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**Chinese import competition, firm-level productivity growth and the distance to the frontier**[1]

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## Abstract

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**Chinese import competition, firm-level productivity growth and the distance to the frontier**

## 1. Introduction

Imports from China have increased substantially in both volume and quality. Chinese firms are now competing with firms in developed economies (Athreye and Kapur 2009; Bergeaud and Verluise 2022; Kügler et al. 2024). In the US, weak productivity growth is associated with Chinese import shocks (Autor et al. 2013, 2016). At the same time, the European Union (EU) has been undergoing rapid economic change. Productivity gaps had been closing, but in the years when Chinese imports had expanded, the 'convergence engine' had stalled (Gil and Raiser, Martin 2012; Kügler et al. 2023). Especially some economically lagging regions of the EU have experienced slow growth. This coincides with the widely debated broader trend of sluggish productivity growth (Goldin et al. 2024). This raises the question about the link between productivity growth and Chinese imports.

For the EU, the firm-level evidence is mixed. For the period prior to the 2008/09 financial crisis documents a growth-enhancing effect of import competition (Bloom et al. 2016), thereby providing empirical support for trade integration models (Melitz and Ottaviano 2008). However, recent evidence (Friesenbichler et al. 2024; Hombert and Matray 2018; Colatone and Crinò 2014; Mion and Zhu 2013; Fromenteau et al. 2019) points to a negative relationship, moderated by multiple dimensions of firm heterogeneity that capture the ability to cope with the pressures of import competition. Negative effects have been attributed to the emergence of Chinese firms as subsidized, cost-competitive technology intensive exporters that have likely benefited from the so-called 'second unbundling' of global trade (Baldwin 2011; Baldwin and Lopez-Gonzalez 2015).

This paper asks whether Chinese import competition can partly explain the asymmetric productivity growth of European firms. It examines the impact of increasing Chinese import competition on incumbent productivity growth. Drawing on evolutionary dynamics, the impact is likely to be moderated by the distance to the “technological frontier” and technological capabilities, respectively. These might be shaped by firms’ productivity levels, sectoral complexity, or the capability of the national innovation system. Our dataset covers firms in the European Union (EU), which provides a viable setting to study the effects of trade and the technological frontier on productivity. The EU is an economic bloc that centrally negotiates trade agreements. At the same time, there is a wide variety of economic activities and performance levels within its borders, covering both frontier and non-frontier firms. Firms and policymakers alike are asking how rising Chinese imports will affect their performance.

Empirically, we use the large-scale, firm-level ORBIS dataset provided by Moody's. We calculate import indicators at a detailed industry level and use them to regress annual changes in labor productivity against changes in import intensity from 2003 to 2022. We then interact these with three measures of the 'frontier'. Our findings, based on approximately 430 thousand firms, suggest that there are productivity catching up processes with respect to both a productivity and a technological frontier. In instrumental variable regressions considering endogeneity, productivity catching up increases when Chinese import intensities increase.

Firms in technologically less complex sectors experience lower productivity growth when Chinese import intensities rise. Consequently, firms in technologically lagging settings face reduced productivity growth. Examining the national innovation system and delineating its frontier reveals statistical evidence of adverse effects. At the level of the national innovation system, we find that firms in less developed economies catch up in terms of total factor productivity, but they are at a disadvantage when it comes to labor productivity growth. As Chinese import intensity increases, labor productivity growth rises, though total factor productivity growth tends to decline.

The contributions to the literature are threefold. First, we exploit the diversity of the EU to test economic theory on the relationship between international competition and performance. Prior work on the effects of import competition and productivity frontiers has been limited to the US at the industry level, using information prior to the financial crisis of 2008-09 (Ding et al. 2016), a period prior to the shift in the Chinese export portfolio towards high-tech products. Our results differ from this work by using different frontier definitions for a rich firm-level dataset for the EU.

Second, we make an empirical contribution by proposing novel ways to measure the technological frontier. The measures are based on both the complexity and innovation economics literature and put in an evolutionary context.

Third, our findings have implications for policy makers in their efforts to fine-tune both industrial and trade policies. The technological frontier moderates the effects of trade with China, which induces asymmetries that are relevant for the centrally negotiated trade policies of the EU.

## 2. Conjectures

Our research is based on a distance to frontier framework where countries that are closer to a "technological frontier" tend to rely more on knowledge, innovation, and selection processes, which are accompanied by more intense competition, be it domestic or trade-induced (Acemoglu et al. 2006). Similarly, firms rely on different competitive strategies depending on where they are positioned in relation to the most advanced firms in their industry both at the domestic and international level. Their adjustments are determined by the internal and external capabilities and resources at the firms' disposal. In the following hypotheses, we test whether rising Chinese import intensities affect performance and, if so, how this effect varies with the position relative to the "frontier" using different measures of the "frontier".

We analyze the impact of import competition from China on European firms. According to economic concepts theorizing about how firms behave (Aghion et al. 2009), we hypothesize that frontier firms escape the entry and discouragement effects of Chinese imports. However, the ability of firms to do so varies according to: (i) the individual performance characteristics of firms, (ii) the structural characteristics of the industry in which they operate, and (iii) the level of economic and institutional development of a country in which a firm operates. In our empirical analysis, we take these three dimensions into account.

**Firm-specific distance to the productivity frontier**

The first conjecture is based on the empirical literature of a frontier definition that is frequently used in the literature (Acemoglu et al. 2006; Ding et al. 2016).

The proxy for a firm's "distance to frontier" can be defined as its proximity to the productivity frontier at the industry level. This reflects how efficient a firm performs given a given set of opportunities, technologies, or market structures across the industry. Aghion et al. (2009) argue that firms on the frontier face an increased threat of entry, which in turn triggers an "escape-entry" effect. Non-innovation would be potentially more costly than innovation. Therefore, import competition from China should be positive for incumbents closer to the technological frontier. Evidence from Chile suggests that this is only true for about 10% of the most productive firms, while import competition suppresses innovation in most other firms (Cusolito et al. 2023).

On the other hand, firm growth may result from aspects other than innovation. These may be more general "capabilities", entrepreneurial attitudes, and business models that are observed. For example, some firms may be active innovators, constantly developing new products or improving their technologies, corporate logistics or the services they provide to customers, while others may prefer to imitate industry leaders. In the context of the EU, where many firms are in the process of catching up, such factors may be particularly relevant. Taken together, this leads us to our first conjecture:

*Conjecture I: An increase in import intensity growth from China has a positive effect on productivity growth for firms closer to the industry-specific productivity frontier, but a negative effect for firms further from the frontier.*

**Technological frontier at the industry-level**

In addition to the country-level institutional environment, the technological intensity of a sector is likely to moderate the effects of import competition. Industries have been shown to differ structurally in terms of knowledge cumulativeness, technological opportunity, appropriability conditions for innovation, capital intensity, and sunk costs associated with entry and exit (Breschi et al. 2000; Sutton 1991; Pavitt 1984; Winter 1984; Levin et al. 1987). In other words, companies differ systematically in how they respond to increased competition and use quality differentiation to avoid it (Aghion et al. 2009). Hence, the responses to import competition in terms of innovation responses from China should also be systematically different across industries, with a differential impact on productivity growth.

