European integration, trade, and globalization: Eastern Europe's response to Chinese competition*

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Abstract

This paper investigates adjustments to Chinese export competition by a group of Eastern and Southeastern European (ESE) countries within EU15 destination-product markets. Using instrumental variables, we evaluate the impact of China's expansion into these markets and document sizable displacements of ESE exports. While the magnitude of these effects might differ across exporters, significant reductions materialize in terms of both export revenues and quantities. Displacements are about 50 percent smaller in time-sensitive industries (i.e. where short delivery times matter), suggesting a source of comparative advantage that arises from exporters' relative geographic proximity to a destination or favorable trade infrastructure, in addition to conventional sources. Further results indicate that goods are shipped to fewer destinations and that the main export destination changes more frequently in response to Chinese competition. This indicates overall fewer, less stable trade relationships and potentially specialization into less exposed market niches.

JEL-Classification: F14, F15, F61, L25

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1 Introduction

The rise of China is a central and ongoing topic in the debate on globalization, which culminated recently in serious reconsiderations of trade-policy agendas in major economies (Fajgelbaum et al., 2019). In several countries, noticeable reductions in manufacturing sector activity and employment since the early 2000s have been attributed to increased Chinese competition (Autor et al., 2013, 2014, 2016; Bloom et al., 2016). In line with their comparative advantage, effects of low-wage country competition are typically stronger in labor and low-skill intensive industries (Bernard et al., 2006).

Such effects are not necessarily limited to economies importing from China. Export revenues of countries supplying goods similar to China's might also decline. Compare, for instance, China's exports to the EU15 with those of Eastern and Southeast European (ESE) countries. Between 1997 and 2007, China's market share increased from 3.9 to 9.8 percent for an average manufacturing product imported in the EU15. In the same period ESE's share increased from 7.2 to 10.2 percent. Despite an ongoing formal European integration process, China's expansion gained momentum after its WTO entry in 2001, while ESE's expansion slowed down.[1]

Which mechanisms could guide the adjustment of ESE exports? It might be expected that China has a comparative advantage in low-skill intensive production over most ESE exporters.[2] A key distinction, however, could also arise considering their relative geographic proximity to the EU15. If time acts as a meaningful barrier to international trade, ESE countries clearly have an absolute advantage over China in EU15 destination markets.[3] Moreover, if short delivery times matter more for some goods than for others, this would result in a comparative advantage for ESE exporters in "time-sensitive" industries. Indeed, empirical research suggests that delays in shipments have adverse effects on countries' export performance, while the magnitude of such effects differs across industries (e.g. Djankov et al., 2010; Hummels and Schaur, 2013). What has not been shown in the literature so far, is whether this mechanism is relevant in the context of Chinese competition.

[1] Average annual increases in import market shares were fairly similar in the years 1997-2001, with 0.38 and 0.44 percentage points per annum for ESE and China, respectively. In subsequent years (2002-2007), ESE shares increased by 0.25 percentage point per year, while China's growth rate was 0.68. These numbers are based on the CEPII Baci trade data set. ESE exporters include the following countries: Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Northern Macedonia, Poland, Romania, Serbia and Montenegro, Slovak Republic, Slovenia, and Turkey.

[2] According to OECD data, in the early 2000s the share of individuals with a tertiary degree was 3 percent in China and above 10 percent in the largest ESE economies.

[3] Using bilateral population-weighted distances from the CEPII gravity data set, Chinese exports to an average EU15 destination bridge about to 8,300km, whereas ESE exports have to bridge only about 1,500km. Sea distances data from CERDI suggest much larger numbers for China: about 20,000km to Belgium, Germany or the Netherlands and about 15,000km to Italy and Greece.

This paper sets out to answer this question, by analyzing the response of ESE exports to China's expansion into EU15 manufacturing product markets. In doing so, we focus first on estimating the general impact of Chinese competition. To establish a causal relationship, we rely partly on methods that are widely used in the related empirical literature (e.g. Autor et al., 2013), but we augment their approach to generate additional variation *across the various destinations* in the EU15. In addition, we exploit trade-liberalization episodes in conjunction with China's WTO entry to support our baseline identification strategy. In the second step of our analysis, we focus on identifying ESE's comparative advantage in time-sensitive industries. In doing so, we obtain a measure of relative time-sensitivity for groups of HS6 products (at the 2-digit HS level), using the data and methodology of Hummels and Schaur (2013).[4] We exploit this measure in different ways to estimate whether ESE exports reveal a differential response to Chinese competition in relatively more time-sensitive industries. We conduct our analysis using product-level information on ESE exports to different EU15 destinations, but also employ customs-level data on Bulgarian exporting firms to explore additional adjustments that cannot be observed in our product-level data.

Our main findings suggest a displacement of ESE exports due to Chinese competition by 12.8 percent between 1997 and 2007. Reductions *within* Bulgarian firms, which we observe over a shorter time period, amount to 3.3 percent. The decline in export revenues both at the product and at the firm level, is accompanied by a contraction in exported quantities. Exploring heterogeneous effects across exporters, we find that countries integrating earlier into the European Union tend to be generally more affected, while exporters with higher real GDP per capita, lower average price levels, and higher inflows of FDI (in percent of GDP) are relatively less affected. Moreover, we observe that large exporting firms and those supplying their products to a larger set of destinations are significantly less affected by Chinese competition. In time-sensitive industries the effects of Chinese competition are about 50 percent smaller. This result continues to hold when we consider additional industry characteristics, such as skill-intensity. In a placebo regression, we find that differential adjustments in time-sensitive industries do not reveal for a group of low-wage Asian countries, whose distance to the EU15 is similar to China's.

Our study contributes to an abundant empirical literature on the impact of Chinese competition in Europe (Bugamelli et al., 2015; Bloom et al., 2016; Utar, 2014, 2018). It relates in particular to findings of Dauth et al. (2014), who suggest that Chinese import competition had only a negligible impact on manufacturing employment in Germany, due

[4]This approach relies on US trade data, which reports shipments by mode of transport and other relevant dimensions, allowing us to replicate their estimates of a markup importers are willing to pay for faster delivery.

to substitution effects between Chinese and other exporters. While previous research by Silgoner et al. (2015) cannot confirm such substitution effects for a set of countries similar to ours, their analysis rests on descriptive statistics and is difficult to compare to related empirical studies on Chinese competition. Hence, our paper is the first to investigate these substitution effects based on an empirical approach that is consistent with this literature and confirms strong substitution effects between Chinese and ESE exports to EU15 markets.

Our findings make a contribution also to the broader literature on competition effects of China's expansion on exports of other low- and middle-income countries (e.g. Hanson and Robertson, 2010; Mattoo et al., 2017). Our approach is most similar to the study of Utar and Torres Ruiz (2013), which focuses on adjustments of Mexican maquiladora plants to Chinese competition in the US market. Our results suggest somewhat smaller, yet comparable, displacement effects for ESE exports. In contrast to their study, we observe a much wider range of exporting and importing countries at a more disaggregated level. By observing 6-digit products categories instead of sectors, we are able to measure the incidence of competition more precisely. Moreover, by observing differential intensification of competition also across destination markets, we can confirm in our robustness checks that our estimates are not driven by an omitted variable bias stemming from general product-level dynamics. This is a key advantage also with respect to several other studies, which typically identify Chinese competition solely at the product or industry level. In addition to this, our data structure allows us to identify novel margins of adjustment, such as a differential impact on multi-destination exporters (at the firm-level), or reductions in the geographic diffusion of ESE exports across EU15 destinations (at the product-level).

Finally, we make a contribution to the literature investigating the role of time in international trade (Djankov et al., 2010; Hummels and Schaur, 2013). Related to this literature and our paper, Evans and Harrigan (2005) argue that the location choice of firms takes geographic proximity into account if timely delivery matters. This is in line also with a more recent theoretical contribution by Deardorff (2014), which highlights that countries can have a "local comparative advantage" in industries due to the presence of trade frictions. To the best of our knowledge, this paper is the first to present empirical evidence on the relevance of such a mechanism, by showing that ESE exports in time-sensitive industries are significantly less harmed by Chinese competition.

Our paper unfolds as follows. Section 2 presents our data and some descriptive statistics that suggest a differential performance of trade in time-sensitive industries. Section 3 focuses on the empirical approach and discusses our identification strategy for evaluating the causal impact of China on ESE exports. Section 4 presents our main findings and robustness checks for both general export competition and for differential adjustments in time-sensitive industries. Additional results and further margins of adjustments are analysed in Section 5, while Section 6 concludes.

2 Data and descriptive statistics

International trade data. For the most part of our empirical analysis we rely on product-level trade data from UN Comtrade. We use the cleaned CEPII BACI92 and BACI96 versions of this data, which reports *free-on-board* (f.o.b.) bilateral trade flows at the HS6 product level at annual frequency. Trade flows are reported in terms of their value (in thousand US dollars) and quantity (in kilograms). HS6 product classifications are subject to revisions over time, so we convert all our data into HS1996 product codes using correspondence tables from the United Nations Statistics Division (UNSD). Our sample of exporting economies is comprised of 16 countries, which we further divide into Eastern European (EEC) and Southeast European (SEE) countries in some parts of our analysis.[5] On the importer side, we distinguish 14 destination markets that constitute the EU15 (Belgium and Luxembourg appear as a single destination in the data). Overall, our sample period spans 11 years (1997-2007), which will allow us to exploit China's WTO accession in 2001 as part of our identification strategy, while excluding years where trade might have been affected by the global financial crisis and the subsequent trade collapse.

We also use firm-level customs data for Bulgarian exports to EU15 product-destination markets to explore further dimensions of the impact of Chinese competition, which might depend on particular firm-level characteristics. The data comes from the Exporter Dynamics Database (EDD), compiled by the World Bank (Fernandes et al., 2016), and spans the period 2001-2006.[6] The EDD data provides us with an identifier for each exporting Bulgarian firm, the HS6 products it exports to a particular destination, as well as the value (in US dollars) and the quantity (in kilograms) of the shipment. In contrast to the product-level trade data described above, which omits shipments at values below 1,000 USD, exports by Bulgarian firms also include smaller amounts. We will account for this discrepancy in the sampling by employing quantity-weighted OLS specifications.[7]

[5] The eight EEC exporters are: Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovak Republic and Slovenia. The eight SEE countries are: Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Northern Macedonia, Romania, Serbia-Montenegro, and Turkey. We do not include the small island economies of Cyprus and Malta, although they also entered the EU in 2004.

[6] Customs data at the firm-product-destination level is available from the EDD for a limited group of countries.

[7] While inspecting inconsistencies in reported shipments between the two data sets, we observed that a substantial part of exports reported for Bulgarian firms, but not in the BACI data, have relatively small values and quantities.

Table 1: Descriptive statistics of product- and firm-level trade data

Panel A: ESE exporting countries, 1997-2007						
Observation in sample	First year (1997)			Last year (2007)		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
EU15 share in total exports (%)	56.7	56.6	14.1	55.3	55.4	11.6
Total # of shipments to EU15	7,467	5,988	5,621	10,369	8,074	5,621
# HS6 products shipped	1,923	2,019	894	2,134	2,195	772
# HS6 per destination	856	847	479	1,012	974	510
# Destinations per HS6	5.3	5.4	1.9	6.7	7.0	2.2
Panel B: Bulgarian firms, 2001-2006						
Observation in sample	First year (2001)			Last year (2006)		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
EU15 share in total exports (%)	81.19	99.70	30.63	78.62	98.28	31.72
Total # of shipments to EU15	34.32	18	46.69	39.86	21	58.00
# HS6 products shipped	33.12	18	43.70	38.32	21	54.26
# HS6 per destination	18.33	10	22.31	20.58	10	29.23
# Destinations per HS6	1.56	1	1.35	1.73	1	1.72

Note: Panel A reports statistics for product-level trade data, based on final estimation sample covering 16 exporting countries, 14 destinations, and 3,903 HS6 manufacturing products. Number of observations: 1,628,298; cross-sections (exporter-importer-HS6): 258,569; average years per cross-section: 6.3. Panel B reports statistics for Bulgarian firm-level trade data. Number of observations: 268,822; cross-sections (firm-importer-HS6): 162,554; average years per cross-section: 1.65.

In Table 1, Panel A, we present some features of our product-level trade data. Exports into the EU15 account for a stable 55 percent of ESE countries' total manufacturing export revenues and an average country roughly reports 7,500 to 10,400 shipments per year. However, variation across exporters is substantial: the least active ESE exporter (Albania) reports 1,046-1,382 shipments per year, while the most active one (Czech Republic) counts 18,366-22,993 annual shipments. Out of a total of 3,903 HS6 product lines in our sample, we note that both the mean and median ESE country exports between 1,900 and 2,200 different products. The highest coverage rate is reached by Czech Republic in 2001 (87 percent) and the lowest by Bosnia and Herzegovina in 1997 (12 percent). Moreover, we observe that exporters ship different goods to different EU15 countries, as we can see from the number of product lines per destination, which is consistently lower than the total number of goods exported in a year. Also the geographic diffusion of exports is limited: the average exporter ships its average product to at most half of the EU15 destination markets (5-7 out of 14).

Panel B shows corresponding statistics for our sample of Bulgarian firms, of which we observe 8,916 units on average per year. For the vast majority EU15 markets are the main, if not the only export destination. However, comparing mean and median numbers for the EU15 share in revenues we note that some firms are substantially more diversified. Similar heterogeneity can be observed in the remaining categories. The average Bulgarian exporter reports between 34 and 39 shipments per year in which it sells between 33 and 38 different products. As in our product-level sample, exporters ship different goods to different destinations. At the intensive firm-product margin, we note that an average firm's average product is exported to only 1-2 destinations on average. Overall, our firm-level sample represents a majority of highly specialized exporters (along several margins) and a minority of (supposedly different) highly diversified firms.

