situation can occur. The theory of comparative advantage predicts that increased international competition could negatively affect some groups in the country. The rise of China as an exporting power is exceptional. It has been manufacturing-driven, in contrast to natural resources as in most other BRICS countries. Using a simple two-country, two-goods Ricardian model Samuelson (2004) showed that productivity gains in one country can benefit that country alone (here China), and permanently hurt another country (or trading bloc) by reducing the gains from trade, despite positive aggregate gains (Samuelson 2004). The modern economic literature on the impact of trade on performance is largely built on models characterised by a gravity structure or that are based on a monopolistic competition model of international trade with cross-country productivity differences

(Arkolakis, Costinot, and Rodríguez-Clare 2012; Autor et al. 2016; Autor, Dorn, and Hanson 2013).

The level of observation is critical when interpreting this empirical result, however. While productivity is measured at the firm-level, imports are measured at the Nace. Rev. 2, 4-digit industry-level. The coefficient therefore means that the effect of increasing industry-wide imports from China have, on average, a negative effect on productivity growth of firms in the respective 4-digit industry. However, firms differ in their capabilities, behaviour and access to resources.

Firm heterogeneity has been documented to moderate the effect of import competition from China (Mion and Zhu 2013; Fromenteau, Schymik, and Tschke 2019). We analyse whether multinational firms are more productive and better able to incorporate the benefits from international trade, and include a dummy variable measuring if a firm is part of a multinational group. In both the OLS and IV regressions that consider global trade trends, the interaction term of being a multinational and the changes in trade intensities warrants weakly significant, negative coefficients. Hence, being a multinational firm helps dampening the negative effects of imports from China.

The magnitude of the dampening effects is contingent on the growth intensity, which is shown in the quantile regressions. These depict the impact of changes in trade intensities on labour productivity growth across the distribution of growth rates. The faster domestic firms grow in their labour productivity the higher the pressures they face from rising Chinese imports

become. The opposite holds for multinational firms. The faster multinationals grow in labour productivity the more they are able to dampen pressures from Chinese import competition.

The descriptive statistics show that the increase in Chinese imports is driven by high-tech goods. China has long been seen as a producer and exporter of goods and services with low skill content in low-quality price-sensitive market segments (Bloom, Draca, and Van Reenen 2016) or competing in a South-South fashion (e.g., Dawar and Chattopadhyay 2002; Lall and Albaladejo 2004). Our data supports recent evidence that Chinese firms are increasingly entering market segments hitherto served by firms from industrialised economies (Autor, Dorn, and Hanson 2013), even though misallocations in emerging economies such as China itself remain (Hsieh and Klenow 2009).

Stage models of economic growth (Acemoglu, Aghion, and Zilibotti 2004) suggest that more (trade induced) competition may impede growth processes in low-tech industries in advanced economies. To examine whether technology intensities explain the different effect of Chinese import intensity growth on productivity growth, we use a sector taxonomy that splits the manufacturing sector according to the technological intensity into high-technology, medium-high, medium-low and low-technology industries and run separate estimations.⁴ The mean Chinese import intensity in high-tech industries in the EU amounts to approximately 12.9%, while in low-tech industries it is less than half of this value (5.4%). The exposure to Chinese imports is more pronounced in medium high-tech and high-tech sectors, refuting the notion of China being a producer of low-cost, low-tech products. The regression results show

⁴ See https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf (accessed on 14th February 2020).

that firms in low-tech suffer lower productivity growth due to increasing trade intensities with China. While firms in medium-low and medium-high tech industries show insignificant results, we uncover a negative, yet weakly significant coefficients for high-tech industries. Hence, different specialisation patterns, measured by sectoral technology intensities, also explain the different impact of increasing Chinese import intensities across firms.

This pattern is broadly reflected by different effects across the geographic location in the EU. Firms in CEE benefit increases in imports from China. The effects for Northern European countries are not statistically significant. Southern European countries face negative effects of increased trade with China.