Firms' industry affiliation has been shown to moderate the effect of import competition from China (Mion and Zhu 2013; Fromenteau et al. 2019). Previous studies have found that low-tech firms are more negatively affected by Chinese imports than high-tech firms (Mion and Zhu 2013). Chinese firms have moved up the quality ladder in international trade. They first developed capabilities in less technologically sophisticated industries and only recently in more sophisticated ones. Hausmann, Hwang, and Rodrik (2007) suggest that the cumulative capabilities and competitive capabilities of incumbents will be further along in the former than in the latter. Thus, an increase in the intensity of competition will have a more positive effect on the productivity growth of incumbents in sectors that are closer to the technological frontier and a potentially negative effect in sectors that are further behind. This leads us to our second conjecture:

*Conjecture II: An increase in import intensity growth from China has a negative effect on within-firm productivity growth in low-tech sectors, but a positive effect in high-tech sectors.*

**Institutional frontier at the country-level**

The institutional environment in which a firm operates, which can be a source of comparative advantage at the country level, is a central aspect of the technological frontier. For example, the trade literature suggests that less developed countries with weak institutions may not benefit from trade (Costinot 2009; Levchenko 2007; Nunn and Trefler 2013). This has been used in firm performance studies (Bravo-Biosca et al. 2016; Hölzl 2009). This is in line with institutional economics, which argues that differences in economic performance are mediated by differences in stocks of tangible and intangible capital, such as infrastructure or human capital, resource endowments, industrial structure, or institutional arrangements and institutional quality across EU member states (Hall and Soskice 2001; O'Mahony et al. 2010). In an empirical analysis, Landesmann and Stöllinger (2019) have also shown that most of the less productive firms are located in countries that are potentially in an economic cachting up process. This leads to the third conjecture:

*Conjecture III: An increase in import intensity growth from China has a positive effect on within-firm productivity growth in frontier economies, but a negative effect in non-frontier economies.*

## 3. Data and variables

Our analysis draws on data from multiple sources to create a novel dataset that captures the development of firm performance, trade relationships, and capabilities at the national, sectoral, and firm levels. Constructing this dataset involved resolving compatibility issues stemming from various classification systems.

ORBIS data, provided Moody's, is used for the computation of the firm-level indicators.[5] This dataset was thoroughly cleaned to remove duplicates due to data updates, outliers, and implausible and missing values. All nominal values were deflated using Eurostat deflators at the most detailed NACE Rev. 2-digit level available. NACE is the EU's statistical classification of economic activities.[6] This is important because increased competition should have a downward effect on prices (Auer and Fischer 2010; Weyl 2019).

The sample spans the period from 2003 to 2022, with sample size varying across specifications due to data availability. For the productivity frontier specification, we include 416,998 firms from twenty-three EU countries, excluding Greece, Lithuania, Estonia, and Malta due to missing data. We use an unbalanced panel of firms, with an average of 11.6 observations per firm. Only active enterprises are considered, and information on insolvent or bankrupt companies is excluded. The sample is consistent with other performance measures. The mean firm-level labor productivity at the country level correlates highly with GDP per capita ($\rho$: 0.80, p-value: 0.000).

[5] See https://www.moodys.com/web/en/us/capabilities/company-reference-data/orbis.html (accessed on 9th May 2025).

[6] The acronym is derived from the French title "Nomenclature générale des Activités économiques dans les Communautés Européennes" (i.e., Statistical classification of economic activities in the European Communities).

### 3.1 Firm performance

The key performance variable is labor productivity, defined as firm-specific value added divided by the number of employees. This indicator has been criticized because it does not take into account the capital intensity of a firm. To address this concern, we include the growth of firm-specific fixed assets in the estimates of labor productivity growth (Syverson 2011).

Cognizant of the discussion about productivity measurement, also use total factor productivity (TFP) indicators. The literature suggests several calculation methods, each of which leads to slightly different results that affect the robustness of the results (Syverson 2011; Rovigatti and Mollissi 2018). Hence, we use information on changes in capital stocks not as a control variable in the regressions, but to estimate a TFP indicator as suggested by Levinsohn and Petrin using cost of material goods as proxy and an Ackerberg-Caves-Fraser correction (Levinsohn and Petrin 2003; Ackerberg et al. 2015). We use cross-country data and estimate the TFP indicator separately for each NACE Rev. 2, 2-digit industry to obtain a sector-specific firm-level productivity indicator. We then use changes in TFP as the endogenous variable rather than labor productivity growth.

### 3.2 Chinese import intensity

We integrated firm-level data with trade data from BACI, a harmonized dataset that includes import information. Following established literature (Bernard et al. 2006; Bloom et al. 2016; Friesenbichler et al. 2024) , we computed a Chinese import intensity indicator using a value share approach. This measure is based on the share of Chinese imports (IMPC) in total imports (IMPTOT) within a given country, year, and NACE Rev. 2, 4-digit industry.

Aligning trade data with the industry classifications assigned to enterprises in ORBIS posed a challenge, as BACI employs a product-based classification rather than an industry classification. BACI uses the "Harmonized System" (HS), a standardised numerical method for classifying traded products. We used two releases of the HS classification: HS92 and HS02. The 6-digit HS92 data were re-coded to HS02, for which a NACE Rev. 1 correspondence table is available. This, in turn, was transformed to NACE Rev. 2 data at the 4-digit level (see Annex B) to align the trade data with the industry classification used in AMADEUS (NACE Rev. 2, 4-digit).

The descriptive statistics reveal a significant surge in the intensity of Chinese imports. In 2003, Chinese imports constituted 4.3% of total imports, a figure that more than doubled to 8.9% by 2022. The growth dynamics vary considerably based on technological intensity. Given the lack of data on firm-specific capabilities and technologies, we draw on a classification system provided by Eurostat, which categorizes sectors according to their technology intensity.[7] Similar taxonomies have been applied in previous studies about competitiveness and trade (Birch et al. 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),

[7] See https://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:High-tech_classification_of_manufacturing_industries (accessed on 8 May 2025).

- medium-low-technology (e.g., basic metals or rubber and plastic products) and
- low-technology (e.g., textiles or furniture).

High-tech exports have grown significantly faster than low-tech exports, as illustrated in Figure 1. For example, low-tech imports from China constituted 5.1% of total imports in 2003, increasing to 6.5% by 2022. In contrast, high-tech exports represented 4.8% of all imports in 2003, rising substantially to 14.3% by 2022.

Figure 1 about here

### 3.3 The productivity frontier at the firm level

Our productivity frontier variable considers cachting up mechanisms and is time-varying. This is an important aspect of the economic dynamics of the EU, where firms in developed and cachting up economies compete in a single market. We measure the distance of a firm to the industry-specific labor productivity frontier firm in percent. The frontier firm threshold is defined as the productivity level at the 95% percentile at the NACE Rev. 2 3-digit level for each observation period. All firms at or above the 95% percentile are identified as frontier firms and our measure takes the value zero. For all other firms in the industry, the distance to the frontier firm is calculated as follows $(LP_{F,s,t} - LP_{i,s,t})/LP_{F,s,t}$, where $LP_{F,s,t}$ indicates the labor productivity threshold for frontier firms $F$ in a given industry $s$ at a certain period $t$. This variable takes on values between zero and one. Higher values therefore indicate a greater distance to the frontier and a greater cachting up potential. The choice of the NACE

3-digit level of industry was motivated by the need to obtain a sufficient number of observations while defining the industry at as granular a level as possible.

The descriptive statistics show a low correlation between the distance to the frontier and the changes in import intensity (ρ:-0.01, p-value: 0.000). In the specification, we use the lagged distance to the most productive percentile because we assume that intra-firm adjustments take some time. Thus, the distance to the frontier firm in the most recent period determines a firm's current productivity growth.

### 3.4 The technology frontier at the sector level

To classify sectors according to their technological intensity, we draw on the complexity literature (Hidalgo and Hausmann 2009; Balland et al. 2022) and compute a proxy of technological content based on product complexity. We use a measure of the technological content of a sector's products based on "complexity scores" (Hidalgo and Hausmann 2009).

To calculate the indicator a matrix *M (j,p)*, which for each exporting country (j) shows the value1 for those products that are exported with comparative advantage (RCA> 1) and otherwise takes the value 0 for the element. The complexity score for each product line at the HS-6-digit level is then obtained from the eigenvector associated with the second largest eigenvalue of the matrix

$$M_{pq} = \sum_j \frac{M_{j,p} M_{j,q}}{k_{j,0} k_{p,0}}, \tag{1}$$

where $k_{j,0} = \sum_p M(j,p)$, and $k_{p,0} = \sum_j M(j,p)$ (Klimek et al. 2012).