Time-sensitive industries. Our paper focuses on identifying a geographic proximity advantage for ESE exporters in EU15 destination markets. To detect this advantage, we focus on differential responses to Chinese competition across industries. Focusing on this dimension is in line with empirical evidence on the trade-response to delays in shipment, which suggests that timely delivery matters more in some sectors than in others. Djankov et al. (2010) identify such differential responses mainly via the product-code descriptions in disaggregated trade data (e.g., fresh and frozen products versus other goods). In our sample of manufacturing products, such an approach is not feasible and potentially also too restrictive. An alternative is offered by Hummels and Schaur (2013), who obtain time-sensitivity estimates for individual industries from a structural model. The advantage of their method is that it does not require subjective judgements about the importance of timely delivery for different goods. Instead, using information on transport mode, duration, and prices, they recover estimates of an additional markup consumers are willing to pay for (a one day) earlier delivery. We use their data and methodology to estimate time-sensitivity parameters at the 2-digit HS industry level.[8]

While the underlying model as well as the empirical approach is explained in detail in Appendix C, one caveat worth pointing out here concerns imprecisely estimated time-sensitivity parameters. We therefore consider two versions of this measure: (i) a simple (i.e. broad) measure, which is based solely on the magnitude of the point estimate; and (ii) an adjusted (i.e. strict) measure, which sets time-sensitivity equal to zero for HS2 sectors where the estimate does not pass the 10 percent significance threshold. The respective frequency distributions of these two measures are presented in Figure C1. Figure 1, shows descriptive

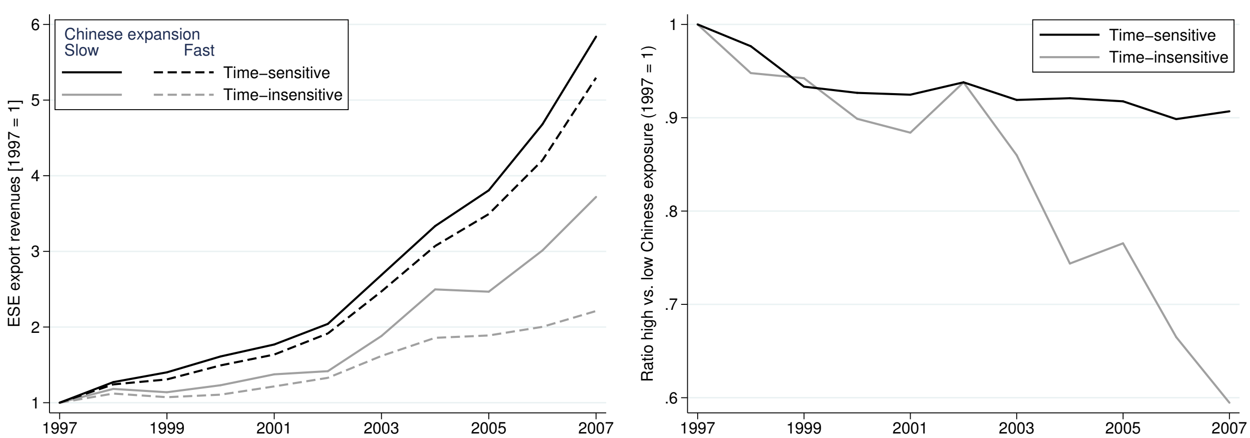
[8]To our convenience, these estimates will be based on US data which should rule out concerns about endogeneity of transport-mode preferences in the EU15.

patterns of ESE export performance in time-sensitive (dark lines) versus time-insensitive (bright lines) industries, using our strict classification. As is evident from Panel (a), exports in the latter group expanded slower throughout our sample period. However, we also note that within this industry group, exports of products competing with China (i.e., where the average annual increase of China's market share in the EU15 was high) fell behind even more. The differences between the solid and dashed lines in Panel (a) are displayed as ratios in Panel (b) for the respective industry groups. ESE exports competing with China grow relatively less in both cases, but the difference is more modest and fairly stable in industries classified as time-sensitive. This pattern provides some indicative support for our hypothesis that ESE exporters might be more resilient to Chinese competition in industries where timely delivery matters.[9]

Figure 1: ESE exports and Chinese expansion in time-sensitive vs. time-insensitive industries

(a) ESE export revenues

(b) Competing vs non-competing



Note: Authors' calculations based on strict measure of time-sensitivity. Panel (a) denotes aggregate export revenues in respective group, relative to base year (1997). Panel (b) displays ratio of exports in fast-versus-slow expanding sectors, normalized to base year (1997). Chinese expansion based on average annual change in import market shares over the sample period. Fast (slow) expansion denotes HS6 products with above (below) median expansion within respective time-sensitivity group.

[9] Table A1 presents some specific examples of time-sensitive industries, using the strict measure. Four of the five most time-sensitive industries belong to the chemical and allied industries. The fifth industry is motor vehicles and parts and accessories thereof. The five least time-sensitive industries are: (i) explosives and pyrotechnic products, which are also part of the chemical industries; (ii) wood pulp and recovered paper; (iii) raw hides and skins; (iv) pearls and precious stones or metals; (v) silk. One might suspect from these examples that time-sensitivity is correlated with other attributes, such as skill-intensity. We will control for confounding factors in our empirical analysis.

3 Empirical approach

In this section we focus on describing our empirical strategy for identifying the impact of Chinese competition on ESE exports that may arise from simultaneous shipments into narrow EU15 destination-product markets. Our evaluation of a geographic proximity advantage for ESE exporters will be based on interacting our main variable of interest with the measures of time-sensitivity introduced above.

3.1 Empirical baseline specifications

Product-level specification. We set up a linear panel regression model of the following form:[10]

$$\ln X_{ijkt} = \alpha + \beta China_{jkt} + \gamma \ln M_{jkt} + \mu_{ijk} + \mu_{ijt} + \nu_{ijkt}. \tag{1}$$

The dependent variable measures the (log) value of shipments from ESE country i to EU15 importer j, in HS6 product k and year t. On the right hand side of the equation we include a variable that captures China's expansion into the same destination-product market, $China_{jkt}$, and, in addition, a control variable that captures aggregate import demand for product k in destination j, $\ln M_{jkt}$. Two sets of fixed effects are included in our baseline specification, which we extend in our robustness checks. μ_{ijt} controls for aggregate time-varying demand and supply shifters (such as business cycle dynamics, bilateral agreements and trade costs, or other country-pair specific factors). The other set of fixed effects, μ_{ijk}, is exporter-importer-product specific. It captures time-invariant, product-specific demand and supply shifters (such as preferences, relative supply capacities, or persistent non-political trade barriers between the two countries). The last term on the right-hand side of Equation (1), ν_{ijkt}, denotes an independent and identically distributed (i.i.d.) error term. When estimating this equation, we follow Moulton (1990) by paying attention to the dimensions of our main variable of interest, $China_{jkt}$, and adjust standard errors for clustering at the destination-product level.

Firm-level specification. We adopt a baseline specification that is analogous to Equation (1) for our firm-level estimation:

$$\ln X_{fjkt} = \alpha + \beta China_{jkt} + \gamma \ln M_{jkt} + \delta \mathbf{X}_{ft} + \mu_f + \mu_{jk} + \mu_{jt} + \nu_{fjkt}. \tag{1'}$$

[10] Our specification is in line with a gravity model where importers devote a constant fraction of their expenditures on foreign varieties and where China's expansion has an impact on the price-level of imports (e.g. Hanson and Robertson, 2010).

As before, our interest focuses on estimating the coefficient β, which indicates the relationship between our dependent variable and Chinese competition intensity in EU15 product-destination markets. Also our control variable for aggregate import demand, $\ln M_{jkt}$, remains the same. In contrast to the previous specification, the dependent variable now measures (log) export revenues of a *firm*, $\ln X_{fjkt}$. Since all firms export from Bulgaria, we drop the exporter subscript i so that fixed effects μ_{jk} and μ_{jt} become destination-product and destination-time specific, respectively. To account for the new firm-level dimension in our data, we augment our previous specification by including a full set of time-invariant firm fixed effects, μ_f, as well as time-varying firm-level controls, denoted by $\mathbf{X}_{ft}$.[11]

3.2 Measurement and identification

3.2.1 Baseline measure of China's expansion

To measure China's expansion in our data, we compute China's import market penetration rate as $China_{jkt} = M_{jkt}^{CN}/M_{jkt}$. It reflects China's share in j's total imports of product k at time t. Such a measure has been used in the related literature before (e.g. Bloom et al., 2016; Mau, 2019), although other studies compute China's overall market penetration rate in a destination.[12] Since we focus on competition between countries that export varieties of the same product to the same *third* market, we are confident that import market shares are an appropriate measure for the purposes of our analysis. Irrespective of which measure is used, estimating Equations (1) and (1′) poses important challenges for identification. OLS estimates will merely inform about the correlation between our dependent variable and China's expansion. Although controlling for aggregate import demand captures some of the potentially spurious correlation, there are reasons to believe that (i) causality runs from ESE exports to China's market shares or (ii) that there exists no causal relationship at all, despite an evident correlation.

[11] As we have shown in Table 1, Bulgarian exporters appear to be rather specialized and typically export their goods to only one destination. Interacting firm fixed effects with an additional dimension would result in a substantial loss of both variation and actual observations in our data. Besides this technical restriction, we note that our firm-level specification is similar to Utar and Torres Ruiz (2013), who also employ individual plant fixed effect. Firm-level control variables will be explained in detail below and capture broadly firms' overall exporting experience as well as their overall size.

[12] The latter approach was adopted by Utar and Torres Ruiz (2013) and in numerous papers investigating domestic responses to import competition (e.g. Bernard et al., 2006; Autor et al., 2013, 2014; Dauth et al., 2014; Bugamelli et al., 2015). Total market penetration rates would be computed as the share of imports from China in total domestic absorption, i.e. $IMPCH = M_{jkt}^{CN}/(M_{jkt}+Q_{jkt}-X_{jkt})$, where M, Q, X denote j's imports, domestic production and exports of good k, respectively. The unavailability of product-level data on domestic production prevents us from computing this measure at the HS6-product level. Indeed, studies employing this measure typically rely on aggregate sector-level data.

Reverse causality can be illustrated with a simple gravity model.[13] China's market share depends on its supply capacities *relative* to all other countries, while any causal effect attributable to China requires that changes stem from its *absolute* supply capacities. Reverse causality would occur if, for instance, ESE exporters' internal structural adjustments allow China to expand in markets previously occupied by these countries. Although this would not reject our hypothesis that Chinese and ESE product varieties are substitutes, the underlying causal force would come from the ESE economies and not from China. Similarly, preference shifts towards Chinese varieties could increase its market share at the expense of ESE exports, while both absolute and relative supply capacities are unchanged. In this case, a negative coefficient for $China_{jkt}$ would originate from spurious correlation, and in both cases, our estimate of β would be inflated and suggest greater than actual displacement of ESE exports due to Chinese competition.

In the context of our study it is also possible that our OLS coefficient exerts attenuation bias. During the period we observe, the majority of countries in our sample integrated with EU15 markets. Either through attaining EU membership candidate status or becoming full members. Besides an almost complete removal of tariff barriers, this entailed also inflows of foreign investment from EU15 countries. Noting that, from the viewpoint of our importing economies, most ESE countries and China had a comparative advantage in labor- and low-skill intensive production, trade liberalization and investments could have spurred growth and productivity in sectors where also China expanded. In fact, there could even be complementarity in sourcing from China and ESE, if trade patterns are driven by general trends in offshoring labor-intensive production activities. As a result, we would observe that our OLS coefficient understates actual displacement effects, due to a simultaneity bias where ESE and Chinese exports grow at the expense of mainly economically more advanced exporters outside our sample. Although the various potential sources of bias could potentially cancel each other out, we will back up our OLS results by employing an instrumental variables approach to extract variation in China's expansion that can be attributed to changes in its own supply capacities.

3.2.2 Instrumental variable approach

Bartik instrument. The empirical literature is fairly consistent in its approach to identifying a causal impact of Chinese competition on manufacturing sector performance in other

[13]Consider a simplified characterization of market shares following Eaton and Kortum (2002): $\pi_{jm} = \frac{(c_m \tau_{jm})^{-\theta}}{\sum_h (c_h \tau_{jh})^{-\theta}}$, where π_{jm} denotes exporter m's fraction in j's total consumption, c_m are unit production costs in country m and $\tau_{jm} \geq 1$ denote bilateral trade barriers. For m being China, market shares change if the numerator (supply conditions in China) or the denominator (supply conditions in the rest of the world, including China and all ESE exporters i) change.

countries. Autor et al. (2013) and Utar and Torres Ruiz (2013) were among the first to employ the shift-share approach of Bartik (1991) in this context. It rests on the assumption that variation in Chinese expansion in j that can be jointly observed in *similar* destinations $n \neq j$ reflects actual changes in Chinese supply capacities, while eliminating variation arising from confounding factors. We select a group of high-income countries to reflect n: Australia, Canada, New Zealand, Norway, and Switzerland. By focusing on relatively small high-income markets, with distance from China comparable to our EU15 destinations, we attempt to rule out that preference shifts in an individual destination or regional production networks determine our predictions of China's expansion.[14]

Note that in the context of our study, observing China's product-market expansion in destinations n is not enough, because it does not inform us about the extent to which it materializes across the different EU15 destinations. We therefore employ an augmented version of this identification approach by assigning destination-specific weights to the import market penetrations rates observed in n:

$$China^{IV}_{jkt} \equiv (China_{kt} \times w_j) = \underbrace{\left(\frac{\sum_n M^{CN}_{nkt}}{\sum_n M_{nkt}}\right)}_{\substack{\text{product-year}\\ \text{variation}}} \times \underbrace{w_j.}_{\substack{\text{destination}\\ \text{variation}}} \tag{2}$$

Our main instrument for Chinese expansion in the EU15 thus represents an interaction of time-varying, product-specific import market penetration in other destinations, $China_{kt}$, with the relative probability of destination j to be penetrated by Chinese exports, w_j.