The control variables show the expected signs. Increases in labour productivity are associated with increases in the capital stock. In addition, firm productivity levels within the EU's industries vary greatly. Some countries, for instance in Central and Eastern Europe, are still in a catching-up process. The coefficient of the industry-level distance-to-the-frontier, a measure of the speed of catching-up processes, corresponds to the catching-up effects typically found in the growth literature.

8.1 Economic impact

We use the coefficients of the quantile regressions reported in **Fehler! Verweisquelle konnte nicht gefunden werden.** to estimate the economic impact of the changes in Chinese import intensities across the distribution of labour productivity growth rates. We distinguish between the effects of domestic and of multinational firms. The impact of import shocks on domestic firms' productivity growth is estimated as the product of the quantile-specific

coefficient of the effect of rising import intensities and import growth ($\beta_{\text{quant, IMP}} \cdot \Delta \text{IMP}$). The impact of shocks on multinational firms' productivity growth is computed as the sum of (i) the product of the quantile-specific coefficient of the effect of rising import intensities and import intensity growth, (ii) the effect of being a multinationals on growth, and (iii) the interaction effect of the joint impact of import intensity growth and being a multinational ($\beta_{\text{quant, IMP}} \cdot \Delta \text{IMP} + 1 \cdot \beta_{\text{quant, NE}} + \beta_{\text{quant, aINT}} \cdot \Delta \text{IMP}$). We estimate the impact of changes in Chinese import intensity on annualised labour productivity growth for the 20%-percentile, the median and the 80%-percentile.

We examine two import intensity shocks. First, we use the mean import intensity growth to simulate the effect on annualised labour productivity growth, all other things equal. Second, we use the mean import intensity growth plus one standard deviation. The second shock is used because we observe substantial variance in the changes of Chinese import intensities. For instance, the 10%-percentile import intensity change shows a decline from one three-year period to another of approximately -1.0%, while at the 90%-percentile import intensity grows by 3.6%.

Table 3 about here

For domestic firms, there is no impact for 25%-percentile, which turns slightly negative for firms growing at the median growth-rate and becomes stronger at the 75%-percentile. These

effects become stronger when the impact of the estimated shock becomes larger, i.e. when one standard deviation is added to the mean growth of the Chinese import intensities.

A different pattern is observed for multinational firms. There is a slight positive effect for low growth-intensities at the 25%-percentile, indicating that multinationals are better able to cope with rising import competition from China, even at low productivity growth intensities. The positive effect further increases at higher growth intensities. Increases in imports from China have a strongly growth-enhancing effect at the 75%-percentile of the productivity growth distribution. Again, increasing the intensity of the shock increases the magnitude of the effect.

8.2 Robustness checks

The key outcome performance variable is labour productivity, defined as the firm specific value added divided by the number of employees. However, this approach has been criticised because it does not consider the capital intensity in the computation of the performance indicator. Hence, we include changes in the capital stock as a control variable in the labour productivity estimations. Total factor productivity (TFP) indicators pose an alternative approach. The literature suggests multiple computational methods, each leading to slightly different outcomes affecting the robustness of the results (Syverson 2011; Rovigatti and Mollissi 2018). To implement further robustness checks, we use the available financial information to estimate an Olley-Pakes productivity indicator. We use pooled cross-country data and estimate the TFP indicator separately for each Nace Rev. 2, 2-digit industry to uncover a sector-specific productivity indicator which we use instead of labour productivity.

The results from the robustness check resemble the core results reported the Annex (see Annex B: Robustness checks). Increasing import intensities from China have led to slower TFP growth over time. Low-tech industries and firms in Southern Europe are strongly affected. The results also suggest a negative effect of increasing import intensities on domestic firms, which is marginally insignificant, however.

The quantile regressions presented in (Table 1) do not consider possible endogeneity. We therefore expand the baseline specification to instrumental variable quantile regressions (Chernozhukov and Hansen 2008; Machado and Santos Silva 2019). The results remain qualitatively unchanged. The negative effect of increasing import intensities becomes stronger the faster firms grow in their labour productivity. The magnitude of the effect is larger than in the quantile regressions reported in Table 1. This analysis is confined to the baseline specification, because the interaction term would imply an additional endogenous variable, while the IV quantile regression estimators only allow for one endogenous explanatory variable.