These scores approximate the sophistication of a product line by extracting latent information from a bipartite network M(j,p) linking product lines to exporting countries. The method analyses co-export patterns of products across countries to provide insights into the specific, unobservable technological capabilities or production factors necessary for producing a good. The rationale is that different technological capabilities are reflected in countries' export specializations. If multiple countries systematically export the same products with a comparative advantage, it is assumed that similar resources and production factors, such as technical know-how and management skills, are involved. Conversely, if a product is exported by only a few countries, this indicates a high level of specialization, allowing these countries to develop unique characteristics. Thus, the complexity score reflects the breadth and depth of the knowledge base required to become a significant exporter (Reinstaller and Reschenhofer 2019; Klimek et al. 2012).

We compute the complexity scores for each HS-6-digit product line. Using correspondence tables provided by Eurostat, we match each product to a corresponding 4-digit industry (NACE Rev.2 4-digit) and construct an aggregate index for the technological content of a sector's exports. We apply country-sector-specific export weights for each year. The technological content of the exports of the same sector across countries will differ depending on the composition of its export portfolio. As the recovered eigenvector takes positive and negative values, we adjust the complexity indicator, so it only takes positive values. Finally, and aligned with the computations for the firm level technological distance indicators, we use the 95% percentile of the complexity value to calculate the sector-country specific distance to the complexity frontier. The obtained indicators are aligned with the previously shown Eurostat taxonomy (see Annex).

### 3.5 The frontier of the national innovation system

To capture the quality of the economy-wide innovation system, we rely on the European Innovation Scoreboard. This database provides a comparative assessment of the innovation performance of EU Member States on an annual basis. The composite ranking relies on a national-level innovation production function, and consists of a wide range of indicators covering structural conditions, knowledge creation, firm-level innovation, throughput and output in terms of new products and services (Hollanders and van Cruysen 2008; Bielińska-Dusza and Hamerska 2021). The indicator is often used to categorize countries as either innovation leaders or followers. We use the cardinal indicator to avoid the classification problem and implement the distance-to-the-frontier computation with the 95%-percentile as the frontier as described above.

Sweden is at the frontier, with Finland second, lagging approximately 6%. The largest distances from the country-level frontier are recorded for Romania (72%) and Bulgaria (69%). The Czech Republic and Italy have the sample's median score of approximately 45%. We use the maximum value of the composite indicator at the country-year level to compute the country-specific distance to the frontier, which we again used in its lagged form. The intensity of Chinese imports in total imports is almost uncorrelated with the distance to the frontier at the country level ($\rho$: 0.008, p-value: 0.000).

## 4. Regression analysis

### 4.1 Specification and estimation strategy

To estimate the impact of trade on within--firm productivity performance, we exploit differences in the exposure to import penetration across countries and industries over time. In our estimation strategy we broadly follow the prior literature (Bloom et al. 2016; Friesenbichler et al. 2024; Yamashita and Yamauchi 2019; Ben Yahmed and Dougherty 2017). We estimate the effect of changes in Chinese import intensities ($\Delta ImI_{s,c,t}$), a firm's distance to the productivity or technological frontier, and the interaction of changes in the Chinese import intensities with the frontier measure on labor productivity growth. The basic productivity growth equation is:

$$\Delta LP_{j,s,c,t} = \beta_1 \Delta ImI_{s,c,t} + \beta_2 DIST\_FRONT + \beta_3 \Delta ImI_{s,c,t} * DIST\_FRONT + \beta_4 \Delta IMP_{s,c,t} + \beta_5 \Delta CAP_{j,s,c,t} + \alpha_s + \alpha_c + \alpha_t + u_{j,s,c,t} \quad (2)$$

where $\Delta LP_{j,s,c,t}$. denotes the change of firm $j$'s labor productivity located in sector $s$ and country $c$ between period $t$ and $t-1$. In addition, we use the changes in total factor productivity as a second productivity indicator, $\Delta TFPP_{j,s,c,t}$:

$$\Delta TFP_{j,s,c,t} = \beta_1 \Delta ImI_{s,c,t} + \beta_2 DIST\_FRONT + \beta_3 \Delta ImI_{s,c,t} * DIST\_FRONT + \beta_4 \Delta IMP_{s,c,t} + \beta_5 \Delta CAP_{j,s,c,t} \quad (3)$$

$\Delta ImI_{s,c,t}$ is the change of the Chinese import share of a given sector and country between $t$ and $t-1$. The variable $DIST\_FRONT$ indicates the lagged distance to the respective frontier measure and takes on values between zero and one. We apply the firm-level productivity frontier, the complexity frontier at the sector level, and the innovation system frontier at the country level. In the first case, the variable varies across firms, sectors, countries and time; in the second case, it varies across sectors, countries and time; in the last case, the variable varies across countries and over time. $\beta_2 > 0$ would suggest the presence of a convergence effect: i.e., in case of the productivity frontier it would mean that firms situated at a greater distance from the frontier will catch-up in terms of productivity growth. However, the most pertinent parameter is the coefficient of the interaction term, $\beta_3$, which takes a non-zero value in instances where the impact of Chinese import intensity growth on the productivity growth of European firms varies according to the location of the firms relative to the frontier defined by the firm, sectoral and national level.

It is conceivable that the total amount of imports may also affects firms' productivity as it captures the trade openness and the degree of foreign competition faced by a sector. Variable $IMP$ controls for total real imports at the NACE Rev. 2 4-digit level. The control variable $CAP_{jsct}$ is the firm-specific capital intensity defined as the stock of tangible fixed assets in real terms. $\alpha_c$, $\alpha_t$ and $\alpha_s$ are country, and time and sector fixed effects; $u_{j,s,c,t}$ denotes the error term.

Serial correlation of the error term is an issue in firm-level regressions of productivity growth. Following the recent literature (Aghion et al. 2018), we use heteroskedasticity and autocorrelation corrected (HAC) standard errors with one lag (Newey and West 1986) in our preferred specification. This approach protects against heteroskedasticity and serial correlation of the form AR(1) in the time dimension of the standard errors. It assumes that firms' actions are independent of other firms and that their actions are less dependent on their behavior further back in time. Singletons, which may bias the results, are excluded.

Following the import competition literature, we also implement a 2SLS-identification strategy to control for the possibility that import dynamics may be endogenous. Unobserved supply and demand shocks could affect trade and performance. This implies that the coefficients may suffer from reverse causality. We therefore use 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; Friesenbichler et al. 2024). The identification idea is that China's rise in the world economy has caused supply shocks to all of its trading partners. Using information for China's other trading partners identifies the exogenous component of China's rising competitiveness and eliminates shocks that are specific to a country, region, or industry.

We calculate the import intensity for a group of extra-EU economies. We use the average of the import intensities of Australia, New Zealand, USA, Canada, Israel and Japan. Calculating the average of the shares avoids bias towards larger economies. The average wealth of this group of countries is broadly comparable to that of the average EU Member State. However, given the differences in competitive positioning and import structures, these are countries for which we do not expect significant correlations between demand or supply shocks and the firms in our sample. In order to test whether the exclusion restriction is satisfied, we implement a proposed procedure at the treatment (i.e., industry-country-year) level (D'Haultfœuille et al. 2021).[8] We do not reject the null hypothesis that the exclusion restriction is satisfied at the one percent significance level. This provides empirical support for using the mean import intensities of this group of countries as an appropriate instrument for Chinese import intensities of EU countries.

### 4.2 Regression results

We test the above conjectures in a series of regressions of productivity growth on changes in trade intensity measured at the NACE Rev. 2 4-digit industry level (see Table I for descriptive statistics).

