WIF○ **■** WORKING PAPERS **622/2021**

Import Competition from China in Manufacturing after the Financial Crisis: Evidence for European Regions

Werner Hölzl

Import Competition from China in Manufacturing after the Financial Crisis: Evidence for European Regions

Werner Hölzl

WIFO Working Papers 622/2021 February 2021

Abstract

This research studies the effect of import competition from China for the period after the financial crisis 2008-09 until 2014. It draws on a unique dataset containing employment information for 248 regions in the EU. The uncovered coefficients are statistically not significant, indicating that Chinese imports were not an important driver of deindustrialisation in Europe in the period analysed. The estimates are imprecise, however. An analysis of the economic importance of the results leads to the conclusion that Chinese import competition was not a primary driving force of European manufacturing employment. Possible explanations for the lack of significant results are discussed.

E-mail: werner.hoelzl@wifo.ac.at

2021/034/W/2817

© 2021 Österreichisches Institut für Wirtschaftsforschung.

Medieninhaber (Verleger), Hersteller: Österreichisches Institut für Wirtschaftsforschung 1030 Wien, Arsenal, Objekt 20 | Tel. (43 1) 798 26 01-0 | https://www.wifo.ac.at Verlags- und Herstellungsort: Wien

WIFO Working Papers are not peer reviewed and are not necessarily based on a coordinated position of WIFO. The authors were informed about the Guidelines for Good Scientific Practice of the Austrian Agency for Research Integrity (ÖAWI), in particular with regard to the documentation of all elements necessary for the replicability of the results.

Kostenloser Download: https://www.wifo.ac.at/wwa/pubid/66879

Import competition from China in manufacturing after the financial

crisis: Evidence for European regions

Werner Hölzl

Austrian Institute of Economic Research (WIFO)

Arsenal Objekt 20

Abstract

This research studies the effect of import competition from China for the period after the

financial crisis 2008/09 until 2014. It draws on a unique dataset containing employment

information for 248 regions in the European Union. The uncovered coefficients are

statistically not significant, indicating that Chinese imports were not an important driver of

deindustrialization in Europe in the period analysed. The estimates are imprecise, however.

An analysis of the economic importance of the results leads to the conclusion that Chinese

import competition was not a primary driving force of European manufacturing

employment. Possible explanations for the lack of significant results are discussed.

Acknowledgements:

For valuable comments I would like to thank Agnes Kügler, Klaus Friesenbichler and Michael

Peneder. For their support with the extensive data compilation I am grateful to Nicole

Schmidt-Padickakudy, Anna Strauss-Kollin, Peter Reschenhofer, and Stefan Weingärtner.

Supported by funds of the Oesterreichischen Nationalbank (Austrian Central Bank,

Anniversary Fund, project number: 17678).

Keywords: trade, employment, China, EU, regions.

JEL: F16, J13, R11

1 Introduction

The past decades led to a decline in trade barriers, transportation and communication costs and has triggered a rapid expansion of trade flows across borders and led also to important changes in world trade. The rise of China as manufacturing powerhouse stands out. Since the 1990s Chinese manufacturing exports skyrocketed. China's share of world manufacturing export grew from 2.9% in 1991 to 11.1% in 2008 and to 13.6 in 2014. Trade integration is usually seen as an economically positive process. Trade-integration fosters productivity growth and employment in the trading countries and benefits consumer via increased product variety. However, the raise of China raises the question whether increased import competition has a negative impact on welfare in importing countries.

Important contributions reported an employment-replacing effect of Chinese imports (e.g., Autor et al. 2013, Malgouyres 2014). These studies consider the Chinese import shock from the 1990s to mid-2000s, where China started to become a manufacturing powerhouse and its exports grew substantially. In this paper we consider a later and shorter period (2009 to 2014) and study the labour market impact of Chinese imports across European regions. During this time Chinese imports did not grow as dramatically as in the 1990s and 2000s. But this should not be seen as a limitation. Chinese manufacturing has undergone rapid technological upgrading in the early 2000s, and – at least in certain industries - now compete on par with firms from high-income countries (Ding, Sun, and Jiang 2015). This has intensified and renewed the political debates about the impact of Chinese imports.

Even more interestingly the European regions were affected by the financial crisis and the European debt crisis. The financial crisis had a profound impact on world trade. In 2009 the volume of world trade declined by around 12%. Declines in imports mirror the decline in demand of manufactured products, while production capacities remain in place. This situation likely increases the intensity of competition and may lead to an exit from marginal domestic firms.

However, our results do not indicate a strong impact of increased Chinese import competition on European manufacturing employment. In fact, the estimation results are disappointing, because they are quite imprecise. After careful analysis of the economic importance of the confidence interval we are able to conclude that the exposure to Chinese imports was not a primary driver of manufacturing employment across European regions.

However, an analysis of industry groupings did not reveal clear indications that the exposure to Chinese imports affected high and low technology sectors differently, even if the growth of Chinese exports was most pronounced in industries classified as high- and the medium-high. technology industries.

The paper is organized as follows: the next chapter embeds the research question in the relevant literature, section 3 presents the data and the econometric framework, section 4 the results. Section 5 provides a discussion of the results and finally section 6 summarizes and concludes the paper.

2 Background and related literature

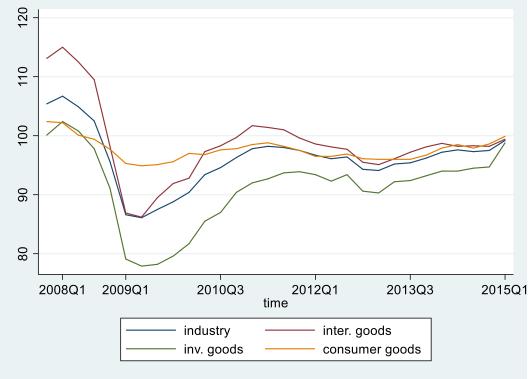
Economists traditionally argue for positive aggregate welfare effects of international trade. While acknowledging that the distributional effects can be uneven, the net gains could in principle be redistributed across countries. Under quite weak assumptions the trade gains would be more than sufficient to offset the losses of those experiencing negative effects from import competition. It is often argued that the positive effects on value added, employment generation and the increased availability of product variety should create incentives for countries to serve their own interest by allowing free trade regardless what other countries do (Feenstra 2015; Fujita et al. 1999). However, there are also models can generate more ambiguous results. For example, based on a simple Ricardian two-country model Samuelson (2004) shows that trade integration can under certain conditions also lead to a situation where world gains of trade are distributed unequally and associated with losses in welfare in one of the trading countries. However, the empirical evidence and the conventional wisdom among economists was for a long time that the negative effects of international trade on labour markets were small compared to gains from trade.

There literature linking trade and labour market outcomes focussed for a long time on the issue of wage inequality between high-skilled and low-skilled labour. This literature was motivated by the fact that the wage premium for skilled labour increased while also the employment of skilled labour increased. However, this prediction has largely been invalidated by the observation that wage polarisation rose not only in high-skill countries but also in low-skill countries. Harrison et al. (2011) provide an overview of this literature. The literature emphasizes also the importance of firm heterogeneity. Melitz (2003) showed that allowing for

heterogenous firms increased import competition should reallocate market shares from lower productivity firms to high productivity firms in international markets.