8.3 Limitations

The aggregate impact of trade with China on employment and productivity has been argued to be balanced in firm level studies (Bloom, Draca, and Van Reenen 2016; Mion and Zhu 2013) but to be negative at the regional level (Autor, Dorn, and Hanson 2013). The evidence that we provide in a pooled cross-country panel suggest negative effects, even though these are dampened, and partly reversed, by a more internationalised and technology intensive firm demography. Our results imply that an industry's aggregate capability to benefit from imports from China is shaped by the composition of multinational and national firms. From an

aggregate perspective, countries with more multinationals are likely to benefit from Chinese imports, while economies dominated by national firms are likely to experience slower productivity growth. This stretches beyond the previous literature on multinationals, which typically discusses productivity effects between parent and subsidiary firms (Farinas and Martín-Marcos 2010; Navaretti, Venables, and Barry 2004).

Like other studies on Chinese import competition, we estimate partial equilibrium models and therefore cannot capture the entirety of the welfare effects of trade. Previous literature has used firm entry and exit information obtained from AMADEUS data (Bloom, Draca, and Van Reenen 2016). We refrain from such an approach with these data. They are a viable source to study within-firm dynamics, firm turnover would require greater levels of representativity that is rather provided by register data.

9. Conclusions

Drawing on the import competition literature, this paper revisits the impact of imports on within-firm productivity. Trade theory argues that import competition spurs growth (Melitz and Ottaviano 2008) which has been supported empirically for European data before the financial crisis 2008/09 (Bloom, Draca, and Van Reenen 2016). We argue that the nature of competition has changed due to transferability of knowledge leading to a further unbundling of value chains (Baldwin 2011). This has been accompanied by Chinese industrial policies. Evidence is mounting that firms facing competition from China find it hard to escape competition through technological upgrading, because China offers technologically intensive products. China has become a high-tech exporter. In addition, price competition is distorted due

to Chinese subsidy policies. Firms in industrialised economies are therefore forced to absorb the import shock through pressure on prices and sales revenues, eventually leading to a negative effect on productivity growth.

We study the effects of growth in Chinese imports on the within-firm productivity growth of firms in the European Union between 2003 and 2016. We use a unique sample of approximately 375,000 firms in the EU drawn from a thoroughly cleaned version of the AMADEUS database. We match firm performance with import data at the Nace Rev. 2, 4-digit level, which was possible after implementing a series of HS-reclassifications.

The regression results show that the nature of competition has changed. While we find a growth-enhancing effect of increasing import intensities prior to the financial crisis, this effect has reversed in the later periods of the sample. The results paint a differentiated picture of the effects. We find that increasing sectoral imports from China impedes the productivity growth of the average firm. However, multinational firms are able to benefit from growing import intensities. The negative effects of competition from Chinese imports are not observed for multinationals, which benefit from trade with China. Both effects become stronger at higher growth intensities. In addition, the effects differ across technology intensities. Low-tech and to a lesser degree high-tech industries are more affected. Medium-low and medium-high tech industries are unaffected by imports from China.

This suggests that the firm demography is relevant in an economy's aggregate capability to benefit from trade with China. Countries with more technology intensive industries or more multinational firms are likely to be better equipped to cope with shocks from trade with China.

Economies dominated by domestic, low-tech firms are likely to experience performance losses competitive pressures. Further empirical findings show that firms in Southern Europe experience negative effects of trade with China, while firms in CEE benefit from higher trade intensities. The results for Northern Europe are insignificant.

Overall, these empirical findings suggest a mixed picture. For many firms, competition has become too fierce for firms to escape competition. Others are able to benefit from trade. The EU-wide, average effects have changed and turned negative over the period studied, however. Competitive pressures from China are expected to accelerate with “Made-in-China 2025”, China’s industrial strategy (Li 2018), which not only seeks to further upgrade the Chinese economy technologically, but also to achieve independence from foreign suppliers in “core products” such as semiconductors, aerospace, IT or biotechnology. Hence, our results add to the debate about trade policies and the effect of Chinese industrial policies, such as competition distorting subsidies, IPRs and market protectionism.