Table II presents the estimation results for the regression equations (2) and (3) outlined in section 4.1. Columns (1) and (2) refer to the equation for estimating labor productivity growth, whilst columns (3) and (4) refer to that for total factor productivity. Columns 1 and 3 illustrate the outcomes of a basic OLS estimation, while columns (2) and (4) present those of the two-stage least squares (2SLS) estimations.

Throughout the observation period, an enhanced import intensity growth ($\Delta ImI$) from China seems to have exerted a predominantly positive effect on firms' productivity growth. Since several interaction terms are included, the baseline effect of a change in import intensity ($\Delta ImI$) refers to firms at the frontier in terms of productivity, sectoral sophistication and national innovation systems. The coefficient in the OLS regression in column (1) is

[8] The country-year-industry level could not be implemented because it was too intensive computationally.

insignificant and very small, but is significantly positive in the 2SLS regression in column (2). For total factor productivity, both coefficients are positive and significantly different from zero (see columns (3) and (4)), supporting the general positive impact of increasing Chinese import competition from China on productivity growth.

Furthermore, the positive effect of Chinese import intensity growth appears to be particularly pronounced for firms situated further away from the productivity frontier. The coefficients of the interaction of the distance to the frontier with import intensity ($\Delta ImI * FRONT_{Firm}$) are positive and statistically significant in both 2SLS regressions (columns (2) and (4)). However, the OLS results are less robust. This is reflected in the insignificant coefficient for labor productivity and the negative coefficient for TFP.

All coefficients of the lagged distance-to-the-productivity-frontier ($DIST\_FRONT_{Firm}$) are positive and significant. Hence, a greater distance-to-the-frontier is associated with faster productivity growth, suggesting a convergence mechanism which is reinforced by increasing Chinese import intensities. The greater the distance to the frontier in the previous period, the higher the current productivity growth of a firm, especially if the import intensity from China increases. Consequently, the results do not support the hypothesis that an increase in Chinese imports has a growth-promoting effect, which becomes negative for firms far away from the frontier (Conjecture I).

Conjecture II states that increasing import intensity from China has a negative effect on productivity growth in low-tech industries, while it has a positive effect in high-tech industries. We use a continuous variable based on product complexity that is higher if a firm operates in a high-tech industry with a more sophisticated product portfolio. Overall, the results presented in Table II show that being active in a less complex industry ($DIST\_FRONT_{Sector}$) has a significant positive effect on productivity growth. This indicates an advantage of technological backwardness. Yet, the coefficients of the interaction term with the import intensity growth measure are negative and statistically significant in both 2SLS regressions (see column (2) and (3)). This is supported be the OLS regression of TFP growth (column (3)), although the respective coefficient in the labor productivity growth regression is insignificant. These results indicate that the growth enhancing effect of being active in less sophisticated sectors is severely diminished by increasing import competition from China. Thus, we find evidence which supports Conjecture II.

Conjecture III states that rising Chinese import intensity has a positive effect on productivity growth in frontier economies, but a negative effect in non-frontier economies. The results presented in Table II offer an ambiguous picture. While the outcomes pertaining to TFP growth would appear to substantiate Conjecture III, the results of the labor productivity growth regressions indicate a contradictory direction. In case of labor productivity growth (columns (1) and (2)), we find significantly negative coefficients of being located in countries with rather modest innovation systems ($DIST\_FRONT_{Country}$). However, the coefficients of the interaction term ($\Delta ImI * FRONT_{Country}$) are significantly positive indicating that increasing import competition from China dampens the LP-growth-reducing effect of being located in countries farther away from the frontier. Therefore, our findings for labor productivity refute Conjecture III.

By contrast, the results for TFP growth in columns (3) and (4) show positive and significant coefficients for $DIST\_FRONT_{Country}$, suggesting an underlying convergence dynamic between countries. However, the significantly negative coefficient of the interaction with import intensity growth in the 2SLS regression (column (4)) suggests that increasing import competition from China is severely disrupting this convergence. These results thus corroborate Conjecture III.

Table II about here

The control variables perform as expected. The coefficients on the growth of both total imports at the industry level and capital stocks remain significantly positive in all regressions. This is consistent with endogenous growth theory, which predicts that an increase in total imports is associated with an increase in competition, which in turn has a positive effect on firms' innovation and productivity performance (Grossman and Helpman 1990).

Eventually, the 2SLS-specification is a statistically viable approach. The instrumental variables are significant in the first stages, and the specification and post-estimation tests support the validity of the estimates (see Table III).

Table III about here

### 4.3 Robustness checks

The sample covers a twenty-year period during which there were distinct macroeconomic phases throughout the business cycle, as well as significant changes in China's export strategies and the sophistication of its exports. The long-run effects are likely to differ by growth periods and to have changed over time (Friesenbichler et al. 2024). Taking the financial and the ongoing effects of the pandemic into account, we generated subsamples of a similar length to ensure a comparable number of observations. This allowed us to re-estimate the specification for four different time windows: (1) 2003 to 2007, the period leading up to the 2008/2009 financial crisis; (2) 2008 to 2014, the years immediately following the financial crisis; (3) 2015-2018, the recovery years; and 2019 to 2022, the years covering both the COVID-19 pandemic and the energy crisis of the year 2022.

Table IV about here

The 2SLS-results in Table IV show that the positive baseline effect of an increase in Chinese import competition ($\Delta ImI$) on frontier firms' labor and total factor productivity is mainly driven by the most recent period (2019–2022). In contrast, rising Chinese imports had a significantly negative impact on productivity growth of domestic frontier firms prior to the financial crisis (2003–2007). During the intervening periods, the respective coefficients were not significantly different from zero.

Moreover, our findings indicate that the particularly beneficial effect of Chinese imports on productivity growth in firms located farther from the frontier ($\Delta ImI *$

$FRONT_{Firm}$), that was presented in Table II, is mainly attributable to the period during and immediately subsequent to the financial crisis (2008–2014). These results apply to both labor productivity and total factor productivity. Conversely, the respective coefficient of TFP is negative for the period preceding the financial crisis (2003-2007), but insignificant in the case of labor productivity. In the more recent phases, no significant effects of changes in Chinese import intensity are observed for firms far away from the frontier.

Firms in sectors further away from the frontier experienced stronger growth than others, particularly in the period immediately following the financial crisis (2008-2014). The impact of changes in Chinese import intensity on firms in frontier versus non-frontier sectors ($\Delta ImI * FRONT_{Sector}$) is ambiguous. Prior to the financial crisis (2003–2007), firms operating in less sophisticated sectors experienced higher labor productivity growth due to an increase in Chinese import intensity than other firms. However, this effect became significantly negative after the financial crisis (2008–2014). For later periods, the sectoral interaction coefficients ($\Delta ImI * FRONT_{Sector}$) are insignificant.

For TFP growth (columns (5)-(8)), the coefficients of the interaction term of Chinese import intensity growth and the sector-level distance to the technological frontier ($\Delta ImI * FRONT_{Sector}$) are significant in all examined periods. Before the financial crisis, growing import intensity from China had a particularly detrimental effect on total factor productivity (TFP) growth for firms in less sophisticated sectors. However, these firms were better placed than those in more sophisticated sectors when the crisis hit. In later periods, however, the interaction term changed back to a negative sign.

This structural shift, triggered by the financial crisis, was subsequently reversed. It is reflected in the results showing the impact of changes in import intensity on firms that drew on different national innovation systems ($\Delta ImI * FRONT_{Country}$). During the financial crisis, firms in countries with less developed national innovation systems experienced a significant positive effect of enhanced Chinese import intensity on labor productivity growth compared to firms located in well-established innovation systems. However, this effect reversed in later periods, becoming a significant disadvantage. In terms of total factor productivity, the coefficient of ($\Delta ImI * FRONT_{Country}$) is significantly positive in the period before the financial crises. However, it turned negative in the aftermath of the 2008 crisis. Hence, firms in countries with less-established national innovation systems experienced a dampening effect on TFP growth due to increasing Chinese import intensities. Also this coefficient changed its sign during the recovery period (2015–2018) and became insignificant in the most recent period (2019–2022).