This is especially relevant for the time period under consideration 2009 – 2014. As Figure 1 shows the downturn associated with the financial crisis in 2009 and the European debt crisis in the aftermath depressed industrial production in the EU-28 countries. Due to this weakness the argument of Melitz (2003) would suggest the possibility of a replacement of marginal domestic firms by imports (from China). This should show up in a reduction of domestic manufacturing employment in the EU- 28 countries. The post-crisis period was a period of subdued manufacturing activity in Europe. Figure 1 also shows that the downturn was less pronounced in consumer goods industries than for the other industries, indicating that the sluggish development of manufacturing activity was related to the slump in private investment that was also a characteristic of the European debt crisis





In this respect it is important to note, that until Autor et al 2013, empirical studies did not find that import competition had substantial negative impacts on labour markets in advanced economies. The disappearance of manufacturing jobs and reduction of the manufacturing

share in aggregate output as well as the increasing wage polarization was primarily associated with technological change. Influences from international trade were considered to be small in comparison (e.g. Feenstra and Hanson 2003, Harrison et al. 2011). The empirical identification of the impact of import competition on labour market outcomes requires to map industryspecific shocks into labour market outcomes. At the macroeconomic level on only a few labour market outcomes are available at annual frequencies. This creates problems of linking labour market outcomes and margins through which labour markets adjust to trade shocks. A possible route for empirical research is to use disaggregated data, provided that frictions to labour market mobility at the firm, the industry or the regional level are large enough to identify the working of an increased import penetration. Bernard et al. (2006) and Bloom et al. (2016) look at industry adjustments. Using US plant data Bernard et al. (2006) found over the time period 1977-1997 plants more exposed to low-cost imports grew more slowly and were more likely to exit. Overall, they found that import competition accounted for approximately 14% of the decline in manufacturing employment. Another strategy is to look at regional labour markets as pioneered by Borjas and Ramey (1995) and taken up in the seminal work by Autor et al. (2013) is an appropriate way to identify the effects of import competition on labour markets, if the mobility of workers across regions is small. In fact, most of the literature on regional adjustments suggests that mobility between regions is quite slow and incomplete.

Since the publication of the paper of Autor et al. (2013) the literature that uses the responses of regional and local labour market outcomes to study the working of import competition from China grew substantially. Autor et al. (2013) investigated the impact of Chinese competition onto local labour markets in United-States during 1991 to 2007 and found that import competition from China led to higher unemployment, lower labour force participation in local labour markets that were more exposed to Chinese import competition. According to their results around 25% of the decline of US manufacturing employment can be attributed to import competition from China. Studies for Europe also exist. Dauth et al. (2014) look at the impact of Eastern Europe and China trade on local labour markets in Germany. They do not

.

¹ An alternative approach is to use the changes in trade policy to identify the trade shocks. This strategy is better suited to the study of developing countries (e.g. Goldberg and Pavcnik, 2007, Topalova, 2010, Kovak 2013). Among developing countries tariffs are quite low, even in trade with China. By the 1990s most advanced industrialised countries had given China privileged (status of most favoured nation) access to their markets, which implies very low average import tariffs. Thus changes in tariffs are not well suited to study the impact of trade shocks on labour market outcomes.

find evidence of strong employment effect of Chinese import competition either inside or outside manufacturing. These findings must be interpreted with the specific context of German-China trade which tends to be much more balanced than the trade of other EU countries with China. Malgouyres (2014) finds that the exposure to import competition from China had substantial impact on French local labour markets, affecting job counts both in the local manufacturing and the local non-manufacturing sectors. In this paper we use regional data for European countries at the NUTS-2 disaggregation level and map national exports to the regional level using a detailed industry breakdown. Then again, Kuegler et al. (2021) do not find significant effects for Austria's NUTS-3 regions.

3 Data

The data used in this research comes from a wide variety of data sources and uses an estimated dataset of detailed regional industry level employment data. This section provides an overview on the sources of the data and how it was processed. to construct indicators used in the regression analysis.

3.1 Import and export Data

The import-export data to construct the import competition indicators comes he harmonised BACI database (Gaulier and Zignago, 2010). This database reconciles trade data at the 6-digit level of the Harmonised System (HS) product classification release 2007. This is data is based on customs declarations that are often inconsistent for a number of reasons. For instance, imports are reported as CIF (cost, insurance and freight) while exports are declared as FOB (free on board), different product classifications might apply, or the final destination is uncertain. Finally, customs authorities have an incentive to be more parsimonious on import rather than on export declarations. The BACI data are purged by biases due to CIF and FOB and the reliability of reported bilateral import and export flows is also considered. ² BACI does not contain industry information. To match the trade data with the industry classification (Nace Rev. 2., 4-digit), we recode the HS 6-digit data to hs02, for which a Nace Rev. 1 correspondence table is available, which again can be transformed into Nace Rev. 2 data at the four-digit level. This allows to associate the import data to NACE 2 4-digit industries that are used to construct the import competition indicator.

² See Gaulier and Zignago 2010.

Before turning to the construction of the regional industry data, let us have a short look at Chinese imports into the EU-28 for the time 2009 and 2014. Table 1 shows that overall Chinese manufacturing imports grew in this period by 8.6%, a bit faster than total extra-EU imports (6.4%). Table 1 reports also shares of Chinese imports in total EU-28 extra-EU imports. The market share of Chinese imports was above 50% of all extra-EU imports in furniture, leather and related products, computers, electrical equipment. wearing apparel in 2014. The largest increases of Chinese imports were recorded in basic metals, motor vehicles, machinery and equipment, chemicals, rubber and plastic and electrical equipment.

Table 1: Imports from China by industry (NACE 2 2-digits), Import shares and growth of imports, 2009 - 2014

NACE code (2-digit)	Industry	Import sh extra-E imports, C chineses i 2009	U28 China of	Growth of imports from China 2009-2014	Growth of total extra- EU28 imports 2009-2014	
10	Food products	6.7	7.0	7.7	6.6	
11	Beverages	1.0	1.1	6.0	3.7	
12	3	14.4	9.9	-8.0	-0.8	
13	Textiles	42.9	47.1	9.0	7.0	
14	Wearing apparel	59.7	57.0	3.3	4.3	
15	Leather and related products	56.0	56.7	8.4	8.2	
16	Wood and products of wood and cork	30.5	36.1	5.2	1.7	
17	Paper and paper products	10.8	15.0	8.0	1.2	
18	Printing and reproduction of recorded media	28.5	32.1	1.6	-0.8	
19	Coke and refined petroleum products	1.0	0.4	-8.4	12.5	
20	Chemicals and chemical products	12.4	15.4	12.8	7.9	
21	Pharmaceutical products and preparations	16.4	17.5	8.7	7.3	
22	Rubber and plastic products	31.8	38.0	12.6	8.7	
23	Other non-metallic mineral products	46.5	46.4	5.6	5.6	
24	Baisc metals	5.6	11.6	17.8	1.7	
25	Fabricated metal products	44.5	46.7	9.0	7.9	
26	Computer, electronic and optical products	45.9	51.8	8.4	5.8	
27	Electronical equipment	45.4	51.5	12.5	9.6	
28	Machinery and equipment	27.8	34.1	13.3	8.7	
29	Motor vehicles, trailers and semi-trailers	4.9	7.6	16.1	6.2	
30	Other transport equipment	11.0	9.7	-0.9	1.6	
31	Furniture	55.7	61.0	5.3	3.4	
32	Other manufacturing	42.1	41.5	3.7	4.0	
С	total manufacturing	100.0	100.0	8.6	6.4	

3.2 Estimation of detailed industry level employment data

Detailed industry level employment data is not available at the NUTS 2 level: Eurostat's Structural Business Statistics are available either at the NUTS2-NACE 2-digit level or at the NUTS0-NACE 4-digits level. These data are not granular enough to allow a satisfactory analysis

of regional import competition. For this reason, we use an updated NACE 4-digit NUTS 2-digit industry structure matrix developed by Unterlass et al 2015, that combines Amadeus firmlevel data provided by Bureau van Dijk with Eurostat data ³ and uses the RAS technique to estimate NACE 4 employment at the NUTS 2 Level. The RAS technique is a method developed in the context of the input-output analysis (see Miller and Blair 2009). The RAS technique is an iterative procedure that adjusts the row and column sums in a way to reconcile the Amadeus information with the aggregates from the official statistics. To construct a disaggregated regional industry structure matrix, a number of issues had to be solved. Appendix A provides a more detailed discussion of these issues and the methodology.