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Tables

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

Estimator	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specification	OLS	IV	OLS	IV	OLS	IV	QUANT	QUANT	QUANT
Δ Import intensity	Basis -0.02 (0.015)	Basis -0.01 (0.049)	Period 0.26*** (0.054)	Period 0.37*** (0.122)	MNE -0.03** (0.016)	MNE -0.09* (0.051)	25%-perc. -0.00 (0.014)	50%-perc. -0.05*** (0.011)	75%-perc. -0.10*** (0.017)
Δ Import * Period			-0.08*** (0.014)	-0.11*** (0.034)					
Δ Import * MNE					0.09** (0.042)	0.47*** (0.111)	0.08* (0.045)	0.12*** (0.035)	0.16*** (0.043)
MNE					0.05*** (0.001)	0.04*** (0.002)	0.02*** (0.002)	0.04*** (0.001)	0.07*** (0.002)
Δ Capital					0.05*** (0.001)	0.05*** (0.001)	0.04*** (0.001)	0.05*** (0.001)	0.07*** (0.001)
Distance, lagged					0.15*** (0.001)	0.16*** (0.001)	0.17*** (0.001)	0.13*** (0.001)	0.13*** (0.001)
Time effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector effects	Y	Y	Y	Y	Y	Y	N	N	N
Country effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Constant	0.29*** (0.006)	0.22*** (0.006)	0.29*** (0.006)	0.22*** (0.006)	0.27*** (0.006)	0.20*** (0.006)	0.15*** (0.005)	0.27*** (0.006)	0.38*** (0.008)
Observations	625,172	625,172	625,172	625,172	624,604	624,604	734,864	734,864	736,567
R ²	0.075	0.075	0.075	0.075	0.077	0.077	0.045	0.038	0.047

Note: Growth rates (denoted by Δ) are measured in logarithmic terms for three-year means, all variables except “distance” in first differences. F-tests of all specifications are highly significant (p-value<0.01). Wald test for joint significance of the interaction effects are all highly significant (p-value<0.01). Robust standard errors in parentheses for specification (1)-(6). Bootstrapped s.e. with 100 replications in specification (7)-(9). *** p-value<0.01, ** p-value <0.05, * p-value <0.1.

Table 2: Labour productivity growth and changes of Chinese trade intensities across technology classes

	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
Tech. Taxonomy	Low	Medium-low	Medium-high	High
Δ Import intensity	-0.26** (0.110)	-0.07 (0.077)	0.13 (0.113)	-0.17* (0.103)
Δ Capital	0.06*** (0.001)	0.06*** (0.001)	0.04*** (0.002)	0.03*** (0.004)
Distance, lagged	0.14*** (0.002)	0.15*** (0.002)	0.16*** (0.003)	0.18*** (0.007)
Time effects	Y	Y	Y	Y
Sector effects	N	N	N	N
Country effects	Y	Y	Y	Y
Constant	0.23*** (0.009)	0.23*** (0.010)	0.20*** (0.011)	0.17*** (0.023)
Observations	226,496	221,312	151,998	25,366
R ²	0.057	0.092	0.092	0.125

Note: This table reports the regression results of the impact of changes in import competition on changes in productivity growth across technology intensities. 2SLS estimators are used. Growth rates (denoted by Δ) are measured in logarithmic terms for three-year means, all variables in first differences. F-tests of all specifications are highly significant (p-value<0.01). Robust standard errors in parentheses, *** p-value<0.01, ** p-value <0.05, * p-value <0.1.

Table 3: Economic impact of trade with China

Quantile	Mean import growth intensities			Mean plus s.d. import growth intensities		
	25%-perc.	Median	75%-perc.	25%-perc.	Median	75%-perc.
MNE	0.84%	1.34%	2.11%	0.93%	1.55%	2.44%
Domestic	0.00%	-0.12%	-0.25%	0.00%	-0.17%	-0.37%

Note: This table reports the annualised economic impact of trade with China for domestic and multinational firms. Drawing on the quantile regression results (**Fehler! Verweisquelle konnte nicht gefunden werden.**), it computes the effect of the changes of the mean trade intensity and the mean plus one standard deviation.