To measure w_j, we use information on Hong Kong re-exports for the years 1999-2001 and compute j's fraction in its total re-exports to the EU15. We motivate this approach by noting that, prior to its WTO entry, China exported many of its goods via Hong Kong which entailed additional surcharges (Feenstra and Hanson, 2004).[15] As shown in Figure A1, this may have changed upon WTO membership, when Hong Kong's share in China's total transport services imports fell persistently from about 20 percent to about 10 percent. Assuming that China's WTO membership lead to improved market access provisions in most of its export destinations, Chinese exporters may have adjusted their shipping routes to sell

[14] Preference shifts in a large single destination markets could have implications for China's multilateral trade performance, if fixed costs of exporting are not fully destination-specific (e.g. Mau, 2017). We therefore exclude the US from our group of high-income destinations although it has been used in other studies (e.g. Bugamelli et al., 2015). Moreover, high-income markets like Japan or Singapore (which were included by Dauth et al. (2014), in addition to our countries), could lead to less precise predictions of Chinese competitiveness, if trade with these countries reflects shipments within regional production networks.

[15] China became a full member of the WTO in December 2001, while Hong Kong has been a full member of the WTO since its formation in 1995. This status was also maintained after the transfer of sovereignty over its territory from the United Kingdom to China in July 1997.

at lower prices by avoiding Hong Kong's re-export surcharges. Although, we cannot directly observe these adjustments, the implication would be that Chinese import market penetration expands relatively faster in destinations where Hong Kong re-exports appeared to be larger.[16] Note that by accounting for patterns of Hong Kong re-exports, our instrument captures both China's general expansion in specific product markets over time, as well as the variation in expansion rates across destinations and especially in the years after China's WTO entry. In contrast to previous studies on Chinese competition, this additional dimension allows us to perform a number of robustness checks that would be typically not feasible when focusing on a single destination market.

Potential caveats. Despite its wide use in the empirical literature, the product-level dimension of our instrument leaves the actual causal source of China's expansion unobserved. As Autor et al. (2013) discuss, it is still possible that demand shocks for imports from low-wage countries (including China and ESE) are correlated across EU15 and other high-income economies. In this event, both our OLS and instrumental variable coefficient would understate the true effect of Chinese competition. However, since our descriptive statistics suggest that the ESE countries mainly export to EU15 destinations, while another large fraction accounts for trade among ESE countries, we argue that simultaneity bias is less likely to play a major role in our instrumental variable.

Another concern could be that China's expansion into high-income markets not only resulted from its own economic reforms and trade liberalizations, but instead resulted from independent, yet complementary, technological change. The late 1990s and early 2000s witnessed major advancements in information and communication technologies (ICTs), which facilitated international outsourcing and offshore production. In such a case, China's expansion would not be exogenous from the viewpoint of a country that contributed to these technological advancements. While this could pose an important threat for identification of import competition in the EU15, we suppose that for our group of exporters Chinese competition is less likely to be a home-made phenomenon. In our robustness checks we implicitly control for this possibility by adding additional fixed effects into our empirical model. As a more general approach to addressing these concerns, we will also employ an alternative identification strategy which exploits China's WTO entry as a quasi-natural experiment to generate variation in exposure to Chinese competition at the HS6 product level. We explain these approaches together with our main findings in the following section.

[16] Figure A2 illustrates the distribution of our destination-specific proxy. Hong Kong re-exports were relatively concentrated in few EU destinations. The largest single economy in the EU15 (Germany) ranks second, after the United Kingdom. Only minor expansions would be expected in the EU15 periphery, such as in Portugal, Greece, Ireland, or Finland.

4 Main empirical findings

4.1 Displacement of exports through Chinese competition

4.1.1 Product-level estimation

Main findings. Table 2 conveys a clear message regarding the relationship between China's expansion into EU15 destination-product markets and ESE countries' export revenues. The first column displays our OLS results and suggests a negative relationship. Using the average expansion of China observed during our sample period, i.e. 5.47 percentage points, this implies a reduction by $5.47 \times 1.222 \approx 6.8$ percent between 1997 and 2007. Column (2) reports the results for our IV specification. The estimated coefficient is larger in absolute terms and suggests a reduction of ESE export revenues by 12.8 percent. This number is close to the displacement effect Utar and Torres Ruiz (2013) calculate for Mexican maquiladora plants selling to the US during the period 1990-2006.[17] In the lower panel of Table 2, we report the main coefficients of interest obtained at the first stage of the IV estimation. We find a positive relationship between the instrument and Chinese import market penetration. The Kleibergen-Paap test statistic, reported at the bottom of our table in column (2), rejects the hypothesis of employing a weak instrument.

We submit these baseline results to a number of robustness checks, which are summarized in Table A2. First, we adjust standard errors for clustering at the HS6-product level. As expected, columns (1) and (2) show that fewer clusters increase the standard error of our main coefficient, but it remains highly statistically significant. In columns (3) and (4), we aggregate variables over all destination markets and treat the EU15 as a single destination. Although standard errors are again somewhat larger, both OLS and IV estimates confirm magnitudes and significance of the previously estimated effects. In the following, we include additional fixed effects and control variables. We begin with including an additional set of product-year fixed effects to control for omitted variable bias stemming from a correlation of China's expansion with general product-level dynamics. While our OLS coefficient for China in column (5) becomes indeed smaller in absolute terms, the corresponding IV coefficient reported in column (6) is essentially unchanged. The same finding reveals in columns (7) and (8) where we include the applied EU tariff on ESE countries' products as an additional control variable. In the final two columns, we allow for the possibility that our main variable of interest is correlated with exporter-specific product portfolio dynamics and include exporter-HS6-year effects. Note that this specification implicitly controls for ESE countries'

[17] In their preferred specification, they report estimates that suggest a reduction by about 18 percent during their sample period, in which China's market share increased by about 7 percentage points. Assuming that same expansion also in our sample, we obtain a reduction by 16.4 percent.

Table 2: China's impact on ESE export values, product-level estimates, 1997-2007

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline specification		Alternative IV: US PNTR		Alternative IV: MFA Quotas	
Dep. var.: log export revenue	OLS	2SLS	Red. form	2SLS	Red. form	2SLS
Main results: OLS and second stage						
China (s_{jkt}^{CN})	-1.222**	-2.343**		-2.807**		-2.648**
	(0.036)	(0.158)		(0.398)		(0.314)
US PNTR			-1.119**			
			(0.167)			
MFA Quota fill rate					-1.161**	
					(0.126)	
Import demand	0.569**	0.576**	0.560**	0.579**	0.530**	0.578**
	(0.006)	(0.006)	(0.006)	(0.007)	(0.010)	(0.012)
First stage results for s_{jkt}^{CN}		Baseline		US PNTR		MFA
Baseline: $s_{nkt}^{CN} \times w_j$		1.830**				
		(0.054)				
Alt. IV: US PNTR				0.399**		
				(0.022)		
Alt. IV: MFA Quota fill rate						0.438**
						(0.030)
Observations	1,628,298	1,628,298	1,628,298	1,628,298	399,507	399,507
N. Clusters	44,669	44,669	44,669	44,669	9,866	9,866
Kleibergen-Paap (F-stat)		1,163.9		337.6		213.4

Note: Standard errors in parentheses clustered at product-destination level. Statistical significance: ^{a} = $p < 0.1$, * = $p < 0.05$, ** = $p < 0.01$. All specifications include exporter-importer-HS6 and exporter-importer-year FEs. Coefficients for log import demand suppressed in first stage results. Results in columns (5) and (6) are based on subsample of textiles and clothing industries (HS Chapters 50-63).

imports from China, which might affect their exporting behavior (either through competition in the domestic market or through imports of intermediate inputs and other changes in their production functions). Despite removing substantial variation in our data by such a specification, we find again that our OLS estimate is lower compared to the baseline, but that our IV coefficient is only marginally affected (i.e., -2.293 instead of -2.343).

Alternative IVs. Returning to Table 2, we also report results for two alternative identification strategies. We first use the reduction of US tariff uncertainty for Chinese exporters, which took place when China entered the WTO and thereby transitioned to permanent normal trade relations (PNTR) with the US. Pierce and Schott (2016) and Handley and Limão (2017) describe this event in detail and show that differences observed at the product level between potentially high Column-2 tariffs and actually applied MFN rates correspond to the pattern of China's accelerated expansion into US markets after 2001.[18] Mau (2017) shows that US PNTR for China also triggered an acceleration of exports to the EU15 and other large high-income destinations.[19] We thus construct an instrument by interacting the simple difference between US Column-2 and MFN tariff rates ($Col2_k - MFN_k$), before PNTR was formally decided (i.e. in 1999), with a period dummy indicating the event of China's WTO entry (WTO_t^{CN}) and with our previously described destination-specific weight (w_j) that predicts differential rates of expansion across EU15 member states. Columns (3) and (4) of Table 2 report both reduced-form and second-stage estimation results for this instrument and we find a negative and statistically significant coefficient for Chinese competition.[20]

Similar findings are reported in columns (5) and (6), where we focus on a subsample of our data comprising the textile and clothing industries (HS Chapters 50-63). In these industries, China experienced reductions in export barriers to the EU in conjunction with its WTO membership and the removal of quotas that were dismantled in several phases in accordance with the WTO Agreement on Textiles and Clothing (ATC). During our sample period, a first round of quota removals became effective for China upon its WTO entry and a second round followed in 2005.[21] Since ESE exporters were usually exempted from these quotas, the removal may have displaced some of their exports when China became eligible to freely choose the amount shipped into EU markets.[22] To evaluate this, we compute for each of the two liberalization rounds the product-specific utilization rate (or "'fill rate") reported during the three years preceding a specific quota removal. We assume that fill rates indicate how binding a quota actually was, so that higher rates should entail a relatively stronger

[18]The uncertainty for Chinese exporters arose from the fact that MFN rates were granted only for the duration of one year and were subject to review and approval by the US Congress before it could be renewed. While the US never actually applied these higher rates on Chinese products, a potential negative decision would have entailed Chinese exporters facing a 28 percentage point increase in applied tariffs on average. At some instances during the 1990s the voting margins in favor of maintaining MFN rates for another year were very small. Upon China's WTO entry, in December 2001, this annual review process was abolished.

[19]Although this event was politically exclusive to US-China trade relations (the EU installed PNTR towards China already in the 1980s), such a "spillover-effect" is in line with theoretical models where firms face significant fixed costs of exporting that are not specific to a particular destination.

[20]Reduced form estimates are shown here to establish the existence of a relationship between the instrument and our dependent variable. 2SLS first- and second-stage coefficients support the causal impact of China as well as its magnitude on ESE exports. We note that the point coefficient in column (4) is quantitatively somewhat larger than in column (2). We attribute this to the simplistic modelling of the time variation for this instrument, which compares only pre- and post-WTO entry periods. Since also standard errors more than double with respect to our baseline IV, this seems to result in a loss of precision in our PNTR-instrument.

[21]Utar (2014, 2018) presents a detailed description of the nature and sequence of these events. See Brambilla et al. (2010) for an analysis of US import quotas on Chinese textile and clothing products.

[22]Some ESE exporters actually did face quotas in the past, but they were removed before the beginning of our sample period and were usually not binding. The originial data set, specifying quota products, allowed quantities and quota utilization rates was retrieved from the *Système Intégré de Gestion de Licenses* (SIGL).

expansion upon the quota removal. We interact fill rates ($fill_k$) with a dummy variable that indicates the period after the quota removal ($remove_{kt}$) and with the destination-specific weights (w_j) we have used also for the other instruments. Our results reported in Table 2 corroborate previous findings and the different specifications overall indicate remarkably similar effects.

Heterogeneous exporters. In Appendix B, we present an extensive analysis of potentially heterogeneous effects across ESE countries in our sample. We conclude that, overall, our baseline results can be viewed as being fairly representative, although some systematic differences appear (see Figures B1-B3). As shown in Table B1, the eight Eastern European countries (EEC) reveal systematically larger reductions in exports than the SEE economies. While part of this difference can be attributed to an influential outlier in the comparison group (Turkey appears to be relatively resilient to Chinese competition), several exporting country characteristics at the beginning of our sample period seem to play a role. While countries integrating earlier into the European Union tend to be generally more affected, we also find that exporters with higher real GDP per capita, lower average price levels, and higher inflows of FDI (in percent of GDP) are relatively less affected. High FDI inflows and low price levels could, for instance, explain why Czech Republic's exports respond less to Chinese competition than its neighbors, Poland and Slovakia (but also Hungary and Slovenia). We also find that displacement effects are smaller in Bulgaria, where FDI inflows were higher and price levels lower than in most other countries (Figure B4).

4.1.2 Firm-level estimations

Main findings. Table 3 reports our findings for Bulgarian firm-level exports to the EU15. Since smaller trade flows tend to remain unreported in the product-level data analyzed above, we employ a probability-weighted OLS estimator in the baseline firm-level regression for comparability.[23] Columns (1) and (2) show the results of our baseline specification without including any firm-level controls, besides a firm fixed effect. Both OLS and 2SLS estimates suggest a negative relationship between Chinese market penetration and Bulgarian export revenues, but coefficient estimates are quantitatively smaller in absolute terms and less precise compared to our product-level findings. They suggest that a standard deviation increase of China's EU15 import market share resulted in about 2.44 percent lower export revenues for an average Bulgarian firm during the six years we observe in this sample.

[23]We use the quantity (measured in kilograms) of the shipment as our probability weight.