3.3 Regional Data

The regional data uses the Nomenclature des unités territoriales statistiques level 2 (NUTS2) regions for the 28 European Union (EU28) countries. In the time period considered in the current study, three vintages of the NUTS2 classification (NUTS codes 2006, and 2010 and 2013) were in vigor. These differed especially in the coding of British, German, Greek, Polish, French and Italian regions.⁴ A second issue relates to missing observations. For this reason Cyprus, Croatia and the Finish region of Aland were not considered in the analysis. Details

Table 2 reports the data sources for the regional data used in the empirical analysis for dependent and control variables. The specific indicators concern the sectoral employment, total employment in the region, the regional unemployment rate population share by education attainment. Unfortunately, no indicators regarding the impact of automation of tasks could be found at the regional or the national level. Descriptive statistics are presented in the next section.

³ Amadeus contains comprehensive information on around 21 million companies for the EU-28 including company addresses (incl. postal codes, city, etc.), current employment and value added.

⁴ We used the correspondence table provides by EUROSTAT for the differed versions of this classification. According to these informations, many changes in Italy, France, Greece and the UK were name and code changes of the regions. These breaks were accommodated by recoding regions. In other cases, e.g. in Germany the switch from NUTS 2006 to NUTS 2010 affected the regions of Brandenburg-Nordost and Brandenburg-Südwest (DE41 and DE42) which were aggregated to one single region (Brandenburg). Here we collapsed these sub-regions to the 2010 NUTS2 revision.

Table 2: Regional Indicators taken from the EUROSTAT database

Indicator	Data Base Name	Description
Employment Unemployment	nama_10r_3empers Ifst_r_Ifu3pers	Employment by sector Unemployment by sex, age
Population by education	edat_lfse_04	Population aged 25-64 by educational attainment level and sex (in %)

3.4 Measurement of import competition

The main measure of local labour market exposure to import competition is the change in Chinese import exposure per worker in a region, as it was used by Autor et al. (2013). Imports are allocated to the region according to its share of national industry (NACE 2, 4-digit) employment:

$$\Delta(ImE)_{it}^{IMP} = \sum_{i} \frac{L_{ijt}}{L_{jt}} \times \frac{\Delta I_{jt}}{L_{it}},$$

where subscript i denotes the region, j the 4-digit industry and t time. ΔI_{jt} is the observed change of imports from China in industry j, L_{it} is the start of period employment in region i.. (L_{ijt}/L_{jt}) is the share of 4-digit industry employment in region i in national 4-digit industry employment at the start of the period.

The differences in $\Delta(\text{ImE})^{\text{IMP}}_{it}$ across regions stem from two sources of heterogeneity across regions namely (a) the different weight of manufacturing vs. non-manufacturing employment in a region and (b) to the regions specialization in industries that are subject to import competition. A third influence is the heterogenous development of imports across countries that is mediated towards the regional level through the specialization in industries subject to import competition.

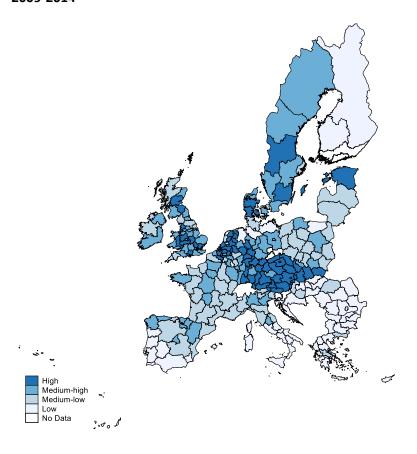
A measure of export exposure to China can be constructed in an analogous way by substituting Imports from China with Exports to China,

$$\Delta(\text{ExE})_{it}^{\text{EXP}} = \sum_{j} \frac{L_{ijt}}{L_{jt}} \times \frac{\Delta E_{jt}}{L_{it}},$$

where subscript i denotes the region, j the 4-digit industry and t time. ΔE_{jt} is the observed change of exports to China in industry j. The employment shares and the start of period employment are the same indicators as used before.

Let us first provide some descriptive statistics for the change of import competition at the regional level. Figure 2 presents the quantiles of the Chinese import exposure per worker in European NUTS 2 regions by quantiles. The highest impact of exports in 2009 to 2014 is experienced in the regions of the manufacturing core in Europe (South and Western Germany, Austria, Czech Republic, Hungary) and in the Benelux countries, UK, Denmark, Sweden and Estonia. A lower import exposure is experienced in Finish, French, Spanish, Italian and Greek regions, as well for Bulgaria, Romania and Poland. However, the correlation between the manufacturing share and the change of imports from china is low (correlation coefficient of 0.10), so that the changes in Chinese imports should not be considered to be simply a demand phenomenon.

Figure 2: Quantiles of changes of Chinese import exposure per worker in European NUTS 2 regions, 2009-2014



⁵ See also Friesenbichler et al. (2017).

-

4 Econometric methodology

4.1 Econometric framework

The basic estimation framework relies on the theoretical framework and the associated empirical approach proposed by Autor et al. (2013). The method was also implemented by Dauth et al. (2014) and Malgouyres (2014) in their analyses of the impact of import competition China on German and French regions. At the regional level the empirical strategy exploits the variation in initial industry specialization across regional labour markets - NUTS-2 level regional information – for the study of regional impacts. It is well known that regions differ in their regional specialisation (e.g. Unterlass et al. 2015), which is also reflected in a varying degree of exposure to import competition (Autor et al. 2013). We construct a measure of import exposure as well as a measure of export exposure (here following Dauth, Findeisen, and Suedekum 2014) by allocating the aggregate change in imports from China at the regional level via the regional employment share of industry in the countries total employment. In the basic regression equation the change in regional (manufacturing) employment, the dependent variable (ΔY_{it}), is linked to the indicators of import exposure ($\Delta (ImE)_{it}^{IMP}$) and a set of additional explanatory variables (X_{it}') that control for confounding factors, $\Delta (ImE)_{it}^{IMP}$

$$\Delta Y_i = \; \alpha \; \; + \beta_1 \Delta (ImE)_i^{IMP} + \beta_3 X'_i + e_i. \label{eq:deltaYi}$$

In some of the specifications we account for export exposure $(\Delta(ExE)_{it}^{EXP})$ in a similar way for exports to China, in order to capture the total effect of the exposure to trade with China:

$$\Delta Y_i = \ \alpha + \beta_1 \Delta (\text{ImE})_i^{\text{IMP}} + \beta_2 \Delta (\text{ExE})_i^{\text{EXP}} + X{'}_i \beta_3 + e_i. \label{eq:deltaYi}$$

This basic regression framework will also be used for the analysis of sector groupings to study the differences between low, medium-low, medium, medium-high and high technology manufacturing industries. Here we will adapt the import and export competition indices and changes in manufacturing employment at the industry grouping level. This allows us to provide with the opportunity to study in more detail the direct effects of import competition

⁶ In all empirical analyses we refer to foreign competition in the form of import penetration and do not consider sales by foreign subsidiaries located in the domestic market (e.g., approximated by FDI).