Table 4: Labour productivity growth and changes of Chinese trade intensities across country groups and countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Country group	South	CEE	North	Germany	France	Italy	Spain	UK	Poland
Δ Import intensity	-0.11** (0.049)	0.57** (0.265)	0.10 (0.104)	0.59*** (0.132)	-0.19 (0.165)	-0.09 (0.054)	-0.16 (0.142)	-0.81** (0.384)	0.15 (1.242)
Δ Capital	0.05*** (0.001)	0.07*** (0.002)	0.03*** (0.001)	0.02*** (0.003)	0.03*** (0.002)	0.06*** (0.001)	0.04*** (0.002)	0.01* (0.005)	0.11*** (0.008)
Distance, lagged	0.16*** (0.002)	0.50*** (0.014)	0.11*** (0.002)	0.08*** (0.003)	0.13*** (0.003)	0.15*** (0.002)	0.17*** (0.004)	0.13*** (0.005)	0.36*** (0.033)
Time effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country effects	Y	Y	Y	N	N	N	N	N	N
Constant	0.13*** (0.002)	0.26*** (0.007)	0.13*** (0.006)	0.07*** (0.006)	0.13*** (0.005)	0.16*** (0.004)	0.16*** (0.004)	0.02*** (0.007)	0.25*** (0.027)
Observations	299,380	137,911	187,881	35,729	61,698	183,259	90,329	30,451	10,617
R ²	0.097	0.089	0.082	0.088	0.095	0.121	0.079	0.082	0.080

Note: This table reports the regression results of the impact of changes in import competition on changes in productivity growth across country groups and for large individual EU Member States. The country group “South” consists of IT, MT, PT, ES; the group “North” of AT, BE, DK, FI, FR, DE, IE, LU, NL, SE, UK; the group “CEE” of BG, HR, CZ EE, HU, LV, PL, RO, SI, SK. 2SLS estimators are used. All estimations in 2SLS. Growth rates (denoted by Δ) are measured in logarithmic terms for three-year means, all variables in first differences. F-tests of all specifications are highly significant (p-value<0.01). Wald test for joint significance of the interaction effects are all highly significant (p-value<0.01). Robust standard errors in parentheses, *** p-value<0.01, ** p-value <0.05, * p-value <0.1.

Annex B: Robustness checks

Table 5: Impact of changes in import intensities on TFP growth

Estimator	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specification	OLS	IV	OLS	IV	OLS	IV	QUANT	QUANT	QUANT
	Basis	Basis	Period	Period	MNE	MNE	25%-perc.	50%-perc.	75%-perc.
Δ Import intensity	-0.00 (0.015)	0.00 (0.048)	0.42*** (0.053)	0.60*** (0.121)	-0.01 (0.016)	-0.07 (0.050)	-0.02 (0.017)	-0.06*** (0.013)	-0.13*** (0.018)
Δ Import * Period			-0.12*** (0.014)	-0.18*** (0.034)					
Δ Import * MNE			0.08* (0.044)	0.51*** (0.118)			0.07 (0.041)	0.09** (0.038)	0.11** (0.045)
MNE					0.06*** (0.001)	0.05*** (0.002)	0.02*** (0.001)	0.05*** (0.001)	0.09*** (0.002)
Distance, lagged	0.11*** (0.001)	0.11*** (0.001)	0.11*** (0.001)	0.11*** (0.001)	0.12*** (0.001)	0.12*** (0.001)	0.10*** (0.001)	0.09*** (0.001)	0.11*** (0.001)
Time effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector effects	Y	Y	Y	Y	Y	Y	N	N	N
Country effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Constant	0.31*** (0.007)	0.23*** (0.007)	0.31*** (0.007)	0.24*** (0.007)	0.29*** (0.007)	0.22*** (0.007)	0.04*** (0.006)	0.16*** (0.006)	0.33*** (0.008)
Observations	619,648	619,648	619,648	619,648	619,082	619,082	730,582	730,582	730,582
R ²	0.056	0.056	0.056	0.056	0.059	0.059	0.033	0.028	0.04

Note: Growth rates (denoted by Δ) are measured in logarithmic terms for three-year means, all variables except “distance” in first differences. F-tests of all specifications are highly significant (p-value<0.01). Wald test for joint significance of the interaction effects are all highly significant (p-value<0.01). Robust standard errors in parentheses, *** p-value<0.01, ** p-value <0.05, * p-value <0.1.