The specification tests support the validity of the 2SLS results (see Table V).

Table V about here

## 5. Discussion

This paper revisits the complex relationship between a firm's exposure to import competition, productivity growth and distance-to-the-frontier. The baseline is given by catching up mechanisms. Firms further away from the productivity frontier experience modest but positive productivity growth in response to increased Chinese competition. This pattern is consistent with a convergence mechanism: laggard firms exploit new opportunities for imitation, process upgrading, or efficiency gains, particularly in tradable sectors where learning from foreign competitors is feasible. Importantly, while the positive effect is not large enough to fully close the gap with frontier firms, it indicates that trade exposure can act as a spur to incremental productivity improvements for firms with room to catch up.

This paper focuses on the heterogeneous effects of import competition on firms positioned at different distances from various economic frontiers. Our contribution lies at the intersection of two major areas of research: the positive impact of trade on firm performance (Melitz and Ottaviano 2008; Bloom et al. 2016) and the more recent evidence documenting adverse effects of Chinese import competition in advanced economies (Friesenbichler et al. 2024; Autor et al. 2013). China offers technology-intensive products and has become a high-tech exporter, which, combined with Chinese subsidy policies, poses a challenge to firms in developed economies. It is unclear whether companies will be able to escape Chinese competition through vertical differentiation in the long run. The rapid accumulation of technology by Chinese firms could lead to a reduction in more ambitious, riskier R&D activities by firms exposed to Chinese competition. As the returns to investment in innovation decline, firms reduce technological exploration and increase technological exploitation (Morandi Stagni et al. 2021).

We advance this literature in three ways: by focusing explicitly on frontier firms versus non-frontier firms; by examining temporal heterogeneity; and by distinguishing between different types of frontiers, namely, productivity, technological, and innovation system frontiers.

While much of the earlier empirical literature establishes average effects of Chinese import penetration (e.g., Bloom et al. 2016, Autor et al. 2016), we differentiate explicitly between firms at the frontier and those lagging. Our findings contrast Ding et al. (2016), who show that Chinese firms near the technology frontier benefit disproportionately from trade exposure. While one might expect these firms to harness competitive exposure to enhance efficiency and innovation, we observe that, in several contexts, rising import intensity is associated with stagnating, or even declining productivity growth among frontier firms. This suggests that intensified competition may crowd out risky innovation or reduce the scope for quality-based differentiation, especially in times of crisis.

We extend the existing literature by tracking the evolution of trade-productivity dynamics across distinct time periods. Most earlier studies focus either on the pre-2008 period (e.g., Bloom et al. 2016) or aggregate across long spans without considering structural breaks. Our extended panel covers a period beyond 2016. Thus, it captures the phase during which China established itself as a major exporter of high-tech products. It also covers different periods of crisis and economic growth.

The temporal perspective reveals structural shifts. The effect of trade on productivity is not constant over time, having been particularly affected by the global financial crisis. While these findings align with those of Friesenbichler et al. (2024), our analysis goes further by examining differential responses among firms situated at varying distances from the frontier. This highlights the dynamic nature of competitive pressures. Firms further away from the productivity frontier consistently benefited from increased trade exposure throughout the sample period. This is in line with catching up dynamics. Yet, this advantage was especially pronounced during and immediately after the financial crisis of 2008/09 when market turbulence, resource reallocation, and intensified global competition created both pressure and opportunity for adaptation. In those years, less advanced firms exited the market or were able to improve processes, absorb technologies, and close part of the gap with frontier firms, particularly in contexts where import penetration intensified (Clementi and Palazzo 2016; Wenzel et al. 2020).

By contrast, the productivity trajectory of frontier firms flattened in the same periods. These firms appeared less able to extract gains from trade during times of macroeconomic instability, possibly due to risk aversion, demand uncertainty, or the rising complexity of competing with Chinese firms on both price and quality. The crisis environment seems to have eroded the returns to innovation for these firms, while providing space for more modest upgraders to gain ground (Archibugi et al. 2013; Paunov 2012).

This temporal differentiation strengthens the case for a dynamic understanding of trade-productivity linkages. One that accounts not only for firm heterogeneity, but also for how macroeconomic shocks reshape the relative advantages of firms at different stages of technological development. The heterogeneous effects of Chinese import competition are not confined to differences in firm-level productivity. Our results demonstrate that both sectoral characteristics and national innovation environments systematically shape how firms respond to rising trade pressures, especially during periods of macroeconomic disruption.

At the sectoral level, firms in less sophisticated industries, characterized by lower technological intensity and simpler export structures, displayed a negative impact of increasing import intensities on labor productivity during the financial crisis. However, in these same sectors, we observe an uptick in TFP growth where import competition intensified. This apparent paradox is consistent with a labor market shock scenario: the crisis and its associated spike in unemployment across the EU may have led firms to expand their labor input disproportionately relative to capital. As a result, output per worker fell or stagnated, while overall input efficiency improved, driven by increased competitive pressure and a reorganization of production processes. Such efficiency gains may have been easier to realize in low-tech sectors, where the scope for basic organizational or process improvements is higher and the reliance on lower-skilled labor reduces adjustment frictions.

Turning to national-level heterogeneity, we also identify divergent effects of import competition growth based on countries' distance to the innovation frontier. For firms in economies with less-developed innovation systems, often located in Southern and Eastern Europe, an increase in import competition during the crisis years was associated with positive labor productivity growth, but negative TFP growth. This decoupling points to a different underlying mechanism: rather than efficiency gains, labor productivity improvements may have been driven by capital deepening, as firms invested in physical assets to maintain competitiveness. However, the absence of corresponding TFP gains suggests that these investments did not translate into more efficient input use. Several factors could explain this pattern: resource misallocation, high adjustment costs in the context of crisis-induced uncertainty, or labor shedding, which may have been more prevalent in countries with weaker employment protections and less institutional support for innovation-driven restructuring.

These coefficients enable us to quantify growth differentials in scenarios with and without Chinese import competition. The baseline scenario considers only the distance-to-the-frontier measures. In the alternative scenario, we add the results of Chinese import competition and the interaction terms between the frontier indicator and the Chinese import competition indicators. Overall, we observe a modest yet significant decrease in labor productivity due to Chinese imports, ranging from 0.01 percentage points (OLS) to 0.3 percentage points (2SLS). Therefore, Chinese import competition reduces labor productivity growth for non-frontier firms by up to one-eighth of the sample-wide mean growth rate. The results for total factor productivity are comparable, but slightly stronger in their magnitude. The main drivers of this effect differ across specifications, but typically are the frontiers related to the sectoral and national innovation system. Altogether, the recently observed productivity slowdown can be partly attributed to Chinese import competition, which has led to a decline in growth for non-frontier firms.

While our analysis provides new insights into the heterogeneous effects of Chinese import competition across different frontiers and time periods, several limitations must be acknowledged. First, the structure of the ORBIS database imposes a within-firm analysis that does not consider entry and exit dynamics, which are central to understanding developments in aggregate productivity and selection mechanisms. Our results capture intra-firm adaptation, and not between-firm reallocation mechanisms. Hence, they may underestimate the full extent of trade-induced restructuring in the corporate sector.

Second, our estimates are derived from partial equilibrium models. While this allows for a precise identification of firm-level responses, it does not capture general equilibrium feedback effects, such as changes in input prices, labor market adjustments, or shifts in demand across sectors and countries. This implies that our findings cannot be interpreted as comprehensive welfare effects of trade liberalization.