⁷ The index *i* refers to country region pairs.

at the level of industry groupings. The equation to be estimated then is when we account for both import and export exposure to China:

$$\Delta Y_{ij} = \, \alpha + \beta_1 \Delta (\text{ImE})^{\text{IMP}}_{ij} + \beta_2 \Delta (\text{ExE})^{\text{EXP}}_{ij} + \textbf{X'}_i \beta_3 + \textbf{e}_i,$$

where index *i* denotes the region, index *j* denotes industry grouping and *t* is time. The control variables are region-specific.

4.2 Identification of trade exposure

This basic framework requires an identification strategy as trade exposure (import competition from China and export competition to China) can be endogenous. The presence of unobserved supply and demand shocks could simultaneously affect the import and export exposures and regional economic and technological performance. We will address this issue by using an instrumental variable strategy that is close in spirit to the approaches used by Autor et al. (2013), followed also by Dauth et al. (2014) and Malgouyres (2014). We will construct import and export exposures for other non-EU industrialised countries. The idea behind using such instruments is that the rise of China (or other countries/regions) in the world economy induced supply shocks for all trading partners. Using information for other countries identifies the exogenous component of rising competitiveness of China (or other countries/regions) and purges shocks that are specific to the country, region, or industry. The instrument is:

$$\Delta (ImE)_{oit}^{IMP} = \sum_{i} \frac{L_{ijt}}{L_{jt}} \times \frac{\Delta I_{Ot}}{L_{it}}.$$

The only difference to the expression of import competition to the previous one is that instead of national imports from China (ΔI_{jt}), Chinese exports to the set of selected high-income countries (ΔI_{Ot}) is used. The identifying assumption underpinning the validity of this instrument is that Chinese exports to these countries are independent from domestic shocks and that the correlation between (domestic) imports from China and Chinese exports to these "other" countries is only driven changes in Chinese export competitiveness.

As emphasized by Dauth et al. (2014) the choice of the countries for the industry group is of crucial importance. Countries should be similar in order to have information on the size of the import shock. At the same time the countries in the identification group should not share the same shocks as the countries under consideration so that the exclusion restriction

appears credible. Therefore, countries highly integrated in trade with the EU should be excluded from the group of "identifying countries". This creates substantial problems, as this leaves us with the US, Canada, Australia, New Zealand, Israel and Japan as industrialized countries.

5 Results

The main interest of the paper is to analyse whether an increase of Chinese imports affects manufacturing employment in European regions. To provide a more detailed picture, we also provide results for sectoral taxonomies using Eurostat's high-tech classification of manufacturing industries based on the NACE Rev. 2 2-digit level. The variable of interest is the import exposure at the regional level (IPW China). We use the manufacturing share, the unemployment rate, the population share with tertiary education (ISCED 5-8), the population share with upper secondary education (ISCED 3-4) and the export exposure to China as control variables. All control variables are measured in 2009 in order to reduce possible impact of contemporaneous effects. Table 3 presents the descriptive statistics for the variables in the analysis.

Table 3: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Δ manufacturing share	257	-0.64	0.98	-4.34	5.88
Δ In manufacturing employment	257	-0.08	0.12	-0.69	0.35
regional unemployment rate	257	8.47	3.88	2.10	26.00
import exposure (ImE china)	257	0.62	1.02	-0.47	10.89
pop. with ISCED 5-8	257	24.38	8.23	8.30	48.60
pop. with ISCED 3-4	257	47.40	15.00	11.40	79.40
export exposure (ExE China)	257	0.35	0.58	-0.30	6.04
instrument	257	6.71	18.81	0.00	27.37

The descriptive statistics show considerable heterogeneity across regions. And show that on average the manufacturing share decreased by 0.64 % and that also manufacturing employment decreased across on average in the European regions. The import exposure as well as the export exposure increased in most of the regions. However, for a small number of regions both the export exposure and the import exposure decreased. There is also considerable variation in the share of population with upper secondary education (ISCED 3-4) and with tertiary education (ISCED 5-8) across the European regions.

The regression results for the change in the employment share of manufacturing are depicted in Table 4, while Table 5 reports the regression results for the change in the log of manufacturing employment. The variable of primary interest is the import exposure (ImE China). For the change in manufacturing share we do not see a result that is statistically different from 0. In fact, the OLS estimates are in addition very imprecise, as the low t-values show. We present 6 specifications: column (1) presents the OLS estimates using only the import exposure (ImE China) as depend variable, column (2) presents the OLS estimated that include all control variables except the export exposure to China and (3) the OLS estimates using the full set of control variables. Columns (4) to (6) present the corresponding IV estimates using the import exposure to China calculated using Chinese imports in other non-EU industrialised countries as presented before as instrument. The use of the instrument improves the precision of the estimates for the change of the employment share of manufacturing reported in Table 4. However, for the change in log manufacturing employment the effect is the opposite, the estimates become less precise.

For the manufacturing share we observe that the positive coefficient that is not statistically significant different from 0, turns negative once the control variables are take into account for both the OLS and IV estimates. However, the control variables themselves are also not statistically significant across the specification with the exception of the population share with upper secondary education (ISCED 3-4). This shows that the manufacturing share increased especially in regions with a larger share of population with upper secondary education. This result suggests that the rise of Chines import exposure between 2009 and 2014 did not lead to significant change in the employment share of manufacturing across European regions.

Table 4 Estimation results change of the employment share of manufacturing

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	IV	IV	IV
VARIABLES		cł	nange in manu	facturing sha	ire	
import exposure (ImE china)	0.0347	-0.0046	-0.0128	0.0318	-1.1176	-0.7044
	(0.58)	(-0.06)	(-0.17)	(0.32)	(-0.90)	(-0.87)
manufacturing share 2009		-0.0198	-0.0236*		0.0063	-0.0106
		(-1.93)	(-2.18)		(0.20)	(-0.54)
reg. Unemployment 2009		0.0088	0.0103		-0.0457	-0.0221
		(0.54)	(0.63)		(-0.71)	(-0.52)
pop. with ISCED 5-8		-0.0091	-0.0115		0.0105	-0.0014
		(-1.17)	(-1.43)		(0.43)	(-0.09)
pop. with ISCED 3-4		0.0269**	0.0265**		0.0271**	0.0264**

		(5.85)	(5.76)		(4.32)	(4.96)
export exposure (ExE China)			0.1513			0.2734
			(1.10)			(1.28)
Constant	-0.6603**	-1.4968**	-1.4262**	-0.6585**	-1.2362*	-1.2086*
	(-9.27)	(-3.72)	(-3.50)	(-7.55)	(-1.99)	(-2.26)
Observations	259	257	257	259	257	257
R-squared	0.001	0.147	0.151		_3,	_3,

Notes: t-statistics in parentheses; ** p<0.01, * p<0.05; instrument: import exposure to China calculated using Chinese imports in other non-EU industrialised countries

The change of the manufacturing share may also be affected by the structural change towards services. Therefore Table 5 also presents the results for the change in log employment as robustness check. Here the results without control variables (specifications (1) and (4)) suggest a positive impact of Chinese imports on manufacturing employment, which is statistically significant also for the OLS specification (column (1)). Once the control variables are taken into account the magnitude of the positive effect is reduced for the OLS estimates and it becomes statistically insignificant. In the IV specifications the sign turns even negative. The control variables show that manufacturing employment was increasing in regions with a larger manufacturing share and in regions with a larger share of both upper secondary (ISCED 3- 4) and tertiary education (ISCED 5-8). In the OLS estimates we also see that regions with a higher unemployment rate experienced in addition decreases in manufacturing employment and the export exposure to China had a positive impact for manufacturing employment. These two control variables do not turn out to be significant in the IV specifications.