Table 6: TFP growth and changes in Chinese import intensities across technology classes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Tech. Taxonomy	Low	Low	Medium-low	Medium-low	Medium-high	Medium-high	High	High
Δ Import intensity	0.12*** (0.024)	-0.18* (0.109)	-0.18*** (0.032)	-0.09 (0.076)	-0.13*** (0.033)	0.10 (0.114)	0.03 (0.039)	-0.26*** (0.102)
Distance, lagged	0.11*** (0.002)	0.11*** (0.002)	0.12*** (0.002)	0.12*** (0.002)	0.11*** (0.002)	0.11*** (0.002)	0.11*** (0.006)	0.11*** (0.006)
Time effects	Y	Y	Y	Y	Y	Y	Y	Y
Sector effects	N	N	N	N	N	N	N	N
Country effects	Y	Y	Y	Y	Y	Y	Y	Y
Constant	0.29*** (0.011)	0.26*** (0.011)	0.48*** (0.184)	0.26*** (0.012)	0.38*** (0.070)	0.19*** (0.012)	0.35*** (0.026)	0.15*** (0.026)
Observations	224,672	224,672	219,408	219,408	150,491	150,491	25,077	25,077
R ²	0.039	0.038	0.077	0.077	0.071	0.071	0.108	0.106

Note: Growth rates (denoted by Δ) are measured in logarithmic terms for three-year means, all variables in first differences. F-tests of all specifications are highly significant (p -value <0.01). Robust standard errors in parentheses, *** p -value <0.01 , ** p -value <0.05 , * p -value <0.1 .

Table 7: TFP growth and changes of Chinese trade intensities across country groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimator	IV	IV	IV	IV	IV	IV	IV	IV	IV
Country group	South	CEE	North	Germany	France	Italy	Spain	UK	Poland
Δ Import intensity	-0.09*	0.49*	0.07	0.65***	-0.19	-0.06	-0.20	-1.20***	0.74
	(0.048)	(0.256)	(0.109)	(0.134)	(0.168)	(0.053)	(0.140)	(0.394)	(1.195)
Distance, lagged	0.12***	0.36***	0.08***	0.04***	0.10***	0.12***	0.14***	0.08***	0.21***
	(0.002)	(0.011)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.026)
Time effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country effects	Y	Y	Y	N	N	N	N	N	N
Constant	0.12***	0.25***	0.15***	0.08***	0.11***	0.14***	0.17***	0.05***	0.25***
	(0.002)	(0.006)	(0.007)	(0.006)	(0.004)	(0.003)	(0.003)	(0.007)	(0.024)
Observations	301,696	137,455	180,497	31,798	61,210	185,496	90,496	28,301	10,605
R ²	0.072	0.063	0.066	0.074	0.079	0.086	0.073	0.064	0.052

Note: Growth rates (denoted by Δ) are measured in logarithmic terms for three-year means, all variables except “distance” in first differences. F-tests of all specifications are highly significant (p -value <0.01). Wald test for joint significance of the interaction effects are all highly significant (p -value <0.01). Robust standard errors in parentheses, *** p -value <0.01 , ** p -value <0.05 , * p -value <0.1 .

