

Köllner, Sebastian

Working Paper

Import penetration and manufacturing employment growth: Evidence from 12 OECD countries

Discussion Paper Series, No. 135

Provided in Cooperation with:

Chair of Economic Order and Social Policy, Julius Maximilian University of Würzburg

Suggested Citation: Köllner, Sebastian (2016) : Import penetration and manufacturing employment growth: Evidence from 12 OECD countries, Discussion Paper Series, No. 135, Julius Maximilian University of Würzburg, Chair of Economic Order and Social Policy, Würzburg

This Version is available at:

<https://hdl.handle.net/10419/148349>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Diskussionsbeitrag Nr. 135

Import penetration and manufacturing employment growth: Evidence from 12 OECD countries

Sebastian Köllner

November 2016

Import penetration and manufacturing employment growth: Evidence from 12 OECD countries

Sebastian Köllner

Diskussionsbeitrag Nr. 135

November 2016

Julius-Maximilians-Universität Würzburg
Lehrstuhl für Volkswirtschaftslehre,
insbes. Wirtschaftsordnung und Sozialpolitik

Sanderring 2

D-97070 Würzburg

Tel.: 0931 – 31 86568

Fax: 0931 – 82744

E-Mail:

sebastian.koellner@uni-wuerzburg.de

Import penetration and manufacturing employment growth: Evidence from 12 OECD countries

Sebastian Köllner*

** University of Würzburg, Department of Economics, Sanderring 2, 97070 Würzburg.*

E-Mail: sebastian.koellner@uni-wuerzburg.de.

November 2016

Abstract

This paper investigates the relationship between growing import penetration and manufacturing employment growth in 12 OECD countries between 1995 and 2011, accounting for various model specifications, different measures of import penetration and alternate estimation strategies. The application of the latest version of the World Input-Output Database (WIOD) that has become available only recently allows to measure the effect of increasing imported intermediates according to their country of origin. The findings emphasize a weak positive overall impact of growing trade on manufacturing employment. However, intermediate inputs from China and the new EU members are substitutes to manufacturing employment in highly developed countries while imports from the EU-27 act as complements to domestic manufacturing production. A three-level mixed model implies that the hierarchical structure of the data only plays a minor role, while controlling for endogeneity leaves the results unchanged.

Keywords: Import Penetration, Manufacturing, Labor Markets, Hierarchical Mixed Model

JEL No.: E24, F16, J23, L60

1 Introduction

In recent decades, the manufacturing sector has experienced a significant downturn in developed economies. Employment and output shares have fallen by up to two thirds since the 1970s. Simultaneously, the role of globalization, which has boosted international trade across a growing number of countries is highly debated. According to World Bank data global trade volume has nearly tripled since 1990 with a special focus on emerging countries, witnessing a spectacular rise in the international exchange of goods and services. Whereas other factors, including skill-biased technological change (Katz and Autor, 1999, Berman et al., 1994, and Machin and Van Reenen, 1998), play a prominent role in explaining labor market developments in the manufacturing sector since the 1970s, trade aspects have drawn increased attention in recent years. Although the impact of technological progress has become more skill-neutral in recent years (Autor et al., 2015), the manufacturing sector continues to become ever less important in terms of employment and output shares (Figure 1). A bulk of papers has since completed to determine the role of globalization and its impact on labor market outcomes.