Table 5 estimation results change of log manufacturing employment

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	IV	IV	IV
VARIABLES		change	e in In manufa	cturing emplo	yment	
import exposure (ImE china)	0.0277**	0.0092	0.0077	0.0190	-0.0448	-0.0020
	(3.76)	(1.28)	(1.08)	(1.52)	(-0.47)	(-0.03)
manufacturing share 2009		0.0044**	0.0037**		0.0056*	0.0039*
		(4.48)	(3.63)		(2.27)	(2.41)
reg. Unemployment 2009		-0.0056**	-0.0053**		-0.0082	-0.0058
		(-3.62)	(-3.46)		(-1.66)	(-1.68)
pop. with ISCED 5-8		0.0034**	0.0030**		0.0044*	0.0032*
		(4.72)	(4.01)		(2.36)	(2.59)
pop. with ISCED 3-4		0.0040**	0.0040**		0.0040**	0.0040**
		(9.28)	(9.17)		(8.40)	(9.12)
export exposure (ExE China)			0.0265*			0.0283
			(2.04)			(1.62)
Constant	-0.0992**	-0.3783**	-0.3659**	-0.0939**	-0.3657**	-0.3628**
	(-11.26)	(-9.93)	(-9.54)	(-8.68)	(-7.66)	(-8.30)

Observations	257	257	257	257	257	257
R-squared	0.052	0.503	0.511			

Notes: t-statistics in parentheses; ** p<0.01, * p<0.05; instrument: import exposure to China calculated using Chinese imports in other non-EU industrialised countries

To provide a better understanding of the regression results Table 6 reports the implied changes in the dependent variable using the results of specifications (3) OLS and (6) IV from Table 4 and Table 5. This table reports the estimated contribution of import competition to the dependent variable and allows to assess the precision of the estimated. To do so we report also the results for the 95%-confidence interval using the upper and the lower endpoints. This provides an assessment of the economic importance of the import exposure to China, even for a unprecise estimate. For the OLS estimates of the change in the manufacturing share the values are -0.10 (lower endpoint), -0.01 (point estimate) and 0.08 (upper endpoint). The OLS estimates suggest a low impact of import exposure to the decline of the manufacturing share, as less than 1/6 of the observed changed can be related to the contribution of import competition even for the lower endpoint (-0.73% of the level of the manufacturing share in 2009). However, the IV estimates are much less precise. The contribution is in the interval [-1.42 pp, 0.55 pp] and the implied contribution the lower endpoint is larger than the average change of the manufacturing share and corresponds to a 10.3% reduction of the manufacturing share. The imprecision can also be seen in the calculations where an increase of the exposure by one standard deviation is used to gauge the impact of a further increase of import competition. The result for the IV results of the manufacturing share show clearly how imprecise the estimates are: the 95% percent confidence interval includes values from -3.77 percentage points (lower endpoint) to 1.46 percentage points (upper endpoint).

Table 6: Implied changes in the dependent variable

			implied change in dependent variable 95% confidence interval mean (depvar) mean + sd (depvar)						sd	mean	
		lower endpoint of the 95% confidence	point	upper endpoint of the 95% confidence	lower	point	upper	mean dependent Variable (change)	dependent Variable (change)	dependent Variable (level)	
dep. Var	specification	interval	estimate	interval	endpoint	estimate	endpoint				
Δ manufacturing share	(3) OLS	-0.10	-0.01	0.08	-0.27	-0.02	0.22	-0.64	0.98	13.79	
∆ manufacturing share	(6) IV	-1.42	-0.43	0.55	-3.77	-1.15	1.46	-0.64	0.98	13.79	
Δ In man. employment	(3) OLS	0.00	0.00	0.01	-0.01	0.01	0.04	-0.08	0.12	4.31	
Δ In man. employment	(6) IV	-0.08	0.00	0.08	-0.22	0.00	0.21	-0.08	0.12	4.31	

However, the implied changes in In manufacturing employment suggest that the impact of the import exposure to China is likely modest in the time period 2009 to 2014. Again, the precision of the estimates is lower for the IV estimates. However, the range is [-0.08 and

0.08] log points with a mean of 0. The OLS estimates are much more precise. From this look at the results the impression emerges that the import exposure to China was not a driving force shaping the development of manufacturing employment in European regions.

To provide a bit more flesh to these results, we investigate the impact of the exposure to Chinese exports at the level of industry groupings. As Chinese exports became more sophisticated during the past decades as China emerged also as a technological powerhouse, one would expect that the results differ across technological intensity of industries. We use the high-technology classification of Eurostat to differentiate between high-tech, medium-high-tech, medium-low-tech and low-technology intensive industry groupings.

Table 7 presents the descriptive statistics for the variables at the sector groupings level used in the analysis. The descriptive statistics show that while for changes in In employment of the sector groupings there is not much difference in the means across the groupings the reduction of the employment shares are more pronounced for the lower technology sectors than for the higher technology sectors. The import exposure increased on average highest for the medium-high-tech sectors and the high technology sectors, for both the EU regions and the instrument that uses imports from other industrialised countries.

Table 7: Descriptive statistics, sector grouping

	tech.					
Variable	Sector	Obs	Mean	Std. Dev.	Min	Max
Δ In employment	high	257	-0.06	0.38	-1.80	1.73
	med-high	257	-0.04	0.23	-2.31	0.70
	med-low	257	-0.06	0.20	-0.67	1.16
	low	257	-0.08	0.21	-2.00	0.77
Δ employment share	high	257	-0.03	0.29	-2.17	1.45
	med-high	257	-0.05	0.66	-4.41	2.66
	med-low	257	-0.15	0.62	-2.91	3.04
	low	257	-0.25	0.65	-4.74	1.90
import exposure (ImE china)	high	257	0.15	0.36	-0.42	3.67
	med-high	257	0.28	0.80	-0.33	10.57
	med-low	257	0.09	0.10	-0.08	0.88
	low	257	0.10	0.14	-0.19	1.25
export exposure (ExE China)	high	257	0.04	0.09	-0.02	1.14
	med-high	257	0.25	0.54	-0.35	5.94
	med-low	257	0.03	0.09	-0.08	1.07
	low	257	0.03	0.05	-0.03	0.38

instrument	high	263	1.52	2.80	0.00	23.02
	med-high	263	3.47	17.10	0.00	27.18
	med-low	263	0.78	1.53	0.00	14.73
	low	263	0.93	1.68	0.00	15.03

Table 8 and Table 9 present the estimation results for the change of the employment share and the change in In employment. We report only the specifications with the full set of controls. For the variable of interest, the exposure to Chinese imports, we do not record statistically significant coefficients for the IV estimates. For the OLS estimates there is one statistically significant results for manufacturing share of low technology grouping (specification 7), however the IV result for the same specification is insignificant and changes sign.