Finally, although we augment the productivity frontier using sectoral and economy-wide indicators, we rely on observed proxies such as export sophistication and metrics from the national innovation system. These proxies may not fully capture the complexity of technological capabilities or institutional quality. Future work could benefit from integrating richer innovation and patent data, as well as firm-level input-output linkages, to further elaborate on the channels through which trade exposure interacts with firm capabilities and context.

## 6. Conclusions

This paper examines whether the impact of increased Chinese imports on within-firm productivity is moderated by technological frontiers. We examine how Chinese import growth impacted the productivity growth of firms in the European Union between 2003 and 2022, distinguishing between those close to and far from the frontiers of productivity, technology, and the national innovation system. Additionally, we explore how these relationships evolved across different periods of economic growth, particularly before, during, and after the global financial crisis. Our sample comprises approximately 430,000 firms in the EU drawn from the ORBIS database. We match firm performance with import data at the NACE Rev. 2, 4-digit level after implementing a series of HS reclassifications.

Our findings reveal that increasing Chinese import competition does not uniformly affect productivity growth. While firms further from the productivity frontier tend to benefit modestly from rising trade exposure - consistent with convergence and learning effects - frontier firms often experience stagnating or negative productivity growth.

Productivity growth is lower for firms in technologically less complex sectors when Chinese import intensities rise. Consequently, firms in technologically lagging settings also face reduced productivity growth. At the national innovation system level, we find mixed effects. Firms in less developed economies catch up in terms of total factor productivity; however, they are at a disadvantage with regard to labor productivity growth. As Chinese import intensity increases, labor productivity growth rises, though total factor productivity growth tends to decline.

We document substantial heterogeneity over time, as these patterns are especially pronounced during periods of crisis, when uncertainty and competitive pressure may discourage high-risk innovation. In less technologically advanced industries, firms experienced declining labor productivity but rising TFP during the financial crisis, suggesting reorganization gains amid labor market shocks. Conversely, in countries with less developed innovation systems, increased import competition was associated with labor productivity gains but falling TFP, indicating capital deepening without efficiency improvements.

Taken together, these results partly attribute the productivity slowdown to Chinese import competition which lowers growth of non-frontier firms. The findings underscore the need for a more nuanced understanding of global trade effects, one that considers firm capabilities, macroeconomic conditions, and systemic innovation environments. The findings suggest that policy responses to trade shocks should be tailored to the institutional and sectoral contexts in which firms operate, with particular attention to supporting innovation capacity and easing adjustment frictions in less advanced settings.

It is anticipated that competition from China will further intensify in light of the country's "Made in China 2025" industrial strategy. China's objective is to further advance its technological capabilities and attain self-sufficiency in the production of "core products," including semiconductors, aerospace, IT, and biotechnology (Li 2018). This suggests that, if China's policies are effective, the net impact on productivity will significantly vary among firms depending on their proximity to the productivity frontier, their technological sector-level frontier, and the national innovation system in which they operate.

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## Tables

*Table I: Descriptive statistics*

| | $\Delta$ LP | $\Delta$ TFP | $\Delta$ ImI | $DIST\_FRONT_{LP}$ | $DIST\_FRONT_{TPP}$ | $DIST\_FRONT_{Sector}$ | $DIST\_FRONT_{Country}$ | $\Delta$ $IMP_{total}$ | $\Delta$ CAP |
|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.021 | 0.006 | 0.003 | 0.608 | 0.593 | 0.229 | 0.446 | 0.019 | 0.030 |
| Median | 0.022 | 0.010 | 0.001 | 0.654 | 0.637 | 0.206 | 0.437 | 0.025 | –0.037 |
| Std. Dev. | 0.527 | 0.514 | 0.022 | 0.253 | 0.246 | 0.201 | 0.145 | 0.211 | 0.578 |
| 10% Perc. | –0.407 | –0.418 | –0.013 | 0.230 | 0.229 | 0.000 | 0.276 | –0.183 | –0.342 |
| 90% Perc. | 0.449 | 0.423 | 0.021 | 0.899 | 0.878 | 0.525 | 0.605 | 0.213 | 0.490 |
| N | 2917367 | 2917367 | 2917367 | 2917367 | 2917367 | 2917367 | 2917367 | 2917367 | 2917367 |

*Table II: The frontier, productivity growth and changes of Chinese trade intensities*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | **LP** | | **TFP** |
| | OLS | 2SLS | OLS | 2SLS |
| Δ ImI | 0.07 | 0.63*** | 0.11** | 0.89*** |
| | (0.046) | (0.231) | (0.046) | (0.231) |
| $DIST\_FRONT_{Firm}$ | 0.57*** | 0.56*** | 0.52*** | 0.59*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Δ ImI * $DIST\_FRONT_{Firm}$ | -0.08 | 0.76*** | -0.17** | 0.46* |
| | (0.078) | (0.261) | (0.078) | (0.268) |
| $DIST\_FRONT_{Sector}$ | 0.04*** | 0.04*** | 0.04*** | 0.05*** |
| | (0.006) | (0.007) | (0.006) | (0.006) |
| Δ ImI * $DIST\_FRONT_{Sector}$ | 0.10 | -0.94** | -0.15** | -1.24*** |
| | (0.080) | (0.387) | (0.061) | (0.260) |
| $DIST\_FRONT_{Country}$ | -0.15** | -1.20*** | 0.07*** | 0.06*** |
| | (0.063) | (0.269) | (0.005) | (0.005) |
| Δ ImI * $DIST\_FRONT_{Country}$ | 0.04*** | 0.04*** | 0.13* | -1.09*** |
| | (0.005) | (0.005) | (0.078) | (0.376) |
| Δ CAP | 0.03*** | 0.03*** | | |
| | (0.001) | (0.001) | | |
| Δ $IMP_{total}$ | 0.04*** | 0.04*** | 0.04*** | 0.04*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Constant | -0.21*** | | -0.39*** | |
| | (0.081) | | (0.078) | |
| Year, Sector, Country FE | | Included | | |
| Observations | 2,734,879 | 2,734,822 | 2,890,212 | 2,734,822 |

Note: This table reports the regression results of the impact of changes in import competition on changes in labor and total factor productivity growth across different "distance to the frontier" (DIST_FRONT) types. ImI denotes the intensity of Chinese imports and IMP the total imports at the country-industry-year level, and CAP the firm specific capital stock. Growth rates (denoted by Δ) are measured in logarithmic differences. Newey-West s.e. in all specification, Constants are not reported, *** p-value<0.01, ** p-value <0.05, * p-value <0.1.

*Table III: Specification tests of the 2SLS regressions*

| | Δ LP | | Δ TFP | |
|---|---|---|---|---|
| | **Test value** | **p-value** | **Test value** | **p-value** |
| 1st stage F-statistic of excl. inst.: Δ Import intensity | F( 4, 2734879): 5144.32 | 0.000 | F(4, 2734879): 5112.61 | 0.000 |
| 1st stage F-statistic of excl. inst.: Δ Import intensity*DIST_FRONTFirm | F(4, 2734879): 4066.12 | 0.000 | F(4, 2734879): 4180.03 | 0.000 |
| 1st stage F-statistic of excl. inst.: Δ Import intensity*DIST_FRONTSector | F(4, 2734879): 2743.74 | 0.000 | F(4, 2734879): 2721.05 | 0.000 |
| 1st stage F-statistic of excl. inst.: Δ Import intensity*DIST_FRONTCountry | F(4, 2734879): 4539.50 | 0.000 | F(4, 2734879): 4503.03 | 0.000 |

Note: This table reports the specification tests of the 2SLSL regressions in Table II.