Table 3: China's impact on Bulgarian exports, product and firm-level estimates 2001-2006

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline specification		Firm seniority	Firm size	Alternative IV: MFA Quotas	
Dep. var.: log export revenue	OLS	2SLS	2SLS	2SLS	Red. Form	2SLS
Main results: OLS and second stage						
China (s^{CN}_{jkt})	-0.651	-1.172^{a}	-1.185*	-1.219*		-1.455^{a}
	(0.786)	(0.598)	(0.598)	(0.596)		(0.859)
Years exporting			0.226**	0.332**	0.385**	0.390**
			(0.052)	(0.052)	(0.102)	(0.102)
N. of Destinations				0.068**	-0.083*	-0.083*
				(0.023)	(0.035)	(0.035)
N. of Products				-0.259**	-0.027	-0.026
				(0.018)	(0.025)	(0.025)
MFA Quota fill rate					-0.465^{a}	
					(0.268)	
Import demand	0.363**	0.229**	0.229**	0.228**	0.208**	0.253**
	(0.094)	(0.025)	(0.025)	(0.025)	(0.032)	(0.041)
First stage results for s^{CN}_{jkt}		baseline	add seniority	add size		MFA
Baseline: $s^{CN}_{nkt} \times w_j$		1.361**	1.361**	1.361**		
		(0.108)	(0.108)	(0.108)		
Alt. IV: MFA Quota fill rate						0.320**
						(0.040)
Observations	268,822	268,822	268,822	268,822	113,359	113,359
N. Clusters	15,738	15,738	15,738	15,738	4,463	4,463
Kleibergen-Paap (F-stat)		158.7	158.6	158.5		63.4

Note: Standard errors reported in parentheses are clustered at the product-destination level. Statistical significance: $^{a} = p < 0.1$, $^{*} = p < 0.05$, $^{**} = p < 0.01$. All specifications include destination-product, destination-year, and firm fixed effects. Coefficients for log import demand and other control variables are suppressed in first stage results. Regression (1) employs weighted OLS, export quantities used as probability weights. Results in columns (5) and (6) are based on subsample of textiles and clothing industries (HS Chapters 50-63).

Columns (3) and (4) show 2SLS results after including a set of time-varying firm-level controls. We first include firm's exporting experience, which we measure by the number of years a firm in our sample exports a given HS 6-digits product.[24] Column (4) includes two additional controls to capture firm size via its diversification (i.e., by counting the maximum number of HS6 products it exports to a specific destination and by counting the maximum number of destinations it serves with a specific HS6 product). Including these variables

[24]This measure is included in analogy to Utar and Torres Ruiz (2013). Like in our results, they find a positive and significant coefficient which suggests that more experienced firms tend to export more.

results in a somewhat larger estimated displacement effects of China's expansion, while the standard errors of the coefficients are unaffected at all stages. Estimates reported in column (4) imply that a standard deviation increase in China's market share in the EU15 leads to a 3.33 percent lower export revenue for Bulgarian firms. In columns (5) and (6), we also employ our alternative instrument, which exploits the removal of EU import quotas on Chinese textile and clothing products in 2002 and 2005.[25] As before, this sample focuses only on the relevant HS Chapters 50-63. Both the reduced-form estimate of the quota removal as well as the corresponding 2SLS estimate of China's market penetration rate confirm a negative impact of Chinese competition. The magnitude of the coefficient reported in column (6) is similar to those obtained in our baseline IV specification in columns (2)-(4).

Heterogeneous effects across firms. In Table B2 we focus on heterogeneous effects across firms, which we investigate by interacting Chinese expansion with different firm-level characteristics. Columns (1) and (2) report OLS and 2SLS results obtained when interacting China's market share with a firm-level indicator, which proxies its relative size based on total export revenues in the first year we observe it in our data. Firms residing in the top 25^{th} percentile of the revenue distribution are considered as being large. Estimates show that these firms are significantly less affected by Chinese competition, which suggests that large firm are either sufficiently productive or more capable in diversifying their export strategies to avoid major displacements of their exports.

In columns (3) and (4), the interaction variable is a binary time-invariant indicator for firms that sold any of their goods to more than one destination, upon the first observation. Both OLS and 2SLS estimates now suggest a large and significant displacement effect for the majority of geographically less diversified firms (recall that the median firm in our sample exports a good to only one destination), while multi-destination exporters are systematically less affected. On the contrary, results in columns (5) and (6) suggest that multi-product exporter (i.e. firms selling several HS6 products to a single destination) are not differently affected by Chinese competition.

Overall, our firm-level analysis confirms the previous finding of a negative and significant impact of Chinese competition on ESE export revenues. As pointed out in our product-level analysis, Bulgarian exports appear to be less affected than other ESE exporters. While part of this difference could be attributed to certain country-specific characteristics, our firm-level results suggest that another part of the explanation could be heterogeneity across exporting

[25]Since our firm-level sample spans are relatively short period, our other alternative IV cannot be used here, due to a lack of pre-WTO entry observations. This complicates also the use of the quota instrument, where the first removal became effective a year after the beginning and the second removal and a year before the end of our sample period.

firms.

One finding that consistently emerges from our analysis — regardless of which data set or sample is being used — is that OLS coefficients tend to underestimate the true displacement effect of Chinese competition. This suggests that simultaneity bias challenges appropriate identification, and that OLS estimates could be interpreted as a lower bound of the actual displacement effect of China on ESE exports.

4.2 Time-sensitive industries and local comparative advantage

Turning to the central question of this paper, we can draw on our previous analysis to infer whether exports in time-sensitive industries are differentially affected by Chinese competition. Such evidence could indicate the existence of a novel source of comparative advantage that can be attributed to the relative geographic proximity between trading economies that facilitates timely delivery. Our results are based mainly on our pooled product-level sample, while firm-level evidence from Bulgaria is presented as part of our robustness checks.

4.2.1 Main findings

Our classification of time-sensitive industries follows the methodology of Hummels and Schaur (2013), which we described in Section 2 and Appendix Section C. We adopt binary indicators in our main specifications, which are based on the median HS2-level observation for time-sensitivity. In columns (1) and (2) of Table 4 we employed our simple measure of time-sensitivity and interact this with China's import penetration rate using OLS and 2SLS estimation, respectively. In both specifications, we detect a significantly smaller displacement effect on ESE exports for time-sensitive industries. Columns (3) and (4) confirm this result for our adjusted measure. Across specifications, time-sensitive industries reveal an about 55-65 percent smaller displacement relative to their comparison group.[26] To test whether these findings mask spurious correlation originating from confounding industry- and product-level characteristics, we augment our baseline specification by including a set of additional interaction terms.

An obvious suspect are intermediate inputs, which Hummels and Schaur (2013) found to be more time-sensitive than other manufactured products on average. This makes intuitive

[26] In Table A3 we show that results are similar for continuous measures of time-sensitivity, which we normalized to have mean zero and a standard deviation equal to one. We also ran regressions for separate samples, which we define according to our binary measure of time sensitivity. The coefficient for China's market share is negative and significant in both cases, but smaller in the time-sensitive sample. Based on the average increase in China's market shares in each subsample, OLS results suggest a reduction by 9.1 percent for time-insensitive goods and 5.5 in the time-sensitive subsample, which implies an about 40 percent smaller displacement effect throughout our sample period.

Table 4: China's impact on ESE exports and time-sensitivity, product-level estimates 1997-2007

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of time-sensitivity:	binary (simple)		binary (strict)		binary (strict)	
Specification:	Baseline		Baseline		add controls	
Dep. var.: log export revenue	OLS	2SLS	OLS	2SLS	OLS	2SLS
China's market share	-1.520**	-3.081**	-1.769**	-3.800**	-2.343**	-5.104**
	(0.043)	(0.163)	(0.046)	(0.180)	(0.106)	(0.370)
× time-sensitive	0.858**	2.547**	1.154**	3.340**	0.925**	2.986**
	(0.069)	(0.212)	(0.066)	(0.201)	(0.072)	(0.235)
× intermediate inputs					0.719**	1.648**
					(0.095)	(0.283)
× contract intensity					0.484**	1.324**
					(0.098)	(0.311)
× skill intensity					0.520**	0.994**
					(0.090)	(0.289)
Observations	1,628,298	1,628,298	1,628,298	1,628,298	1,628,298	1,628,298
N. clusters	44,669	44,669	44,669	44,669	44,669	44,669
Kleibergen-Paap (F-stat)		609.0		582.0		72.3

Note: Standard errors reported in parentheses are clustered at the product-destination level. Statistical significance: $^{a} = p < 0.1$, $^{*} = p < 0.05$, $^{**} = p < 0.01$. All specifications include log import demand as a control variable (coefficients suppressed) as well as exporter-importer-HS6 and exporter-importer-year FEs.

sense, when we think about regional production networks in which products (or parts of them) enter and exit several countries before the final good reaches the consumer. However, focusing on intermediate inputs also implies that we focus on a relatively early stage of the production process, which ignores the possibility that ESE exporters could be involved also in later stages where final goods require timely delivery.[27] To test whether time-sensitivity is confined to intermediate inputs, we include an additional (binary) interaction term for HS6 products that are classified as such in the Broad Economic Categories (BEC rev.4) nomenclature. We also consider the possibility that time-sensitivity is correlated with products that can be considered as being contracting intensive. Conceptually, this concerns activities that are more difficult to coordinate, because specifications of the production process are more complex and require more supervision and communication between contracting parties. Such problems might be easier to overcome if contracting parties are more closely located geographically. Nunn (2007) provides a measure of contracting-intensity using input-output tables and computing the share of inputs that are differentiated goods in the Rauch (1999)

[27] Evans and Harrigan (2005) illustrate time-sensitivity at final stages in the US apparel industry.

classification (larger shares result in higher contracting costs). We employ this measure as a binary variable that takes a value equal to one for products reporting above-median contract intensity.[28] Finally, we include a measure of skill intensity, which has revealed as a key dimension for differential exposure in several other studies evaluating the impact of Chinese competition (e.g. Autor et al., 2013; Utar and Torres Ruiz, 2013; Utar, 2014, 2018; Bugamelli et al., 2015). Time-sensitivity and skill intensity could be correlated if timely delivery requires higher management and ICT operation skills. To measure skill intensity, we use data from Amiti and Freund (2010) and include it as an above-median based, binary indicator variable in interaction with China's market share.[29]

Columns (5) and (6) of Table 4 suggest that all our additional attributes reveal comparatively lower displacement of ESE exports. However, we find that our coefficient for time-sensitivity remains positive and highly significant, despite a slight downward correction with respect to columns (3) and (4). Interestingly, adding each of these industry-level characteristics separately into our estimation equation suggests that most of this downward correction can be attributed to the inclusion of intermediate-inputs as control variable. The other two controls barely affect our baseline results (see Table A4). This suggests that time-sensitivity captures a source of comparative advantage that can be attributed to geographic proximity and trade within regional production networks. Skill- and contracting-intensity denote separate channels for the determination of trade patterns. Quantitatively, our results in columns (5) and (6) imply an about 40-60 percent smaller displacement effect of Chinese competition in time-sensitive industries.

4.2.2 Robustness checks

Placebo regressions and intra-European distances. We submit these baseline results to additional robustness checks to test some intuitive implications of a geographic proximity advantage. First, we run placebo regressions for a set of Asian low-wage exporters.[30] These countries also compete in exports with China (Eichengreen et al., 2007; Greenaway et al., 2008), but should not be endowed with a geographic proximity advantage for shipments to Europe. Results are displayed in columns (1)-(4) of Table A5. Although OLS estimates do suggest significantly smaller displacements in time-sensitive industries, this advantage is

[28]The original data from Nunn (2007) reports contract intensity at the 5-digit NAICS level. We use correspondence tables from Pierce and Schott (2009) to map this measure to HS6 products.

[29]Their measure of skill-intensity reflects the share non-production workers in total employment for Indonesian manufacturing industries in 1992. Amiti and Freund (2010) argue that relative factor use in Indonesia's manufacturing sector is a good proxy of relative factor use in China and find that China's export growth during the early 2000s was driven by less skill-intensive products.

[30]The countries included are: Bangladesh, Cambodia, India, Indonesia, Pakistan, Philippines, Sri Lanka, Thailand, and Vietnam.

considerably smaller compared to our ESE exporters and not supported in our IV specifications. In contrast to this, skill-intensive activities continue to reveal a differential impact, which is also quantitatively comparable to our baseline results.

As a second robustness check we hypothesize that if geographic proximity really matters, this should reveal more prominently in short-distance trade relationships between ESE and EU15. Using bilateral population-weighted distances from the CEPII gravity database we define distant trade relations at a general 1,500 kilometer threshold (which roughly reflects the distance between the median country pair in our sample). According to this threshold, each ESE exporter i has both distant and non-distant EU15 partners j.[31] Columns (5) and (6) of Table A5 report OLS results for sub-samples of geographically proximate and distant country pairs, respectively. Displacement effects appear to be generally smaller for distant trade relations and time-sensitive industries reveal about 50 percent lower displacement in this sample. In the sub-sample of proximate trade partners, time-sensitive industries suggest even 70 lower displacement. In columns (7) and (8) we infer this dimension further, by estimating a three-way interaction coefficient for China's market share in the full sample. While time-sensitive industries as well as distant trade relationships appear to be systematically less affected by Chinese competition, we confirm by our three-way interaction at the bottom of the table that the advantage in time-sensitive industries is systematically smaller for ESE exports to relatively distant EU15 destinations.[32]

Firm-level evidence for Bulgaria. In Table A6 we report results on differential responses in time-sensitive industries relying on Bulgarian firm-level data. Despite lower general displacement and Bulgaria's comparatively disadvantageous location in the Southeast of Europe, the main mechanisms should reveal also on this data. Columns (1) and (2) show results for general displacement effects in two sub-samples, reflecting time-insensitive and time-sensitive industries. We define as time-*in*sensitive those industries having a time sensitivity below the median and as time-sensitive those reporting above-the-median time sensitivity. We identify a statistically significant negative coefficient for the effect of Chinese competition only when focusing on firms exporting time-insensitive products. Employing our simple binary measure of time sensitivity in interaction with Chinese expansion, however, does not confirm this result. Columns (3) and (4) suggest that, even if we consider the three highest -*quartiles* of time-sensitive industries, the interaction coefficient is positive

[31] Bulgaria, Romania and Turkey mainly trade on distance (i.e. about 66, 53, and 91 percent of their observed shipments). On the importer side, Ireland, Portugal, and Spain are always classified as distant destinations, while the UK follows with about 65 percent of its observations reflecting distant trade.