Table 8: Estimation results change of the employment share, sector groupings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
technology	hi	gh	mediu	m-high	mediu	m-low	lov	v
VARIABLES			char	nge in em _l	oloyment sh	nare		
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
import exposure (ImE						-		-
china)	-0.0185	-0.6105	-0.1107	-1.0440	-0.4988	13.4960	0.6027*	3.9021
	(-0.36)	(-1.65)	(-1.31)	(-1.74)	(-1.26)	(-0.33)	(2.13)	(-0.96)
				0.0273				
manuf_share	-0.0067*	-0.0075	0.0164*	*	-0.0063	0.0363	-0.0068	0.0080
	(-2.13)	(-1.91)	(2.21)	(2.40)	(-0.95)	(0.27)	(-1.01)	(0.49)
								-
unemp	-0.0014	-0.0077	0.0142	-0.0089	0.0105	-0.0337	0.0180	0.0126
	(-0.28)	(-1.07)	(1.25)	(-0.44)	(1.06)	(-0.24)	(1.73)	(-0.40)
pop. with ISCED 5-8	-0.0048	-0.0034	-0.0056	-0.0026	0.0080	0.0398	-0.0027	0.0146
	(-1.94)	(-1.06)	(-1.04)	(-0.38)	(1.64)	(0.40)	(-0.54)	(0.86)
pop. with ISCED 3-4	-0.0007	0.0008	0.0082*	0.0064	0.0201**	0.0074	0.0042	0.0062
	(-0.47)	(0.42)	(2.54)	(1.57)	(7.01)	(0.18)	(1.41)	(1.35)
export exposure (ExE	1.0416*	1.6470*					-	-
China)	*	*	-0.0627	-0.0301	0.4040	8.6014	5.3430**	2.4235
	(4.88)	(3.61)	(-0.60)	(-0.23)	(0.57)	(0.34)	(-6.27)	(-0.84)
			-		-			-
Constant	0.1873	0.2111	0.6073*	-0.3313	1.2629**	-0.7077	-0.3507	0.4635
	(1.51)	(1.37)	(-2.14)	(-0.85)	(-5.03)	(-0.39)	(-1.35)	(-1.22)
Observations	257	257	257	257	257	257	257	257
R-squared	0.096		0.102		0.192		0.165	

Notes: t-statistics in parentheses; ** p<0.01, * p<0.05; instrument: import exposure to China calculated using Chinese imports in other non-EU industrialised countries

Table 9: Estimation results change of In employment, sector groupings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
technology	hi	gh	mediur	n-high	mediun	n-low	lo	w
VARIABLES			(change in	ln employm	ent		
-	OLS	IV	OLS	IV	OLS	IV	OLS	IV
import exposure (ImE	-	-						
china)	0.0523	0.4632	-0.0068	-0.3926	0.0593	2.2339	0.1300	0.2608
	(-0.78)	(-1.10)	(-0.24)	(-1.79) 0.0104	(0.49)	(0.28) -	(1.32)	(0.26)
manuf_share	0.0011	0.0006	0.0059*	*	0.0009	0.0063	0.0022	0.0018
	(0.27)	(0.13)	(2.36)	(2.51)	(0.42)	(-0.24)	(0.94)	(0.44)
	-	-						
unemp	0.0078	0.0122	0.0052	-0.0043	0.0002	0.0076	0.0032	0.0041
	(-1.21)	(-1.49)	(1.36)	(-0.59)	(0.08)	(0.27)	(0.89)	(0.54)
	-					-		
pop. with ISCED 5-8	0.0007	0.0003	0.0017	0.0030	0.0052**	0.0001	0.0007	0.0002
	(-0.23)	(0.07)	(0.92)	(1.18)	(3.49)	(-0.01)	(0.40)	(0.05)
				0.0030				
pop. with ISCED 3-4	0.0009	0.0020	0.0037**	*	0.0071**	0.0092	0.0021*	0.0020
	(0.50)	(0.87)	(3.38)	(1.99)	(8.08)	(1.15)	(1.98)	(1.77)
export exposure (ExE						-		
China)	0.3991	0.8193	-0.0072	0.0063	0.0241	1.3475	-0.2119	-0.2966
	(1.42)	(1.58)	(-0.20)	(0.13)	(0.11)	(-0.26)	(-0.71)	(-0.42)
Constant	0.0395	0.0230	- 0.3809**	-0.2668	- 0.5456**	- 0.6385	- 0.2651**	- 0.2619**
	(-0.24)	(-0.13)	(-3.96)	(-1.89)	(-7.11)	(-1.75)	(-2.93)	(-2.78)
	, ,	. ,	, ,	. ,	, ,	. ,	, ,	• •
Observations	257	257	257	257	257	257	257	257
R-squared	0.023		0.102		0.277		0.041	

Notes: t-statistics in parentheses; ** p<0.01, * p<0.05; instrument: import exposure to China calculated using Chinese imports in other non-EU industrialised countries

The IV estimates are less precise than the OLS estimates. The estimation results do not indicate that the high or medium-high technology sectors are affected more by the import exposure to Chinese exports, as the patterns of changes in export exposure would suggest. Table 10 displays the implied changes in the dependent variable for the regressions in Table 8 and Table 9 and shows in a clearer way that the precision of the IV estimates is very poor compared to the OLS estimates, especially for the change in employment shares. The low precision of the IV estimates, also in comparison to the results for the manufacturing sector as a whole presented before, prevents any the interpretation of the results. It is not possible to assess based on the values of the confidence interval, that the import exposure is not a driving force in the changes of manufacturing employment across the industry groupings. It is also not possible to assess the differential impact of increased exposure to Chinese exports at the level of sector groupings based on the regression results presented here. No indication emerges that high-technology or low-technology sectors are affected differently

by the exposure to Chinese imports, even if the rise in import exposure was larger for the medium-high and high tech sectors than for the medium-low and low-tech industries.

Table 10: Implied changes in the dependent variable: sector groupings

implied change in dependent variable 95% confidence interval											
			mean (depvar)			mean + sd (depvar)			mean	sd	mean
			lower endpoint of the 95% confidence	point	upper endpoint of the 95% confidence	lower	point	upper	dependent Variable (change)	dependent Variable (change)	dependent Variable (level)
dep. Var	technology	specification	interval	estimate	interval	endpoint	estimate	endpoint			
∆ emp. share	high	(1) OLS	-0.02	0.00	0.01	-0.06	-0.01	0.04	-0.03	0.29	0.63
∆ emp. share	medium-high	(3) OLS	-0.08	-0.03	0.02	-0.30	-0.12	0.06	-0.05	0.66	3.76
Δ emp. share	medium-low	(5) OLS	-0.12	-0.05	0.03	-0.25	-0.10	0.05	-0.15	0.62	3.88
Δ emp. share	low	(7) OLS	0.00	0.06	0.11	0.01	0.14	0.27	-0.25	0.65	4.55
∆ In employment	high	(1) OLS	-0.03	-0.01	0.01	-0.09	-0.03	0.04	-0.06	0.38	1.04
∆ In employment	medium-high	(3) OLS	-0.02	0.00	0.01	-0.07	-0.01	0.05	-0.04	0.23	2.92
Δ In employment	medium-low	(5) OLS	-0.02	0.01	0.03	-0.03	0.01	0.06	-0.06	0.20	3.08
Δ In employment	low	(7) OLS	-0.01	0.01	0.03	-0.02	0.03	0.08	-0.08	0.21	3.25
∆ emp. share	high	(2) IV	-0.20	-0.09	0.02	-0.68	-0.31	0.06	-0.03	0.29	0.63
Δ emp. share	medium-high	(4) IV	-0.63	-0.30	0.04	-2.41	-1.13	0.15	-0.05	0.66	3.76
Δ emp. share	medium-low	(6) IV	-8.40	-1.22	5.96	-17.84	-2.59	12.66	-0.15	0.62	3.88
Δ emp. share	low	(8) IV	-1.14	-0.37	0.39	-2.81	-0.92	0.97	-0.25	0.65	4.55
Δ In employment	high	(2) IV	-0.19	-0.07	0.05	-0.65	-0.23	0.18	-0.06	0.38	1.04
Δ In employment	medium-high	(4) IV	-0.23	-0.11	0.01	-0.89	-0.42	0.04	-0.04	0.23	2.92
Δ In employment	medium-low	(6) IV	-1.24	0.20	1.64	-2.63	0.43	3.49	-0.06	0.20	3.08
Δ In employment	low	(8) IV	-0.16	0.03	0.21	-0.40	0.06	0.53	-0.08	0.21	3.25