Table 8: Labour productivity growth and changes of Chinese trade intensities across quantiles (Instrumental Variable Quantile Regression)

	(1)	(2)	(3)
	IV-QUANT	IV-QUANT	IV-QUANT
	25%-perc.	50%-perc.	75%-perc.
Δ Import intensity	0.09 (0.059)	-0.04 (0.055)	-0.17*** (0.064)
Δ Capital	0.06*** (0.001)	0.06*** (0.001)	0.07*** (0.001)
Distance, lagged	0.18*** (0.002)	0.18*** (0.001)	0.18*** (0.001)
Time effects	Y	Y	Y
Sector effects	Y	Y	Y
Country effects	Y	Y	Y
Constant	0.12*** (0.007)	0.25*** (0.007)	0.39*** (0.008)
Observations	736,567	736,567	736,567

Note: Growth rates (denoted by Δ) are measured in logarithmic terms for three-year means, all variables in first differences. F-tests of all specifications are highly significant (p-value<0.01). Standard errors in parentheses, *** p-value<0.01, ** p-value <0.05, * p-value <0.1.

Annex C: The dataset

AMADEUS data

The AMADEUS database is a product of Bureau van Dijk for company information and contains 21 million companies across Europe.⁵ The data offer a rich source for financial information and firm characteristics (e.g., sector, location, ownership and governance structures). The data is provided in different annual releases.

Using multiple releases:

To obtain a large sample beginning in 2004, we use biennial releases from 2012 through 2018 (i.e. 2018, 2016, 2014 and 2012). Appending releases brings about a range of challenges with respect to data consistency. First, each release uniquely characterises a firm over time using a Bureau van Dijk identifier. However, these identifiers may change over time for the same firm so that the identifier is not unique across different AMADEUS releases. Hence, appending the firms using uncleaned identifiers would lead to biased results. We generated harmonised identifiers using information about identifier changes provided by Bureau van Dijk (see <http://idchanges.bvdinfo.com/>, accessed on 5 August 2020) and therefore create a consistent panel of firms using multiple releases. Second, later releases provide more recent data. Hence, some firms may show different values for the same variable in the same year. We use the most frequent observation if there are duplicates, assuming that the most recent information is the most accurate. If the most recent information was missing, we used the mean value of all other observations.

Data cleaning:

⁵ See <http://idchanges.bvdinfo.com/> (accessed on 14th February 2020).

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

- Firms' financial figures is obtained from balance sheet data, which may use fiscal years, however. We used the calendar year as a reference point and therefore assign deviating information to a given year. Firms whose fiscal years ends before June were assigned to the previous year.
- Monetary values were deflated using Eurostat deflators at the Nace Rev. 2, 2-digit level. We used deflators for the entire manufacturing sector if deflators were missing at the industry level. Since deflators for Malta were not available, deflators for Italy were used instead.
- Negative values of the variables sales, employees, costs of materials and costs of employees were replaced by missing values.
- The dataset contains information on a firm's value added. If this information was missing, we created a variable on value added defined as the sum of operating profits and the costs of employees.
- Bureau van Dijk provides information on the firm's activity status. The variable may take the following forms: Active, Active (dormant), Active (insolvency proceedings), Dissolved, Dissolved (liquidation), Dissolved (merger or take-over), Inactive (no precision), Unknown. We restricted the sample to active firms only.
- We restrict the definition of the capital stock to tangible assets only. AMADEUS also provides data on intangible assets. Yet, these include goodwill and therefore do not exclusively measure a firm's knowledge stock with respect to its assets.

- We confine the analysis to EU Member States in 2016, the last year available. We could not include firms in Greece, Lithuania and Cyprus, because information on value added was missing. In addition, we had to drop firms in Luxembourg and Malta due to small sample sizes in some specifications.

Olley-Pakes productivity estimators

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

Entry and exit information were not considered. Albeit AMADEUS data offers an interesting sample to study firm performance across countries and industries, it does not pose a complete representation of firms in a given (domestic) sector, which impedes the computation of market shares that underlie the thought of including firm entry-exit. Moreover, international competition further challenges the definition of relevant markets.