[32] Additional estimates using a continuous measure of distance (i.e. log kilometer distance between i and j) confirm results reported here.

but statistically insignificant. Similar results are found for our strict measure in columns (5) and (6). While OLS results suggest about 50 percent smaller displacement in time-sensitive industries, a statistically significant interaction coefficient is revealed only in our IV specification. Firms in industries characterized by a time sensitivity higher than the first quartile are significantly less affected by Chinese competition in the EU15. These findings suggest that there is a tendency for smaller displacements in time sensitive industries also when employing firm-level data from one of the most remote ESE exporting countries. Yet, this result is much less clear-cut compared to the pooled sample on product-level exports.

Altogether, our robustness checks support our previous conclusions that differential responses to Chinese competition in time-sensitive industries seem to capture an additional source of local comparative advantage for ESE exporters in EU15 destination markets. China and other distant competitors exert lower competitive pressure in such industries, due to lack of relative supply capacities in such industries. As this advantage decays with distance also among ESE exporters, it might be most easily exploited by countries that are relatively centrally located in Europe.

5 Additional results

In addition to our main findings, we exploit here the rich information in our data to investigate some further dimensions in exporters' adjustments to Chinese competition. We first focus on distinguishing effects on export quantity and unit values to assess which one of these two determinants of export revenue is driving the effect of Chinese competition on export performance. Furthermore, we investigate how ESE exports adjust in terms of the geographic diffusion of single product lines facing Chinese competition.

5.1 Quantities and unit-values

Table 5 displays results jointly for product-level ESE exports (Panel A) and firm-level Bulgarian exports (Panel B). We can compare them to those for export revenues, shown in Tables 2 and 3 of the previous section. Columns (1) and (2) report baseline OLS and IV estimates for the effect of Chinese competition on the quantity of exports, while columns (3) and (4) present findings for quantity adjustments in time-sensitive industries (using our strict measure). Corresponding results for export unit-values are shown in columns (5)-(8).

Starting with Panel A, coefficients for China's impact on ESE export quantities are somewhat smaller than those identified previously for export revenues. Based on China's observed expansion during the sample period, export volumes decrease by 5.6 percent ac-

Table 5: Volume and unit values of exports, product-level estimates on ESE sample and firm-level estimates on Bulgarian exporters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Product-level estimates								
Dependent variable:	log Quantity (kg)				log Price (unit value)			
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
China (s_{jkt}^{CN})	-1.024**	-1.879**	-1.581**	-3.374**	-0.198**	-0.463**	-0.188**	-0.426**
	(0.040)	(0.178)	(0.049)	(0.194)	(0.018)	(0.075)	(0.023)	(0.083)
× time-sensitive			1.176**	3.425**			-0.021	-0.086
			(0.075)	(0.225)			(0.034)	(0.094)
Observations	1,628,298	1,628,298	1,628,298	1,628,298	1,628,298	1,628,298	1,628,298	1,628,298
N. Cluster	44,669	44,669	44,669	44,669	44,669	44,669	44,669	44,669
Kleibergen-Paap (F-stat)		1,163.9		582.0		1,163.9		582.0
Panel B: Firm-level estimates								
Dependent variable:	log Quantity (kg)				log Price (unit value)			
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
China (s_{jkt}^{CN})	-0.585*	-2.167**	-0.732**	-2.723**	0.059	0.948**	0.194**	1.345**
	(0.242)	(0.599)	(0.137)	(0.624)	(0.052)	(0.290)	(0.057)	(0.284)
× time-sensitive			0.804**	2.579**			-0.341**	-1.843**
			(0.200)	(0.626)			(0.103)	(0.326)
Observations	268,822	268,822	268,822	268,822	268,822	268,822	268,822	268,822
N. Cluster	15,738	15,738	15,738	15,738	15,738	15,738	15,738	15,738
Kleibergen-Paap (F-stat)		158.516		68.747		158.516		68.747

Note: Standard errors in parentheses adjusted for clustering at the destination-product level. Statistical significance: $^a = p < 0.1$, $^* = p < 0.05$, $^{**} = p < 0.01$. Log import demand included in all specifications, but not reported. Panel A: all specifications include exporter-destination-product and exporter-destination-year fixed effects. Panel B: all specifications include destination-product, destination-year, and firm fixed effects. Firm-level controls have been included but are not reported here (Firm seniority, N. of Products, N. of Destinations).

cording to the OLS specification in column (1). This corresponds to about 84 percent of the previously estimated 6.8 percent reduction in export revenues. The remaining 16 percent can be attributed to lower average unit values, as reported in column (5). We find similar relative contributions in our IV specifications. Firm-level regressions in Panel B suggest different patterns. In contrast to our previous findings for firm-level export revenues, export quantities reveal a sharp reduction while export unit values increase in response to Chinese competition. The increase is substantial and compensates almost 50 percent of the revenues lost due to lower export volumes. Since quantity effects in column (2) appear fairly similar in Panels A and B, these results indicate that heterogeneous responses across ESE exporters might be driven also by differential responses in unit-value responses. Although such differential effects could be due to several reasons, one explanation for the case of Bulgaria could be that their relatively high FDI inflows facilitated quality upgrading of firms' exports.[33]

Turning to the differential responses in time-sensitive industries, we observe in Panel A that they can be fully attributed to smaller displacement effects of export volumes. This suggests that ESE's local comparative advantage in time-sensitive exports does not originate from any systematic differences in the price response to Chinese competition, but instead reflects higher resilience to external competition. Similar conclusions can be drawn from the firm-level results in Panel B, columns (3) and (4), where export quantities in time-sensitive industries are less responsive to increased Chinese competition. Moreover, while export unit-values generally increase as competition intensifies, time-sensitive sectors do not indicate such adjustments. If anything, export unit values in such industries decrease, which might indicate that firms lack incentives to upgrade their products as long as they are resilient to external competition thanks to their proximity advantage.

5.2 Geographical diffusion of ESE exports

We investigate three additional outcome variables that capture how ESE exports diffuse across EU15 destinations in response to Chinese competition. Focusing on this dimension allows us to explore a novel margin of adjustment, which takes place *within* products but across destinations. This dimension has remained largely unexplored in the literature, mainly because existing studies typically focus on a single destination market. Findings by Holmes and Stevens (2014), however, suggest that Chinese competition could force firms to focus their sales on a different and narrower customer-base (which is typically related to more customized products). Although we cannot observe such details in our data, changes in the customer-base can be measured by (i) counting the number of destinations to which an average ESE exporter sells a particular product; and by (ii) observing the distribution of product-level export revenues across destinations. We construct a Herfindahl-Hirschmann concentration index (HHI) for this purpose. Moreover, we analyze stability of ESE trade relationships within HS6 product categories by constructing a binary variable that takes a value equal to one whenever the main export destination for a good changed between the current and previous observation. Increasing frequency of changes in the main export destination would indicate greater instability in ESE trade relationships and potentially also greater uncertainty about future export revenues.

Table 6 presents the results. The first two columns suggest a significant decrease in the

[33] We highlighted FDI inflows as a potential source of higher resilience to Chinese competition in the discussion of heterogeneous effects across ESE countries in Appendix Section B.1 and the discussion in Section 4.1. Ciani and Imbruno (2017) find that FDI inflows contributed to average improvements of export quality among Bulgarian firms thanks to positive forward spillovers.

Table 6: Diffusion of ESE exports across destinations, product-level estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	ln(#dest)		HHI		Switch main	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
OLS and second-stage estimation						
China's market share	-0.166**	-0.178*	0.023*	0.004	0.126**	0.390**
	(0.032)	(0.077)	(0.012)	(0.552)	(0.024)	(0.066)
Import demand	0.172**	0.172**	-0.046**	-0.046**	-0.012**	-0.013**
	(0.004)	(0.004)	(0.001)	(0.001)	(0.003)	(0.003)
First-stage estimation: s_{kt}^{CN}						
China's market share $n \neq j$		0.295**		0.295**		0.271**
		(0.015)		(0.015)		(0.015)
Observations	394,071	394,071	394,071	394,071	342,296	342,296
N. Cluster	3,921	3,921	3,921	3,921	3,892	3,892
Kleibergen-Paap (F-stat)		411.0		411.0		341.1

Note: Product-level estimation of aggregated sample. Standard errors in parentheses adjusted for clustering at the product-level. Statistical significance: $^a = p < 0.1$, $^* = p < 0.05$, $^{**} = p < 0.01$. Coefficients for log import demand suppressed in first-stage estimation results. All specifications include exporter-HS6 and exporter-year fixed effects. Columns (5) and (6) based on shorter sample period (1998-2007) by construction of dependent variable.

number of destinations ESE exporters reach within an HS6 product category. Both OLS and IV estimates report fairly consistent coefficients, despite some loss of precision in the latter. Columns (3) and (4) indicate a very small, positive, and only marginally significant relationship between the concentration of revenues in a particular destination country and Chinese competition. Given that the absolute number of export partners decreases, an increasing concentration of exports could have been expected also at the intensive margin (within persisting destinations). In turn, the results suggest that exports to remaining destinations tend to be more evenly distributed, if anything. Finally, columns (5) and (6) suggest a clear pattern of increasingly frequent revenue switching. This suggests that ESE exporters, besides reducing revenues and quantities of their shipments in response to Chinese competition, also trade with fewer countries, while they experience increased instability in their main source of export revenues.

6 Concluding remarks

We analyze the impact of increased Chinese competition in EU15 markets on export revenues of 16 Eastern and Southeast European countries during the early 2000s. Our identification strategy exploits the exogenous intensification of competition within narrow destination-product markets, which we derive from the evolution of its exports in comparable high-income markets and from trade linkages existing before China's accession to the WTO.

We find that export revenues of ESE countries decline in response to China's expansion and confirm this result also in an auxiliary data set of Bulgarian firms. Displacements are sizeable and comparable to those found in a related study for Mexican exports to the US (Utar and Torres Ruiz, 2013). We present new evidence explaining differential effects across, by showing that China's impact varies depending on initial exporter conditions, such as average price levels or FDI inflows at the beginning of the sample period. We confirm that the reductions in export revenues reflect actual exporting activity, as they are mainly explained by reductions in actual export quantities.

Our paper highlights some important and novel margins of adjustment that have not been documented before. First, reductions in export revenues are accompanied by reductions in the number of export destinations served, as well as more frequent changes of the main export market for a specific product. Second, our firm-level analysis suggests that larger and multi-destination exporters in Bulgaria are systematically less affected by Chinese competition in the EU15 market. And finally, export reductions are substantially smaller in industries for which timely delivery matters.

This last result suggests the existence of a local comparative advantage in time-sensitive industries, ESE exporters derive from their geographic proximity and shorter delivery times to the EU15. Firms' or countries' ability to ensure timely delivery reveals as an important determinant of competitiveness. From a policy perspective, this implies that specializing in such industries and providing a functioning transport infrastructure can shield exporters from external competition. Providing such infrastructure may be viewed as a complementary strategy to investments in training and education, which fosters comparative advantage in skill-intensive activities.

Another implication of this result is that exporters located too far away from a specific destination market face an important barrier to accessing specific market segments and develop supply capacities in certain industries. In this respect, distance from (and prolonged delivery times to) large high-income markets may impose limits to countries' export diversification potential, which is typically conceived as a way to promote economic development.

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Appendix

A Additional material

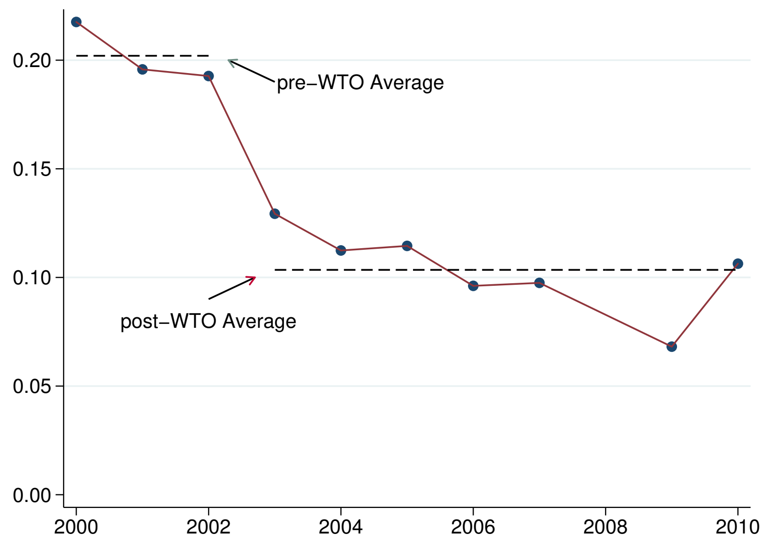
Table A1: Examples of time-sensitive and time-insensitive industries, adjusted measure

HS Section	Section name	HS2 Chapter	Chapter description
Most time-sensitive (top 5)			
VI	Chemicals and allied industries	38	Chemical products n.e.c.
VI	Chemicals and allied industries	34	Soap, Organic surface-active agents; Washing, lubricating, polishing or scouring preparations; Artificial or prepared waxes, Candles and similar articles, Modelling pastes, Dental waxes and dental preparations with a basis of plaster
VI	Chemicals and allied industries	35	Albuminoidal substances; Modified starches; Glues; Enzymes
VI	Chemicals and allied industries	32	Tanning or dyeing extracts; Tannins and their derivatives; Dyes, pigments and other colouring matter; Paints, varnishes; Putty, other mastics; Inks
XVII	Vehicles, Aircraft, Vessels	87	Vehicles; Other than railway or tramway rolling stock, and parts and accessories thereof

HS Section	Section name	HS2 Chapter	Chapter description
Least time-sensitive (bottom 5)			
VI	Chemicals and allied industries	36	Explosives; Pyrotechnic products; Matches; Pyrophoric alloys; Certain combustible preparations
X	Wood and wood products	47	Pulp of wood or other fibrous cellulosic material; Recovered (waste and scrap) paper or paperboard
VIII	Hides and Skins, Leather, Furskins	41	Raw hides and skins (other than furskins) and leather
XIV	Pearls, Precious stones and metals	71	Natural, cultured pearls; Precious, semi-precious stones; Precious metals; Metals clad with precious metal, and articles thereof; Imitation jewellery; Coin
XI	Textiles and textile products	50	Silk

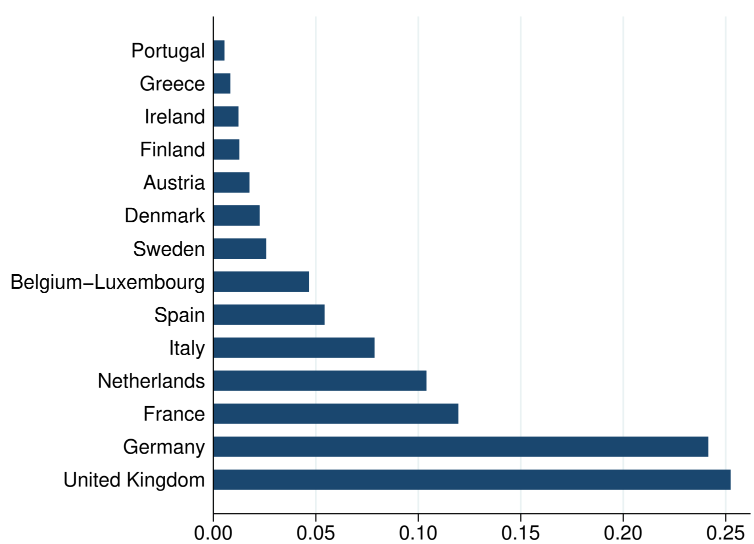
Note: Authors' compilation. Section and chapter descriptions based on information from *Foreign Trade Online* (https://www.foreign-trade.com/reference/hscode.htm).