*Table IV: Productivity growth, the frontier, and changes of Chinese trade intensities across time periods (2SLS)*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | 2003 - 2007 | 2008 - 2014 | 2015 - 2018 | 2019 - 2022 | 2003 - 2007 | 2008 - 2014 | 2015 - 2018 | 2019 - 2022 |
| | Δ LP | Δ LP | Δ LP | Δ LP | Δ TFP | Δ TFP | Δ TFP | Δ TFP |
| Δ ImI | -4.15** | -0.46 | -0.34 | 5.94*** | -2.52* | -0.77 | -0.00 | 5.77*** |
| | (2.098) | (0.494) | (0.516) | (0.625) | (1.391) | (0.507) | (0.520) | (0.617) |
| $DIST\_FRONT_{Firm}$ | 0.64*** | 0.62*** | 0.53*** | 0.53*** | 0.65*** | 0.63*** | 0.56*** | 0.59*** |
| | (0.033) | (0.004) | (0.004) | (0.004) | (0.024) | (0.004) | (0.004) | (0.005) |
| Δ ImI * $DIST\_FRONT_{Firm}$ | -6.64 | 1.88*** | 0.20 | -0.28 | -5.59* | 2.42*** | -0.93 | 0.00 |
| | (4.111) | (0.656) | (0.681) | (0.360) | (2.878) | (0.677) | (0.693) | (0.361) |
| $DIST\_FRONT_{Sector}$ | 0.29 | 0.04*** | 0.01 | -0.02 | 0.20* | 0.05*** | 0.01 | -0.02 |
| | (0.177) | (0.013) | (0.016) | (0.020) | (0.120) | (0.013) | (0.016) | (0.020) |
| Δ ImI * $DIST\_FRONT_{Sector}$ | 11.93* | -1.47* | 1.17 | -1.84 | -9.39** | 1.57* | -2.10*** | -8.64*** |
| | (7.243) | (0.840) | (1.170) | (1.212) | (4.723) | (0.813) | (0.605) | (0.940) |
| $DIST\_FRONT_{Country}$ | -13.06* | 1.13 | -1.95*** | -8.53*** | -0.05 | 0.04*** | -0.06*** | -0.08*** |
| | (6.995) | (0.838) | (0.615) | (0.966) | (0.091) | (0.008) | (0.018) | (0.025) |
| Δ ImI * $DIST\_FRONT_{Country}$ | -0.12 | 0.05*** | -0.08*** | -0.10*** | 8.22* | -1.89** | 2.54** | -1.58 |
| | (0.136) | (0.008) | (0.018) | (0.025) | (4.747) | (0.819) | (1.138) | (1.200) |
| Δ $IMP_{total}$ | 0.03*** | 0.03*** | 0.02*** | 0.02*** | 0.25** | 0.05*** | 0.00 | 0.04*** |
| | (0.003) | (0.001) | (0.001) | (0.002) | (0.108) | (0.003) | (0.004) | (0.004) |
| Δ CAP | 0.33** | 0.05*** | 0.00 | 0.04*** | | | | |
| | (0.159) | (0.003) | (0.004) | (0.004) | | | | |
| Year, Sector, Country FE | | | | Included | | | | |
| Observations | 441,497 | 1,062,320 | 689,354 | 541,651 | 441,497 | 1,062,320 | 689,354 | 541,651 |

Note: This table reports the two-stage least squares regression results of the impact of changes in import competition on changes in labor and total factor productivity growth across different "distance to the frontier" (DIST_FRONT) types. ImI denotes the intensity of Chinese imports and IMP the total imports at the country-industry-year level, and CAP the firm specific capital stock. Growth rates (denoted by Δ) are measured in logarithmic differences. The full sample was divided into four segments, with regression analyses conducted separately for each period (2003-2007, 2008-2014, 2015-2018, and 2019-2022). Newey-West s.e. in all specification, Constants are not reported, *** p-value<0.01, ** p-value <0.05, * p-value <0.1.

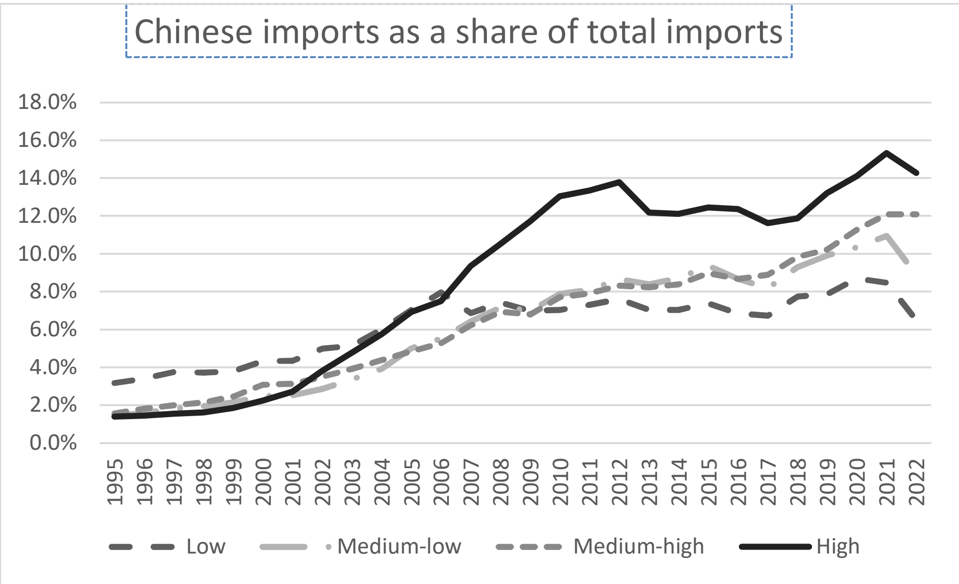
*Table V: Specification tests of the 2SLS regressions across periods*

| | Δ LP, 2003-2007 | | Δ LP, 2008-2014 | | Δ LP, 2015-2018 | | Δ LP, 2019-2022 | |
|---|---|---|---|---|---|---|---|---|
| | **Test value** | **p-value** | **Test value** | **p-value** | **Test value** | **p-value** | **Test value** | **p-value** |
| 1st stage F-statistic of excl. inst.: Δ Import int. | F(4, 441249): 235.99 | 0.000 | F(4, 1062067): 1975.75 | 0.000 | F(4, 689104): 1240.90 | 0.000 | F(4, 541404): 3214.34 | 0.000 |
| 1st stage F-statistic of excl. inst.: Δ Import intensity*DIST_FRONTFirm | F(4, 441249): 200.46 | 0.000 | F(4, 1062067): 1445.58 | 0.000 | F(4, 689104): 1032.60 | 0.000 | F(4, 541404): 2600.11 | 0.000 |
| 1st stage F-statistic of excl. inst.: Δ Import intensity*DIST_FRONTSector | F(4, 441249): 183.99 | 0.000 | F(4, 1062067): 1155.22 | 0.000 | F(4, 689104): 662.25 | 0.000 | F(4, 541404): 2982.15 | 0.000 |
| 1st stage F-statistic of excl. inst.: Δ Import intensity*DIST_FRONTCountry | F(4, 441249): 658.07 | 0.000 | F(4, 1062067): 1677.17 | 0.000 | F(4, 689104): 1264.19 | 0.000 | F(4, 541404): 2282.37 | 0.000 |
| Kleibergen-Paap rank Wald F statistic | 43.64 | | 825.89 | | 480.65 | | 702.61 | |
| | **Δ TFP, 2003-2007** | | **Δ TFP, 2008-2014** | | **Δ TFP, 2015-2018** | | **Δ TFP, 2019-2022** | |
| | **Test value** | **p-value** | **Test value** | **p-value** | **Test value** | **p-value** | **Test value** | **p-value** |
| 1st stage F-statistic of excl. inst.: Δ Import int. | F(4, 441250): 229.27 | 0.000 | F(4, 1062068): 1961.72 | 0.000 | F(4, 689106): 1221.48 | 0.000 | F(4, 541405): 3210.16 | 0.000 |
| 1st stage F-statistic of excl. inst.: Δ Import intensity*DIST_FRONTFirm | F(4, 441250): 204.87 | 0.000 | F(4, 985039): 1485.01 | 0.000 | F(4, 689106): 1056.57 | 0.000 | F(4, 541405): 2522.08 | 0.000 |
| 1st stage F-statistic of excl. inst.: Δ Import intensity*DIST_FRONTSector | F(4, 441250): 191.63 | 0.000 | F(4, 985039): 1148.80 | 0.000 | F(4, 689106): 611.28 | 0.000 | F(4, 541405): 2972.65 | 0.000 |
| 1st stage F-statistic of excl. inst.: Δ Import intensity*DIST_FRONTCountry | F(4, 441250): 657.19 | 0.000 | F(4, 985039): 1666.41 | 0.000 | F(4, 689106): 1243.11 | 0.000 | F(4, 541405): 2279.85 | 0.000 |
| Kleibergen-Paap rank Wald F statistic | 2.10 | | 919.20 | | 333.31 | | 686.74 | |