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

Matching patent information from AMADEUS with PATSTAT

The AMADEUS database includes patent information, which is obtained from the European Patent Office (EPO). To study patent performance, we use data obtained from PATSTAT, an EPO dataset providing additional information in the field of patent intelligence and statistics.⁶ We use the patent publication identifier provided in AMADEUS to merge PATSTAT information to the dataset. PATSTAT uses the same identifier, defined in the variable “PAT_PUBLN_ID in PATSTAT”. This additional information provides us with an application ID of each patent which is assigned to BvD identifiers. This allows us to quantify the patenting behaviour of each firm and is the basis for the subsequent patent analysis (e.g., citation weights, patent counts). A downside of this approach is the focus on publication identifiers, which restricts the sample to cited patents.

PATSTAT consists of three individual databases of which we are using two. The PATSTAT Biblio contains bibliographical data relating to more than 90 million patent documents from 90 patent offices. The PATSTAT Legal status includes legal status data of a patent from more than 40 patent offices.

⁶ See <https://data.epo.org/expert-services/index.html> (accessed on 6 August 2020).

BACI data

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

COMTRADE provides two sets of series for any given trade flow if both commercial partners report the transaction to the UN. Exports are generally reported on a Free on Board (FOB) basis, while the related imports from the trading partner are reported including Costs for Insurance and Freight (CIF). While the two series should be identical for any given product and year (except for the CIF positions), in practice these data prove to be often inconsistent (Gaulier and Zignago 2010). BACI establishes consistency in the bilateral trade flows reported by the exporting and the importing country. It uses mirror flows to complete missing reports. It also estimates approximations for the correct CIF costs which are then used to make import and export series between trade partners consistent. Trade data for Luxembourg was missing; trade information for Belgium were used for firms located in Luxembourg.

Matching trade and industry classifications

Matching trade with industry information is a common issue in trade research, because different classifications are used and classifications themselves are changed over time to consider technological and structural developments reflected by economic activities. Correspondence tables are, if at all, only available for certain versions. BACI's trade data is available at the product level using the Harmonised System Codes. To obtain a sufficient time coverage, we use the classification from 1992 (hs92, 6-digit level). This system differs from the industry

classification (Nace Rev. 2., 4-digit), which is used in the firm level dataset. To match the trade with the industry classification, we draw on correspondence tables. However, these are not available for hs92, which is why we recode hs92 to hs02, a later classification. This allows us to match the hs02 codes with NACE Rev1, an older industry 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 led to a division of some 4-digits classes to multiple other classes. We distributed these values evenly across the respective classes.

We use harmonised trade data obtained from the BACI database to construct measures of import competition. The database builds on the COMTRADE database provided by the United Nations which contains detailed import and export data reported by statistical authorities of close to 200 countries starting from 1962 to the most recent year.⁷ The database reconciles the declarations of the exporter and the importer to the United Nations. The reported data are inconsistent for a number of reasons. For instance, imports are reported as CIF (cost, insurance and freight) while exports are declared as FOB (free on board), different product classifications might apply, or the final destination is uncertain.⁸ The data are purged by biases due to CIF and FOB and the reliability of the reported is also considered.

Matching trade with industry information is a common issue in trade research, because different classifications are used and classifications themselves are changed over time to consider technological and structural developments reflected by economic activities. Correspondence

⁷ See <http://comtrade.un.org/> (accessed on 13th February 2020).

⁸ See Gaulier and Zignago 2010 and http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=37 (retrieved on 5th February 2020).

tables are, if at all, only available for certain versions. BACI's trade data is available at the product level using the Harmonised System Codes. To obtain a sufficient time coverage, we use the classification from 1992 (hs92, 6-digit level). This system differs from the industry classification (Nace Rev. 2., 4-digit), which is used in the firm level dataset.

To match the trade with the industry classification, we draw on correspondence tables. However, these are not available for hs92, which is why we recode hs92 to hs02, a later classification. This allows us to match the hs02 codes with NACE Rev1, an older industry 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. AMADEUS provides a list of primary and secondary four-digit industries, which we match with trade data. We use only information on a firm's primary affiliation, because using information on secondary affiliations has not been found to alter the results (Bloom, Draca, and Van Reenen 2016). The conversion process led to a division of some 4-digits classes to multiple other classes. We distributed these values evenly across the respective classes.