Figure A1: Chinese imports of transportation services from Hong Kong, share of total



Note: Authors' calculations based on data from World Bank Trade in Services Database (https://data.worldbank.org/data-catalog/trade-in-services). Data starts in 2000, information for 2008 missing.

Figure A2: Distribution of Hong Kong re-exports across EU15 destinations, 1999-2001



Note: Authors' calculations based on data from UN Comtrade. Shares indicate fractions of total Hong Kong re-exports to EU15 destinations.

Table A2: Robustness of China's impact on ESE exports, product-level estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Clustering and aggregation				Additional fixed effects and controls					
	Cluster HS6		Aggregate destinations		HS6-year FE		Additional control		Exporter-HS6-year FE	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
China (s^{CN}_{jkt})	-1.222**	-2.343**	-1.529**	-2.044**	-0.661**	-2.026**	-0.661**	-2.040**	-0.646**	-2.293**
	(0.058)	(0.240)	(0.108)	(0.267)	(0.032)	(0.548)	(0.032)	(0.549)	(0.036)	(0.590)
Import demand	0.569**	0.576**	0.588**	0.589**	0.429**	0.435**	0.429**	0.435**	0.448**	0.456**
	(0.010)	(0.010)	(0.017)	(0.017)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Applied tariff							-2.459**	-2.454**		
							(0.136)	(0.136)		
Observations	1,628,298	1,628,298	394,071	394,071	1,626,480	1,626,480	1,626,480	1,626,480	1,516,895	1,516,895
N. Clusters	3,903	3,903	3,921	3,921	44,344	44,344	44,344	44,344	42,795	42,795
Kleibergen-Paap (F-stat)		444.9		411.0		191.0		191.1		178.2
Clustering dimension	HS6	HS6	HS6	HS6	HS6-dest.	HS6-dest.	HS6-dest.	HS6-dest.	HS6-dest.	HS6-dest.
Exporter-importer-year FE	✓	✓			✓	✓	✓	✓	✓	✓
Exporter-importer-HS6 FE	✓	✓			✓	✓	✓	✓	✓	✓
Exporter-year FE			✓	✓						
Exporter-HS6 FE			✓	✓						
HS6-year FE					✓	✓	✓	✓		
Exporter-HS6-year FE									✓	✓

Note: Standard errors in parentheses adjusted for clustering in different dimensions. Statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table A3: Continuous time-sensitivity measure, broad and strict; product-level estimates 1997-2007

	(1)	(2)	(3)	(4)
Measure of time-sensitivity:	Broad (SD=1)		Strict (SD=1)	
Dep. var.: log export revenue	OLS	2SLS	OLS	2SLS
China's market share	-1.006**	-1.660**	-1.134**	-2.064**
	(0.041)	(0.183)	(0.036)	(0.158)
× time-sensitive	0.841**	2.476**	0.597**	1.687**
	(0.083)	(0.311)	(0.042)	(0.128)
Observations	1,628,298	1,628,298	1,628,298	1,628,298
N. clusters	44,669	44,669	44,669	44,669
Kleibergen-Paap (F-stat)		595.1		609.0

Note: Standard errors reported in parentheses are clustered at the product-destination level. Statistical significance: $^a = p < 0.1$, $^* = p < 0.05$, $^{**} = p < 0.01$. All specifications include log import demand as a control variable (coefficients suppressed) as well as exporter-importer-HS6 and exporter-importer-year FEs.

Table A4: Time-sensitivity estimates, individual inclusion of controls

	(1)	(2)	(3)	(4)	(5)	(6)
Control variable:	intermediate inputs BEC (rev.4)		contract intensity Nunn (2007)		skill intensity Amiti and Freund (2010)	
Dep. var.: log exports	OLS	2SLS	OLS	2SLS	OLS	2SLS
China's market share	-1.858**	-3.816**	-1.818**	-4.440**	-1.807**	-3.815**
	(0.049)	(0.178)	(0.077)	(0.371)	(0.046)	(0.179)
× time-sensitive	0.998**	3.035**	1.167**	3.485**	1.026**	3.098**
	(0.069)	(0.215)	(0.069)	(0.216)	(0.069)	(0.210)
× intermediate inputs	0.508**	1.168**				
	(0.073)	(0.282)				
× contract intensity			0.057	0.668*		
			(0.075)	(0.303)		
× skill intensity					0.570**	1.137**
					(0.089)	(0.290)
Observations	1,628,298	1,628,298	1,628,298	1,628,298	1,628,298	1,628,298
N. clusters	44,669	44,669	44,669	44,669	44,669	44,669
Kleibergen-Paap (F-stat)		145.0		144.0		315.3

Note: Standard errors reported in parentheses are clustered at the product-destination level. Statistical significance: $^{a} = p < 0.1$, $^{*} = p < 0.05$, $^{**} = p < 0.01$. All specifications include log import demand as a control variable (coefficients suppressed) as well as exporter-importer-HS6 and exporter-importer-year FEs.

Table A5: Time-sensitivity estimates, placebo regressions and ESE distance to EU15

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Low-wage Asia's exports (placebo)				ESE exports (distances to destination)			
Specification:	Baseline		add controls		$\leq 1,500$	$> 1,500$	bilateral distance	
Dep. var.: log export revenue	OLS	2SLS	OLS	2SLS	OLS	OLS	OLS	2SLS
China's market share	-0.834**	-0.770**	-1.064**	-1.083**	-2.141**	-1.100**	-2.139**	-5.091**
	(0.045)	(0.189)	(0.096)	(0.336)	(0.059)	(0.061)	(0.059)	(0.238)
× time-sensitive	0.350**	0.146	0.194**	-0.102	1.487**	0.577**	1.487**	4.347**
	(0.066)	(0.185)	(0.075)	(0.224)	(0.082)	(0.095)	(0.082)	(0.255)
× intermediate inputs			0.292**	0.656*				
			(0.085)	(0.255)				
× contract intensity			0.186*	0.322				
			(0.088)	(0.258)				
× skill intensity			0.561**	0.898*				
			(0.101)	(0.360)				
× distant$_{ij}$							1.030**	3.679**
							(0.079)	(0.321)
× time-sens. × distant$_{ij}$							-0.911**	-2.769**
							(0.118)	(0.351)
Observations	767,418	767,418	767,418	767,418	1,100,535	527,763	1,628,298	1,628,298
N. clusters	38,703	38,703	38,703	38,703	35,630	34,525	44,669	44,669
Kleibergen-Paap (F-stat)		431.5		86.5				296.2

Note: Standard errors reported in parentheses are clustered at the product-destination level. Statistical significance: $^a = p < 0.1$, $^* = p < 0.05$, $^{**} = p < 0.01$. All specifications include log import demand as a control variable (coefficients suppressed) as well as exporter-importer-HS6 and exporter-importer-year FEs. The variable distant$_{ij}$ takes a value equal to one for observed bilateral (population-weighted) distances of more than 1,500 kilometers in the CEPII Gravity Dataset.

Table A6: China's impact on Bulgarian firm-level exports and time-sensitivity, 2001-2006

	(1)	(2)	(3)	(4)	(5)	(6)
Time-sensitivity measure:	Simple (broad)				Adjusted (strict)	
	Below Median	Above Median	Interaction: Above first quartile		Interaction: Above first quartile	
	OLS	OLS	OLS	2SLS	OLS	2SLS
Dep. var.: log export revenues						
China	-1.575*	-0.428	-0.462**	-1.662**	-0.508**	-1.810**
	(0.652)	(0.954)	(0.174)	(0.618)	(0.174)	(0.619)
China × time-sensitive			0.179	0.984	0.256	1.339*
			(0.214)	(0.651)	(0.214)	(0.658)
First stage results for China's expansion						
$s_{nkt}^{CN} \times w_j$				1.750**		1.768**
				(0.185)		(0.187)
$s_{nkt}^{CN} \times w_j \times$ High Quartile				-0.686**		-0.715**
				(0.208)		(0.209)
Observations	137,070	129,414	268,822	268,822	268,822	268,822
N. Clusters	7,262	8,379	15,738	15,738	15,738	15,738
Kleibergen-Paap (F-stat)				71.8		70.5

Note: Standard errors reported in parentheses are clustered at the product-destination level. Statistical significance: $^{a} = p < 0.1$, $^{*} = p < 0.05$, $^{**} = p < 0.01$. All specifications include destination-product, destination-year, and firm fixed effects. Log import demand and other firm-level control variables (Firm seniority, N. of Products, N. of Destinations) have been included in these specifications but coefficients are not reported in this Table.

B Heterogeneous effects across exporters

B.1 Differential effects across countries

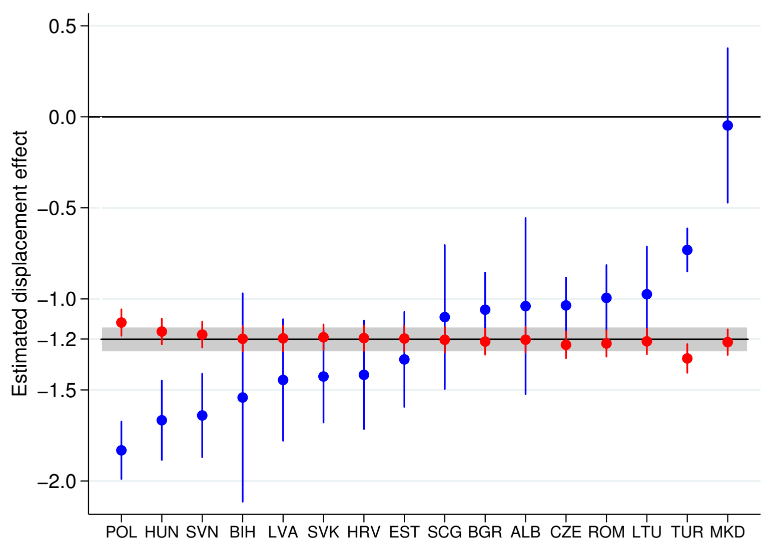
Our sample encompasses exporting countries at different stages of economic development, and we might expect differential responses to Chinese competition across these countries. In particular, assuming that Chinese exports partly expand due to lower relative prices, the level of economic development and the average price level of exports across ESE countries could play a role in determining exposure to Chinese competition.

Exporter and country-pair specific coefficients. We first check whether our results are generally driven by individual exporting countries. To evaluate this, we add an additional term into our specification which interacts our main variable of interest with an exporter-specific dummy variable:

$$\ln X_{ijkt} = \alpha + \beta s_{jkt}^{CN} + \beta_i (s_{jkt}^{CN} \times \mathbf{D}_i) + \gamma \ln M_{jkt} + \mu_{ijk} + \mu_{ijt} + \nu_{ijkt}, \tag{B.1}$$

The estimate of β_i will inform about the *differential* effect of Chinese export market competition on country i, relative to other ESE exporters. Furthermore, $(\hat{\beta} + \hat{\beta}_i)$ will inform us about the overall magnitude of the displacement of i's exports. We summarize OLS estimates of Equation (B.1) graphically in Figure B1. The vertical axis denotes the magnitude of the point estimate for Chinese competition and the solid horizontal line, surrounded by the shaded area, denotes the displacement effect and 95-percent confidence interval we obtained from our baseline specification in Table 2, column (1). Red dots and vertical lines denote the estimated base-effect, $\hat{\beta}$, obtained from Equation (B.1). The blue dots and vertical lines denote the respective effect estimated for the individual exporter, $(\hat{\beta} + \hat{\beta}_i)$.