6 Discussion of the results

The results presented in this paper suggest, even if many of the estimation results are imprecise, that Chinese import competition was not a driving factor of the decrease of manufacturing employment in the time in the aftermath of the financial crisis and during the European debt crisis. This result is interesting from a public policy perspective, therefore a careful discussion of limitations of the results is in order. Beside data limitations two different explanations con be put forward to explain our results: (a) the time period is to short to indicate strong structural shifts in manufacturing employment and (b) that the time period does not cover an import shock of large magnitude.

The time period is short. This has advantages and disadvantages. First the results indicate that the downturn in Europe did not lead to a replacement of European manufacturing firms and manufacturing employment by Chinese imports into the European Union. While it can be argued that the time horizon is too short to capture the working of the structural changes set into motion by import competition, the nature of a crisis period should accelerate such changes, if Chinese imports are a driving force behind it.

The level of disaggregation is high, the main results refer to regional manufacturing employment. Results using sectoral taxonomies did not lead to meaningful results, as the estimates were not precise enough. This does preclude a more precise message on what industries were affected more strongly by the Chinese import exposure in the time period

2009 to 2014. This is not to say, that certain industries or firms may not be affected more strongly than other industries or firms. However, if Chinese import exposure would by a primary driving force of manufacturing employment in Europe, we would expect to find more significant negative impacts both at the level of manufacturing employment and at the level of industry grouping employment. This is not the case: The absence of clear negative effects is partly due to the heterogeneity of regions, industries and firms that makes the estimates imprecise but not only. If Chinese imports were a driving force shaping the fate of European manufacturing employment, we would expect that this manifests itself at aggregate level. More detailed studies of competition in specific industries at the firm level are needed to assess the effects of Chinese import exposure on the productivity, competition, and employment in these sectors.

Thus, our results suggest that, while the import competition from China in the 1990s and 2000s associated with the rise of China as a manufacturing powerhouse can be considered as an import shock, the growth of Chinese exports from the 2000s onwards is a much more gradual process. Moreover, the rise of import exposure is highest in the industrial core of Europe covering Germany, Austria the Czech Republic, Slovakia, Belgium, the Netherlands and the Scandinavian countries. This suggests that part of the rise of Chinese exports may be related to demand effects, not to supply shocks. These demand effects need not to lead to a process of substitution of production by imports, but compensation mechanisms could work in a way that losses in employment are compensated by gains in employment. These compensation mechanisms are those mechanisms which are generally emphasized by trade economists when they talk about gains from trade, because international trade allows countries to improve their allocation of given factor-endowments by specialization on the basis of comparative costs.

From an empirical perspective a first drawback of the present analysis is that it was not possible to go include data before 2008 in the analysis due to changes in the economic classification of activities (NACE). A comparison to other five-year time period before the financial crisis would have allowed a comparison of results and allowed to present a clearer picture of the working of import exposure on European manufacturing employment. The time period from 1990s to the 2000s were the time of the rise of China as a manufacturing powerhouse.

A second drawback of the analysis is that we cannot control for the heterogeneous impact of ICT and automation on manufacturing employment. No regional indicators are available that would allow to pin own the heterogeneity of automation and ICT on manufacturing. This would have allowed to pin assess the importance of import exposure to China compared to the employment effects of automation, robotization and ICT in manufacturing. Very likely this would have helped to make the estimates more precise. It is very likely that the driving force shaping European manufacturing employment is less related to Chinese imports but more to the heterogeneity of adoption of technology across sectors and regions.

7 Summary and Conclusions

This paper has used detailed import exposure data to study the impact of changes of the Chinese imports on European manufacturing employment in European regions in the aftermath of the financial crisis. The central hypothesis behind the selection of the time period 2009 to 2014 was that times of crisis would lead to speed up of competitive selection processes. The weakness of Europe in the aftermath of the financial crisis and during the European debt crisis should amplify the working of economic selection by pushing marginal firms out of the market. The empirical results are disappointing. Not because the results are statistically insignificant but also because the precision of the estimates is quite low, especially for the more disaggregated analysis using sector groupings. The low precision of the results is most likely related to the heterogeneity of the impact across regions and industries. However, a careful assessment of the precision and economic size of the statistically insignificant results at the level of the manufacturing sector reveals that the range of results (95% confidence interval) allows to conclude that Chinese import exposure was not a primary driver of regional manufacturing employment in this time period.

Further research is clearly needed to answer the question posed in this paper. A longer time horizon is needed to confirm that the results reported in this paper are not due to the short time period considered in this analysis. The impact of import competition on manufacturing employment may be associated with a longer time lag. Moreover, a more precise identification of industries/regions that gain or lose from Chinese import competition is needed to assess the overall welfare effects and impact on European manufacturing in more detail.

References

- Autor, David H., David Dorn, and Gordon H. Hanson. 2013. 'The China Syndrome: Local Labor Market Effects of Import Competition in the United States'. The American Economic Review 103 (6): 2121–2168.
- Bernard, Andrew B., J. Bradford Jensen, and Peter K. Schott. 2006. "Survival of the Best Fit: Exposure to Low-Wage Countries and the (Uneven) Growth of US Manufacturing Plants." Journal of International Economics 68(1):219–37.
- Bloom, Nicholas, Mirko Draca, and John Van Reenen. 2016. 'Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity'. The Review of Economic Studies 83 (1): 87–117.
- Borjas, George and Valerie Ramey (1995) Foreign competition, market power, and wage inequality. The Quarterly Journal of Economics, 110(4), 1075-1110
- Dauth, Wolfgang, Sebastian Findeisen, and Jens Suedekum. 2014. 'The Rise of the East and the Far East: German Labor Markets and Trade Integration'. Journal of the European Economic Association 12 (6): 1643–75.
- Ding, Sai, Puyang Sun, and Wei Jiang. 2015. 'The Effect of Import Competition on Firm Productivity and Innovation: Does the Distance to Technology Frontier Matter?' Oxford Bulletin of Economics and Statistics. Feenstra 2015;
- Feenstra, Rorbert .C. and Gordon H. Hanson (2003) Global Production Sharing and Rising Inequality: A Survey of Trade and Wages. In: Choi, K. and Harrigan, J., Eds., Handbook of International Trade, Basil Blackwell, London.
- Feenstra, Robert C. 2015. Advanced International Trade: Theory and Evidence. Princeton university press
- Friesenbichler, Klaus, Glocker, C., Hölzl, W., Kaniovski, S., Kügler, A., Reinstaller, A., Streicher, G., Stehrer, R., Stöllinger, R., Leitner, S., Hanzl-Weiss, D., Reiter, O., Adarov, A., Bykova, A., Siedschlag, I., Di Ubaldo, M. and Studnicka, Z., "Drivers and Obstacles to Competitiveness in the EU: The Role of Value Chains and the Single Market", Background documents for the European Semester, European Union, 2017, https://ec.europa.eu/docsroom/documents/28183/attachments/1/translations/en/rendition s/native.
- Fujita, Masahisa, Paul R Krugman, Anthony J Venables, and Massahisa Fujita. 1999. The Spatial Economy: Cities, Regions and International Trade. Vol. 213. Wiley Online Library.
- Gaulier, Guillaume, and Soledad Zignago. 2010. 'Baci: International Trade Database at the Product-Level (the 1994-2007 Version)'. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1994500.
- Goldberg, P. K. and Pavcnik, N. (2007). 'Distributional effects of globalization in developing countries'. Journal of Economic Literature, 45 (1), 39–82.
- Harrison, Ann., McLaren, J. and McMillan, M. (2011). Recent Perspectives on Trade and Inequality. Annual Review of Economics, 3 (1), 261–289.
- Kovak, Brian K. 2013. 'Regional Effects of Trade Reform: What Is the Correct Measure of Liberalization' American Economic Review 103(5):1960–76.
- Kuegler, Agnes, Friesenbichler, K. and Hirsch, C. (2021), Labour Market Effects of Trade in a Small Open Economy, WIFO Working Papers No 624, WIFO, Vienna.
- Malgouyres, Clement (2014). 'Chinese imports competition's impact on employment and the wage distribution: evidence from French local labor markets', Working Paper, EUI ECO, 2014/12.
- Melitz, Marc J. 2003. 'The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity'. Econometrica 71 (6): 1695–1725.
- Miller, Ronald E. and Peter D. Blair (2009) Input-Output Analysis: Foundations and Extensions, Cambridge University Press.
- Samuelson, Paul A. 2004. 'Where Ricardo and Mill Rebut and Confirm Arguments of Mainstream Economists Supporting Globalization'. The Journal of Economic Perspectives 18 (3): 135–146.