Note: This table reports the specification tests of the 2SLSL regressions in Table IV

## Figures

*Figure 1: Share of Chinese imports in total imports by sectoral technology intensity*




Note: This figure illustrates the increase of Chinese imports in the import portfolio by a high-tech classification proposed by Eurostat. High tech and medium-high tech imports rise faster than low-tech and medium-low-tech imports.
See https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech_classification_of_manufacturing_industries

## Annex A

*Table A1: The frontier, labor productivity growth and changes of Chinese trade intensities across periods (OLS)*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | 2003 - 2007 | 2008 - 2014 | 2015 - 2018 | 2019 - 2022 | 2003 - 2007 | 2008 - 2014 | 2015 - 2018 | 2019 - 2022 |
| | Δ LP | Δ LP | Δ LP | Δ LP | Δ TFP | Δ TFP | Δ TFP | Δ TFP |
| Δ ImI | -0.09 | 0.19** | -0.06 | -0.17 | -0.09 | 0.18** | -0.06 | -0.02 |
| | (0.120) | (0.086) | (0.108) | (0.128) | (0.120) | (0.088) | (0.111) | (0.121) |
| $DIST\_FRONT_{Firm}$ | 0.17*** | 0.20*** | 0.17*** | 0.15*** | 0.17*** | 0.20*** | 0.17*** | 0.17*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Δ ImI * $DIST\_FRONT_{Firm}$ | -0.15 | -0.07 | -0.21*** | -0.13** | -0.13 | -0.12 | -0.17** | -0.17*** |
| | (0.106) | (0.067) | (0.077) | (0.063) | (0.094) | (0.075) | (0.077) | (0.060) |
| $DIST\_FRONT_{Sector}$ | 0.00 | 0.05*** | -0.02 | -0.02 | 0.01 | 0.05*** | -0.01 | -0.01 |
| | (0.022) | (0.015) | (0.018) | (0.021) | (0.023) | (0.016) | (0.018) | (0.021) |
| Δ ImI * $DIST\_FRONT_{Sector}$ | 0.18 | -0.38** | -0.05 | -0.66*** | 0.19 | -0.37** | -0.19 | -0.69*** |
| | (0.161) | (0.158) | (0.171) | (0.150) | (0.161) | (0.161) | (0.177) | (0.142) |
| $DIST\_FRONT_{Country}$ | 0.00 | 0.05*** | -0.02*** | -0.03** | 0.00 | 0.08*** | -0.02*** | -0.05*** |
| | (0.005) | (0.005) | (0.008) | (0.012) | (0.006) | (0.006) | (0.008) | (0.012) |
| Δ ImI * $DIST\_FRONT_{Country}$ | 0.00 | 0.16** | 0.07 | -0.29** | 0.00 | 0.14** | 0.03 | -0.19 |
| | (0.058) | (0.064) | (0.110) | (0.120) | (0.057) | (0.068) | (0.112) | (0.120) |
| Δ $IMP_{total}$ | 0.03*** | 0.04*** | 0.04*** | 0.03*** | | | | |
| | (0.002) | (0.001) | (0.001) | (0.002) | | | | |
| Δ CAP | 0.01** | 0.05*** | 0.00 | 0.04*** | 0.01** | 0.04*** | 0.00 | 0.03*** |
| | (0.004) | (0.003) | (0.004) | (0.003) | (0.004) | (0.003) | (0.004) | (0.003) |
| Year, Sector, Country FE | Included | | | | | | | |
| Observations | 378,161 | 944,846 | 716,098 | 523,778 | 398,805 | 985,289 | 739,900 | 565,909 |

Note: This table reports the regression results of the impact of changes in import competition on changes in labor and total factor productivity growth across different "distance to the frontier" (DIST_FRONT) types. ImI denotes the intensity of Chinese imports and IMP the total imports at the country-industry-year level, and CAP the firm specific capital stock. Growth rates (denoted by Δ) are measured in logarithmic differences. The sample covers the period 2003-2022. OLS regressions with Newey-West s.e. in all specifications. Constants are not reported. *** p-value<0.01, ** p-value <0.05, * p-value <0.1.

**Annex B**

### ORBIS data

The ORBIS database is a product of Moody's and contains over 550 million entities companies across the globe.[9] The data provide a rich source of financial information and company characteristics (e.g., sector, location, ownership and governance structures).

Data cleaning:

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.
- 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.

[9] See https://www.moodys.com/web/en/us/capabilities/company-reference-data/orbis.html (accessed on October 29, 2024).

- We restrict the definition of capital stock to tangible assets only. ORBIS 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 2022, the most recent year available. We could not include firms in Greece, Lithuania, Estonia and Malta 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.

Levinsohn-Petrin productivity estimators

The Levinsohn-Petrin estimators require information on intermediates. As a proxy variable, we use material costs, which is available in the data. Entry and exit information is not taken into account. Although the ORBIS 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.

### 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.[10] The data is adjusted for distortions due to CIF and FOB. The reliability of the reported data is also taken into account.

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

[10] See Gaulier and Zignago 2010 and https://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=37 (retrieved on 21 May 2025).

NACE Rev. 1 to NACE Rev. 2, which is used in the firm-level dataset. AMADEUS provides a list of primary and secondary 4-digit industries, which we match to the trade data. We only use information on a firm's primary affiliation, as using information on secondary affiliations has not been found to change the results (Bloom et al. 2016). The transformation process resulted in some four-digit classes being split into several other classes. We distributed these values evenly across the classes.

### The Eurostat Taxonomy and sectoral complexity

We implement the previously shown Eurostat taxonomy to validate the complexity indicator. The proposed complexity scores increase with sectoral technology intensity. Specifically, low-tech industries have a mean complexity score of -0.53, medium-low-tech industries have a score of 0.20, medium-high-tech industries have a score of 0.53, and high-tech industries have a score of 0.76. Firms in industries with a relatively low distance to the frontier include the manufacture of basic pharmaceutical products and preparations (NACE 21) and the manufacture of motor vehicles, trailers, and semi-trailers (NACE 29). In contrast, the mean distance to the sectoral complexity frontier is highest in the manufacture of textiles (NACE 13) and the manufacture of wearing apparel (NACE 14). The average sectoral distance indicator also varies across countries, but to a lesser extent, indicating within-country dispersion. The highest distances to the complexity frontier are found in Bulgaria, Portugal, and Romania, while the lowest are in Germany and Austria. The sectoral distance indicator is almost uncorrelated with the growth of import intensity (r: -0.02; p-value: 0.000). The sectoral distance-to-the-frontier indicator exhibits little variation over time, as it primarily reflects structural characteristics. The variance in this indicator is lower in high-tech sectors compared to low-tech sectors. Drawing on the Eurostat taxonomy, we find that the mean distance to the sectoral frontier is 11.2% for low-tech sectors, 8.5% for medium-low-tech sectors, 8.7% for medium-high-tech sectors, and 5.3% for high-tech sectors.