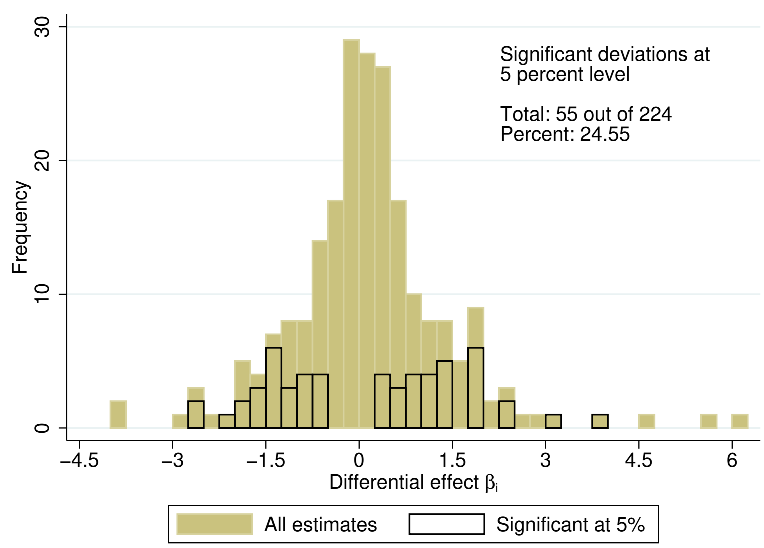
Figure B1: Exporter specific displacement effects versus baseline



Note: Author's calculations. Shaded area with solid line: baseline result from Eq. (1). From Eq. (B.1): red – base-effect $(\hat{\beta})$; blue – individual effect $(\hat{\beta} + \hat{\beta}_i)$; vertical lines – 95-percent confidence intervals.

Comparing the base effects reported in Figure B1, we find that no single exporting country in our sample drives our baseline result. If this were the case, we would have seen that red dots and confidence intervals do not overlap with the grey area. Only for two exporters (Poland and Turkey), point estimates reside just outside this area. Turning to the exporter-specific coefficients, indicated by the blue points, we find that some exporters do reveal differential responses. At one end of this spectrum, this concerns countries with significantly stronger displacement effects, such as Poland, Hungary and Slovenia. At the other extreme, Turkey and Northern Macedonia are significantly less affected than the rest of the ESE countries in our sample. Northern Macedonia, with a point estimate just below zero, appears to be entirely unaffected by Chinese competition. For the rest of our exporters we observe point estimates ranging fairly close to our baseline results, i.e. from slightly above -1.0 to slightly below -1.5. Some of them reveal differential effects at the 10 percent level of statistical significance, such as Bulgaria, for which $\hat{\beta}_i = 0.175$ suggests an about 14 percent smaller displacement effect compared to the rest of the sample.

Figure B2: Country-pair specific displacement effects; distribution of interaction coefficients



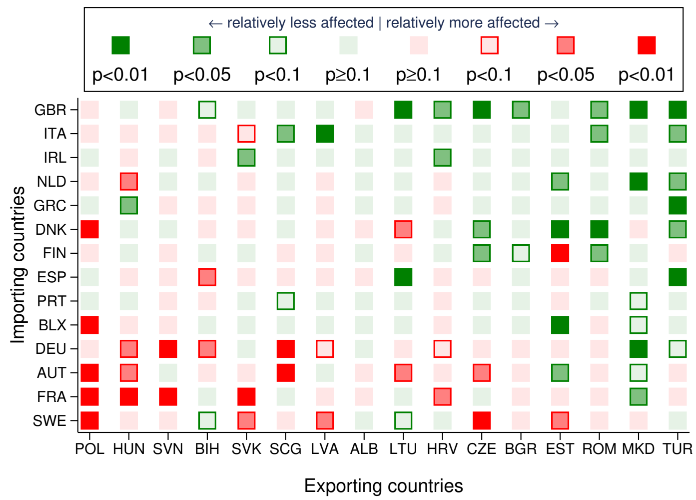
Note: Author's calculations based on 224 regressions for individual country-pair effects of Chinese competition on ESE exports. Histogram shows frequency of $\hat{\beta}_{ij}$ magnitudes. Lined bars denote frequency of significant deviations from base-effect at 5 percent level.

Exploring these dimensions further, we also estimated separate coefficients for each exporter-importer pair ij.[34] The overall distribution of estimated interaction coefficients, $\hat{\beta}_{ij}$, is displayed in Figure B2. For about three out of four country pairs, we find no statistically significant difference from the baseline effect. The remaining pairs indicate either larger or smaller displacement, with interaction coefficients $\hat{\beta}_{ij} = [-3, 3]$. Looking at individual ij-pairs in Figure B3, we observe that the less exposed exporters identified above (Turkey and Northern Macedonia) reveal significant deviations in about 50 percent of the EU15 destinations. On the importer side, we find frequent cases of systematically smaller

[34] With 14 importers and 16 exporters, we ran 224 regressions to obtain indication for differential effects in all possible combinations.

displacement in the United Kingdom and Italy, while displacement tends to be more pronounced in Sweden, France, Austria and Germany. We cannot infer any obvious systematic relation to importing country characteristics, but we explore those across exporters in the following subsection.

Figure B3: Differential effects of Chinese competition for individual country pairs



Note: Author's calculations based on repeated estimates of baseline product-level OLS specification with respective country-pair interaction. Positive coefficients (suggesting weaker responses) are colored in green, whereas negative coefficients (suggesting stronger responses) are colored in red. The intensity of the colors indicates different levels of statistical significance (see legend).

EEC vs SEE and exporter characteristics. In Table B1, Panel A, we present results for alternative exporter specific interaction terms with our main variable of interest.[35] We begin with a simple dummy variable for the eight Eastern European countries (EEC), which became full EU members in 2004. This country group appears to face systematically larger displacement effects of Chinese competition. In column (2) we use another measure that captures exporters' relative stage in the EU integration process, measuring the fraction of HS6 product lines exported to the EU15 free of tariffs at the beginning of our sample period (1997-1999). We find again a negative and significant interaction coefficient. In column (3)-(4) we confirm our previous conjecture that that countries at higher stages of economic development and with higher price levels are differently affected by Chinese competition.

We also check whether ESE exporters receiving higher inflows of FDI (measured in percent of GDP) reveal different effects. This seems to be the case if we include FDI individually,

[35]Information about the data sources and construction of interaction variables are provided in the footnote of Table B1.

in column (5), but the sign and magnitude becomes ambiguous in columns (6) and (7). Overall, results suggest that exporters at more advanced stages of the EU integration process, and those with higher price levels of output experience systematically larger reductions in their export revenues. Economically more advanced countries appear to be less affected, after controlling for prices, trade integration with the EU and FDI inflows.[36]

In the lower Panel of Table B1, we revisit these results with a restricted sample that excludes Turkey from our control group. The reasons for doing so are twofold: (i) Turkey appeared to potentially bias our baseline estimates upwards, as it reveled to be systematically less affected by Chinese competition, while accounting for a large portion of our observations (about 13.4 percent); (ii) this relative resilience might be due to a number unobserved characteristics, which make Turkey different from the rest of our ESE exporters. For instance, it was never part of the former Eastern Bloc of Socialist economies and it was also subject to different EU integration policies after the breakdown of the Soviet Union. Hence, excluding Turkey from our sample will help us understand to what extent our findings in Panel A are driven by a single potential outlier in our data.

In columns (1) and (2) of Table B1, we observe that the differential effect for early integrating economies is indeed smaller once we exclude Turkey from the sample. Instead of 57 percent, Panel B suggests only 37 percent larger displacement of EEC relative to SEE exporters. The relative magnitudes of interaction coefficients in columns (3) and (4) also reveal some changes. More interestingly, however, column (5) suggests that higher FDI inflows into the exporting countries are associated with significantly *smaller* displacement effects, which is the opposite of what we found in Panel A. This relationship remains robust across all our alternative specifications that exclude Turkey from our sample and suggests that FDI inflows may have contributed to higher competitiveness of ESE exporters *vis-à-vis* China. In our full specifications, reported in columns (6) and (7) of Panel B, we confirm our previous findings that higher prices undermine competitiveness while higher stages of economic development contribute to relatively higher resilience.[37] The last column of our table further suggests that EEC countries are no longer systematically more affected, once we control for more specific exporter characteristics. Early trade integration, as measured by the fraction of tariff free product lines, however, remains significant. We interpret this correlation as indicative for a EU integration process that contributed to economic restructuring and favored larger displacement by Chinese exports.

[36] In Figure B4, we show differences and commonalities between EEC and SEE exporters in terms of the country characteristics we take into consideration.

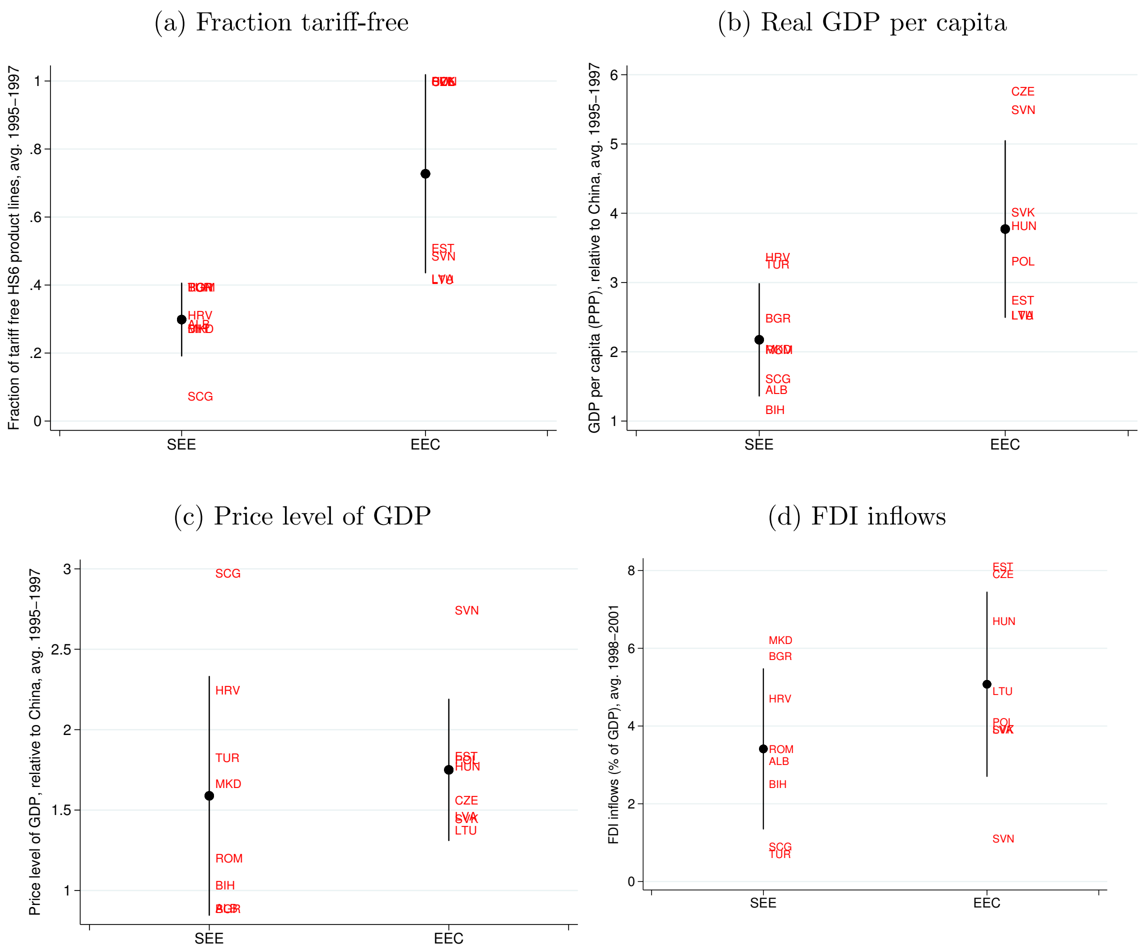
[37] An explanation for the latter result could be that more advanced economies export different varieties of a good that compete less with Chinese varieties in a destination. This would be in line with the literature on relative export quality which influences the elasticity of substitution derived from prices (e.g. Schott, 2008).

Table B1: Differential impact of China across ESE exporters, product-level data, 1997-2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. var.: log export revenue	Individual interactions					Combined	
Panel A: Full sample - 16 ESE exporters							
China (s^{CN}_{jkt})	-0.919**	-0.757**	-0.953**	-1.029**	-1.221**	-0.913**	-1.059**
	(0.046)	(0.068)	(0.102)	(0.059)	(0.036)	(0.107)	(0.112)
× EEC$_i$	-0.525**						-0.472**
	(0.057)						(0.103)
× Free HS6$_i$		-0.726**				-1.132**	-0.679**
		(0.097)				(0.140)	(0.171)
× (log) GDPpc$_i$			-0.225**			0.612**	0.606**
			(0.081)			(0.117)	(0.117)
× (log) Price-level$_i$				-0.398**		-0.650**	-0.370**
				(0.099)		(0.128)	(0.143)
× FDI inflow$_i$					-0.073**	-0.006	0.059
					(0.025)	(0.033)	(0.037)
Observations	1,628,298	1,628,298	1,628,298	1,628,298	1,628,298	1,628,298	1,628,298
N. Clusters	44,669	44,669	44,669	44,669	44,669	44,669	44,669
Panel B: Restricted sample - 15 ESE exporters (excl. Turkey)							
China (s^{CN}_{jkt})	-1.052**	-0.964**	-1.068**	-1.057**	-1.363**	-0.884**	-0.942**
	(0.063)	(0.082)	(0.104)	(0.059)	(0.042)	(0.106)	(0.113)
× EEC$_i$	-0.391**						-0.177
	(0.069)						(0.120)
× Free HS6$_i$		-0.521**				-0.925**	-0.781**
		(0.105)				(0.144)	(0.171)
× (log) GDPpc$_i$			-0.215**			0.302*	0.337**
			(0.081)			(0.125)	(0.128)
× (log) Price-level$_i$				-0.584**		-0.474**	-0.391**
				(0.103)		(0.130)	(0.143)
× FDI inflow$_i$					0.110**	0.164**	0.168**
					(0.035)	(0.042)	(0.042)
Observations	1,409,858	1,409,858	1,409,858	1,409,858	1,409,858	1,409,858	1,409,858
N. Clusters	42,913	42,913	42,913	42,913	42,913	42,913	42,913

Note: Standard errors in parentheses clustered at product-destination level. Statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All specifications include exporter-importer-product FE, exporter-importer-year FE and log import demand as controls. EEC$_i$ is a dummy variable for 8 ESE exporters becoming EU members in 2004; Free$_i$ measures trade integration with the EU15 by the fraction of observed tariff-free HS6 product lines exported (average 1997-1999); GDPpc$_i$ denotes real GDP per capita relative to China (output-based measure, in chained PPPs, as reported in PWT 9.0; average 1995-1997). Price-level$_i$ denotes price levels of output relative to China (as reported in PWT 9.0; average 1995-1997); FDI inflow$_i$ in percent of GDP, normalized to mean zero and standard deviation of one (original from WDI database, average 1998-2001).