Topalova, Petia, 2010. 'Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India.' American Economic Journal: Applied Economics, 2 (4): 1-41.

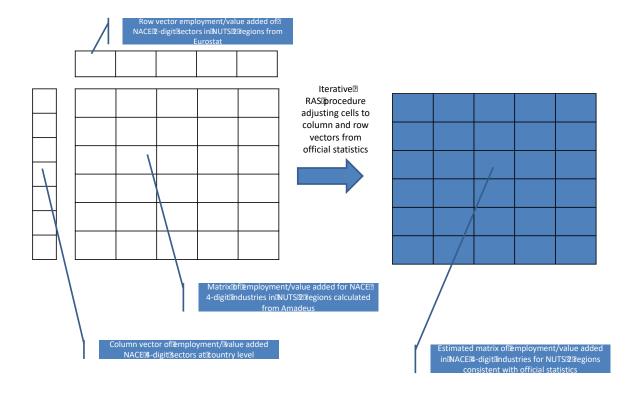
Unterlass, Fabian, Andreas Reinstaller, Johanna Vogel, and Klaus Friesenbichler. 2015. The Relationship between Export and Technological Specialisation Profiles across EU Member States and Regions and the Identification of Development Potentials. Final Report Carried out for the European Commission, Directorate-General Internal Market, Industry, Entrepreneurship within the Framework Service Contract No. ENTR/2009/033. Vienna: Austrian Institute of Economic Research (WIFO).

Appendix:

A. An overview on the construction of the detailed regional industry employment data

Fehler! Verweisquelle konnte nicht gefunden werden. provides an overview on how we used the RAS method to construct detailed regional industry employment data. RAS calculates row (the sum of a NACE 4-digits sector over regions within a country) and column sums (i.e. the sum of NACE 4-digits sectors within a NACE 2-digits sector in a NUTS2 region) of a matrix and compares them with the correct counterparts taken from official statistics (i.e. SBS statistics). Using an iterative procedure adjusting the row and column sums to the official statistics the procedure allows calculating a refined matrix were the values within the matrix are consistent with the official statistics. Finally, employment and value-added shares a NACE 4digits industry of a region can be calculated within a country.

Figure 3: Schematic representation of the RAS procedure



To apply the RAS technique using Amadeus and Eurostat data required to set up the Amadeus data in the following four steps:

Step 1: Assigning Amadeus firm level data to NUTS2 regions.

The result of this step is a concordance list of Bureau van Dijk (BvD) Identification numbers from Amadeus and NUTS2 regions. To assign Amadeus firms to NUTS2 regions we first used concordance lists from Eurostat containing postcodes and corresponding NUTS2 Codes. These lists were available only for 16 EU countries (AT, BE, BG, CZ, EE, DE, DK, HR, HU, IT, LT, LV, MT, PT, RO, SK), whereas some of them were irrelevant as for some countries the NUTS0 level (country) equals the NUTS2 level. In other words, Estonia (EE), Lithuania (LT), Latvia (LV) and Malta (MT), but also Cyprus (CY) and Luxembourg (LU) only have one NUTS2-level (i.e. EE00). The postal codes NUTS concordance for UK was taken from the ONS.

For the remaining EU28 countries (i.e. EL, ES, FI, FR, IE, NL, PL, SE and SI) we generated a concordance list. We geocoded the postal codes and cities taken from Amadeus (i.e. assigned coordinates to each of the postal codes and cities) using the open source software program QGIS. To identify and correct wrongly assigned NUTS2 regions to postal codes or cities, we geocode different combinations of country code, postal code and city and compared the results. Furthermore, we use the Clear and Simply database available online. This database also includes geocoded postal codes and cities. However, the database is not fully reliable but is an additional source for crosschecking our address-NUTS2 assignments.

The resulting list was then completed manually using extractions from Eurostat's webportal WebILSE, if the geocoding delivered contradicting results. Furthermore, typing errors in the Amadeus data (e.g. wrong postcodes or cities) had to be adapted. Our final list of regions followed the 2010 NUTS revision.

Step 2: Impute missing values in Amadeus

The starting point for imputing missing values in Amadeus is Eurostat's Structural Business Statistics database on the country-NACE 4-digits level. Missing values in the official dataset are filled up via inter- and extrapolations. We have restricted the sample manufacturing (NACE (Rev. 2) C). Employment and value added are then imputed in the Amadeus firm level data via inter- or extrapolation. If no data were available, we used sector averages to impute them.

Step 3: Calculating regional aggregates for NACE 4-digit industries in NUTS2 regions

Based on the steps described above we calculate sectoral aggregates for NUTS2 regions using the imputed Amadeus firm level databases. The aggregates are calculated by summing up employment and value added within NACE 4-digits industries in NUTS2 regions. However, it needs to be taken into account that these aggregates were not representative as neither all companies are covered, nor the covered companies represent a representative sample.

Step 4: Adjusting regional aggregates to official statistics

Using RAS techniques outlined above, in the final step we compared our regional NACE 4-digits aggregates with official SBS data. We finally calculated employment shares each NACE 4-digit industry in a region has within a country.

Despite all the cautions taken, inconsistencies occurred as firms were assigned to a NACE 4-digits industry in Amadeus but according to the official statistics there should not be a firm. The same holds for the other way round, if the official statistics claim that firms are active within an industry in a country, but we do not have any firms in Amadeus assigned to the industry. In these cases, the RAS approach does not converge and therefore our regional aggregates for industries do not fit always the official statistics. However, typically only a very small share of NUTS2-NACE 4-digit cells does not converge. For these cases, we crosschecked our data and to manually corrected the data, for instance by dropping firms included in the Amadeus database.