Figure B4: Eastern vs Southeast European exporters



Note: Tariff information based on data from World Integrated Trade Solutions (WITS). Data for real GDP and price level of GDP from Penn World Tables 9.0. FDI inflow figures based on data from the World Development Indicators database.

B.2 Differential effects across firms

Multi-product and multi-destination firms. The theoretical and empirical literature gives mixed suggestions for a differential impact of Chinese competition on larger firms. While multi-product or multi-destination firms might be assumed to be bigger and more productive, thus less affected, the opposite effect is also possible. In particular, Holmes and Stevens (2014) document patterns suggesting that larger firms are more exposed to Chinese competition and, hence, suffer also more. The reason is that larger firms have more standardized production processes and focus more on large-scale consumption varieties than smaller firms that are flexible to customize their production. While such patterns have been documented for US data, it is questionable whether this would be confirmed as well for Bulgaria. We first assess whether introducing a different proxy for firm size changes our findings. We build a variable for large firms which defines a firm as large if it reports revenues above the 75^th percentile of firm-level export revenue in the first year in which it starts exporting. This variable is constant for the following years in which the firm is present in our database. OLS and 2SLSreported in Table B2, show that large firms are significantly less affected by Chinese competition. Relying OLS estimates we observe that large firms are 50 percent less affected by Chinese competition.

We then analyze the differential impact of Chinese competition across firm types by classifying multi-product firms as those selling several HS6 products in the same year to any EU15 destination. Likewise, we define multi-destination firms as those exporting the same HS6 product to at least two destination countries in one year. In both cases we use the first observation available for a firm so that its status as a multi-product or multi-destination firm is time-invariant. Evidence shows that multi-destination firms are less harmed by Chinese competition in the various destination markets. The result in column (3) is confirmed by a corresponding IV estimate in column (4). On the contrary, estimates on multi-product firms show that the impact of Chinese competition does not differently affect the performance of these firms. Moreover, the impact of Chinese competition on firms exporting only one product across different destinations does not appear to be statistically significant. Chinese competition has negative impact on exporters selling their products to only one destination rather than on exporters supplying only one product.

Table B2: Large Firms, heterogeneous effects on multi-destination and multi-product Firms

	(1)	(2)	(3)	(4)	(5)	(6)
	Large Firms		Multi-destination		Multi-product	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep. var.: log export revenue						
China (s^{CN}_{jkt})	-0.545**	-2.359**	-1.376[a]	-8.131**	-0.979	-0.953
	(0.136)	(0.639)	(0.801)	(1.451)	(1.121)	(0.976)
China × Large Firm	0.282*	1.743**				
	(0.119)	(0.287)				
China × Multi-destination			0.731*	3.714**		
			(0.372)	(0.650)		
China × Multi-product					0.084	-0.231
					(0.909)	(0.738)
Import demand	0.213**	0.227**	0.371**	0.285**	0.367**	0.229**
	(0.023)	(0.025)	(0.093)	(0.030)	(0.085)	(0.025)
Firm Seniority	0.327**	0.322**	0.614*	0.304**	0.567*	0.226**
	(0.052)	(0.052)	(0.266)	(0.052)	(0.282)	(0.052)
N. of Products	-0.259**	-0.260**	0.146*	-0.248**		
	(0.018)	(0.018)	(0.059)	(0.018)		
N. of Destinations	0.069**	0.065**			0.610**	0.003
	(0.023)	(0.023)			(0.090)	(0.022)
First stage results						
$s^{CN}_{nkt} \times w_j$		1.377**		30.803**		1.181**
		(0.108)		(4.038)		(0.125)
$s^{CN}_{nkt} \times w_j \times$ Large		2.398**				
		(0.109)				
$s^{CN}_{nkt} \times w_j \times$ Multi-destination				2.058**		
				(0.090)		
$s^{CN}_{nkt} \times w_j \times$ Multi-product						3.312**
						(0.224)
Observations	268,822	268,822	268,822	268,822	268,822	268,822
N. Clusters	15,738	15,738	15,738	15,738	15,738	15,738
Kleibergen-Paap (F-stat)		79.187		34.236		79.235

Note: Standard errors reported in parentheses are clustered at the product-destination level. Statistical significance: $^{a} = p < 0.1$, $^{*} = p < 0.05$, $^{**} = p < 0.01$. All specifications include destination-product, destination-year, and firm fixed effects. Regression (3) and (5) employ weighted OLS, export quantities used as probability weights. For those specifications including two instrumental variables we report first stage estimates only for the instrumented variable of interest.

C Estimating time-sensitivity

In an attempt to measure differential time-sensitivity across product categories, Hummels and Schaur (2013) exploit detailed shipping mode information in US trade data and estimate industry-specific markups firms are willing to pay to import a good via air freight instead of sea shipment. This markup informs about the value of fast delivery that is attributed to a particular good. Products for which the value of time is higher are considered as being relatively more time-sensitive.[38] We argue that such goods should also reveal higher resilience towards Chinese competition in ESE exports, given their geographic proximity to EU15 destinations. To test this hypothesis, we use the data from Hummels and Schaur (2013) to replicate their methodology and to obtain a cross-sectional measure of time-sensitivity at the 2-digit HS sector level.

Model. Hummels and Schaur (2013) assume a simple demand function in which consumers purchase goods depending on its price, its quality, and the time it takes for delivery.

$$q_i^z = E\left(\frac{p_i^{z*}}{v_i^z \exp(-\tau \cdot days_i^m)}\right)^{-\sigma} \tag{C.1}$$

Given expenditure E, price p_i^z and quality v_i^z offered by a firm z located in exporting country i affect demand for its variety q_i^z. Besides this, the number of days it takes to ship a good from i to the destination market negatively enters the demand function with an elasticity parameter τ. Shipping times depend on the mode of transport m, which can be either ocean cargo o or airfreight a. Since this model considers import demand by the US, there is no destination-specific subscript and the demand system is initially assumed to be the same across products.

On the supply side, firms v face fixed costs F of exporting and also charge differently, depending on the mode of transport. Shipping charges g_i^m depend on the location of the exporter and the transport mode, where for any i airfreight is more expensive than ocean cargo: $g_i^a > g_i^o$. With shipping charges being proportional to the quantity of a shipment (not its value), profits of the firm result as follows:

$$\pi(z)_i^m = \frac{(z + g_i^m)}{\sigma - 1} E\left(\frac{(z + g_i^m)/\theta}{v_i^z \exp(-\tau \cdot days_i^m)}\right)^{-\sigma} - F \tag{C.2}$$

Defining mode-specific ad-valorem shipping costs from exporter i as $f_i^m = (1 + g_i^m / p_i^m)$, and assuming that airfreight generally takes only one day to arrive at the destination, Hum-

[38] Hornok (2012) provides evidence that the European integration process has boosted trade in such time-sensitive products disproportionately, as border waiting times and other trade barriers were dismantled.

mels and Schaur (2013) derive the following relative export revenue equation for a firm z shipping via air:[39]

$$\ln \frac{r(z)_i^a}{r(z)_i^o} = \sigma\tau\left(days_i^o - 1\right) + (1-\sigma)\ln\left(\frac{p_i^a}{p_i^o}\right) - \sigma\ln\left(\frac{f_i^a}{f_i^o}\right) + \sigma\ln\left(\frac{v_i^a}{v_i^o}\right) \tag{C.3}$$

To take this specification to more aggregated data (i.e. product-level trade data), firm-level revenues are multiplied by the number of z_i^m-type firms, N_i^m:

$$\ln \frac{R_i^a}{R_i^o} = \sigma\tau\left(days_i^o - 1\right) + (1-\sigma)\ln\left(\frac{p_i^a}{p_i^o}\right) - \sigma\ln\left(\frac{f_i^a}{f_i^o}\right) + \sigma\ln\left(\frac{v_i^a}{v_o^z}\right) + \ln\left(\frac{N_i^a}{N_i^o}\right) \tag{C.4}$$

Estimation. To estimate this equation, Hummels and Schaur (2013) exploit detailed US import data for the period 1991-2005, where they observe the exporting country i, 6-digit HS products k, arriving at coast $c = \{east, west\}$, by mode m, at time t. The observable variables used for the estimation in our paper are the quantity of a shipment (in kilograms), the total value of a shipment (in US dollars), and shipping charges (in US dollars), so that we estimate the following regression equation:

$$\ln \frac{X_{ikct}^a}{X_{ikct}^o} = \sigma\tau\left(days_{ic}^o - 1\right) + (1-\sigma)\ln\left(\frac{uv_{ikct}^a}{uv_{ikct}^o}\right) - \sigma\ln\left(\frac{f_{ikct}^a}{f_{ikct}^o}\right) + \varepsilon_{ikct}, \tag{C.5}$$

where uv_{ikct}^m denotes unit value of the shipment, to proxy prices, and $\varepsilon_{ikct} = \sigma\ln\left(\frac{v_i^a}{v_o^z}\right) + \ln\left(\frac{N_i^a}{N_i^o}\right) + \mu_{ikct}$ denotes the error term. We estimate this model separately for each HS2 sector, including exporter-HS6 fixed effects. Our estimates of time-sensitivity are then computed by dividing the estimated $\widehat{\sigma\tau}$ from the transit time variable in the equation by $\hat{\sigma}$ obtained from the relative freight-charges. As Hummels and Schaur (2013) also show for separate 5-digit end-use categories in Appendix Figure A3, we obtain different estimates across sectors, where statistically significant estimates at the 10 percent level are strictly positive.[40]

In Figure C1 we present our obtained estimates. In Panel (a), we display the distribution of time-sensitivity estimates and highlight those observations that report statistically significant coefficients at the 10 percent level. They are strictly positive and range between 0 and 0.05. In Panel (b) we set all insignificant estimates equal to zero, following the definition of our strict definition of time-sensitivity, and highlight the observations that range above median as we use the binary indicator for our regressions. The results in Panel (a) broadly resemble the pattern documented by Hummels and Schaur (2013, Fig.A3), who estimate

[39] Details of this derivation are shown in their online appendix section A2.2.

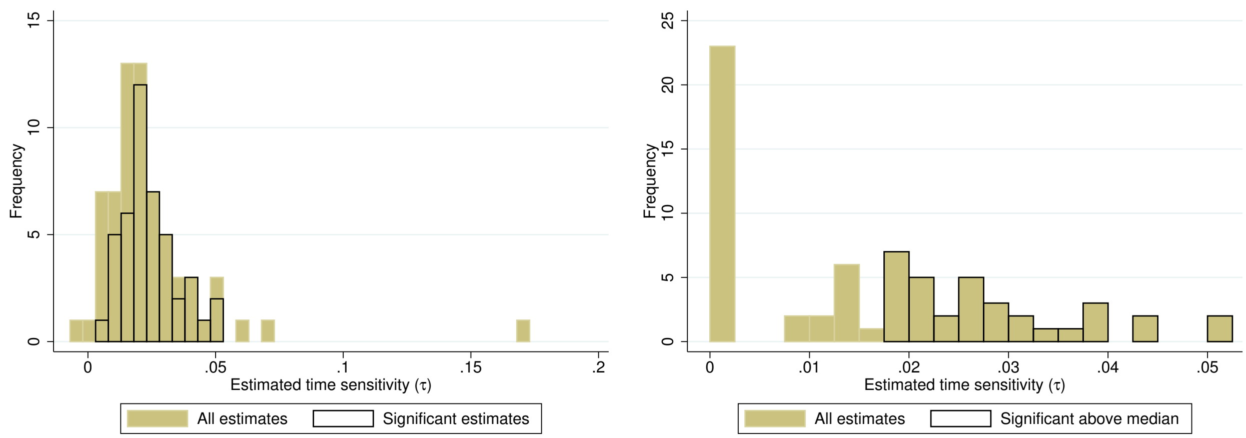
[40] The data and code for running these regressions are provided in the supplementary materials to their original publication (`https://www.aeaweb.org/articles?id=10.1257/aer.103.7.2935`).

individual coefficients for 5-digit end-use categories. Figure C2 shows that time-sensitive sectors also reveal a lower price elasticity of demand.

Figure C1: Distribution of time sensitivity across HS2 sectors

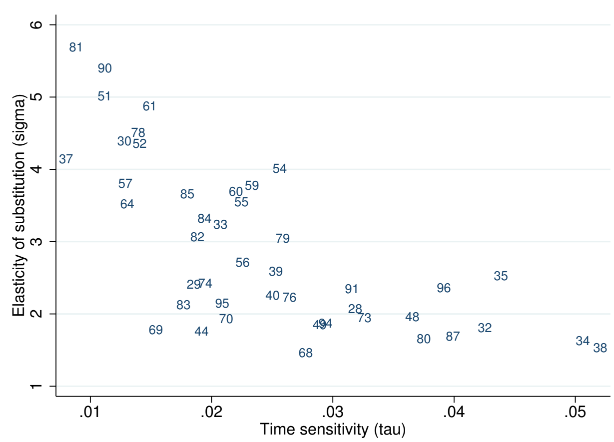
(a) Baseline

(b) Adjusted



Note: Estimated time sensitivity using data and methodology from Hummels and Schaur (2013). Panel (a) baseline results. Panel (b) adjusted results, after setting insignificant estimates equal zero. Sample restricted to manufacturing sectors, i.e. HS Chapters 28-96.

Figure C2: Correlation between time-sensitivity and the elasticity of substitution



Note: Estimated time sensitivity and substitution elasticity using data and methodology from Hummels and Schaur (2013). Sample restricted to manufacturing sectors, i.e. HS Chapters 28-96, with statistical significance of 10 percent or higher.