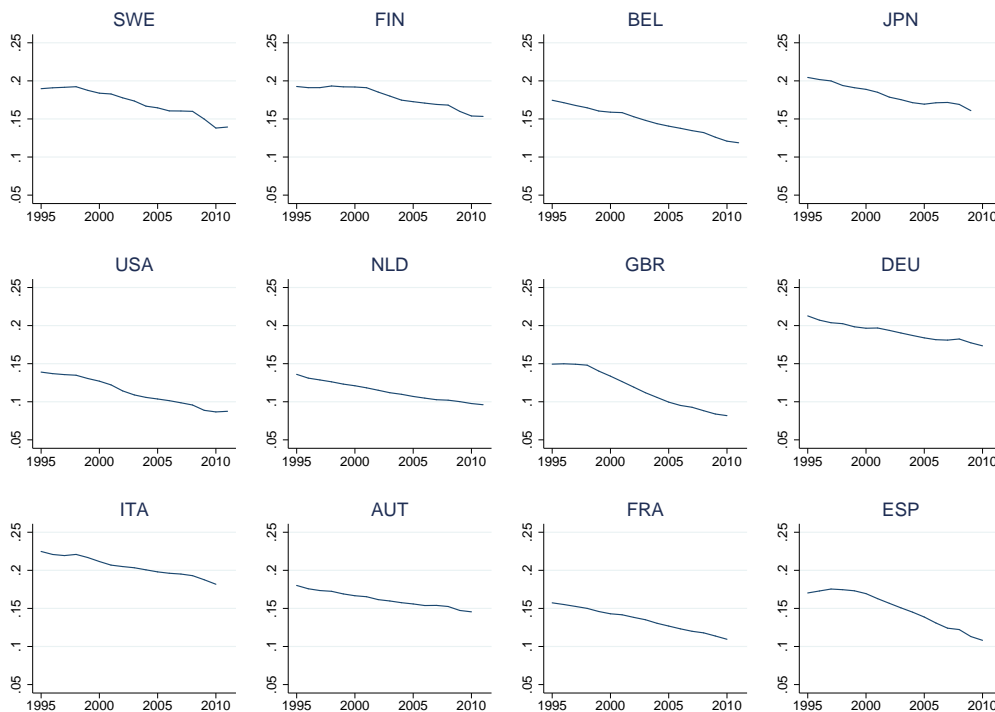


Figure 1 Manufacturing employment as share of total employment, 1995 = 100.

Thus far, previous research on the trade-employment nexus has focused on single countries using firm-level data, whereas cross-national analyses on this topic have been rather scarce. While country-specific investigations offer a profound analysis for the particular case, they may say little about the overall impact

of growing import penetration across several highly developed economies. Moreover, employing a cross-nationally comparable dataset, instrumental variable strategies may not prove suitable to adequately account for the hierarchical structure of the data.

As production is increasingly fragmented across borders international trade mainly comprises the exchange of intermediate inputs rather than final goods (Timmer et al., 2013). Using data on trade of final goods would therefore underestimate the true level of exchange between different countries. The World Input-Output Database (WIOD) whose latest version has been available only recently provides a possibility to account for the trade intensity within the production process offering comparable data on imported intermediate inputs on a two-digit level for the period from 1995 to 2011 (Timmer et al., 2015). Combining this database with several other sources results in a unique dataset to explore the effect of import penetration on manufacturing employment growth for 12 developed economies. The data also allows to measure the impact of import competition for different countries of origin, therefore enabling more specific statements on the role of growing trade intensity.

We make use of recent advances in data availability by investigating the impact of growing import penetration on manufacturing employment growth for 12 OECD countries representing more than three quarters of total GDP in the OECD.¹ In doing so, the contribution of the paper is threefold. First, we enlarge the sample and empirically examine the trade-employment nexus for a range of highly developed economies, thereby measuring an overall effect of growing import competition on manufacturing employment growth across different countries. Second, the overall effect of imported intermediate inputs on employment growth is split up according to the country of origin. Finally, the application of a multilevel mixed model allows to elucidate the influence of offshoring on employment growth at different levels.

From a theoretical point, growing international trade should exacerbate the situation of those performing tasks which are most vulnerable to offshoring (Autor et al., 2015). Following a standard Heckscher-Ohlin approach, two countries being differently endowed with capital and labor should engage in those stages of production for which the factor in need is relatively abundant. Thus, growing trade with emerging markets, like China, may enforce labor-abundant production in these countries, while strengthening capital-intensive stages of production in rich economies.

The findings point to a positive and weakly significant link between import competition and manufacturing employment growth in the 12 OECD countries. The results are partly robust to several model specifications, alternate estimation strategies as well as different measures of import penetration. When splitting up intermediates according to their country of origin, one can observe a negative impact of inputs from China

¹The countries are Sweden, Finland, Belgium, Japan, the United States, the Netherlands, United Kingdom, Germany, Italy, Austria, France, and Spain.

on employment growth, which is significant in a majority of our specifications. With regard to the BRIC nations (Brazil, Russia, India, China), the relationship is insignificant when controlling for exports of raw materials from those countries, indicating that the negative impact of Chinese intermediates is mitigated by trade with other countries. Additionally, intermediate inputs from the *new* EU members (EU-12)² exert a negative impact on employment growth, while the opposite is true for inputs from the European Union in general (EU-27). Apparently, intermediates from the EU-12 substitute for manufacturing production in the OECD countries, whereas imports from the *old* EU members acts as a complement, thereby increasing domestic manufacturing employment growth.

The inclusion of several covariates leaves the main results unchanged confirming the stability of our model. We therefore control for the current account balance, the share of high-skilled in 1996, the strictness of employment protection legislation, and an interaction term, which combines total factor productivity (TFP) and imported intermediate inputs. Additionally, the sample is split into two periods and 4-year averages to discard cyclical influences. Re-estimating the baseline regressions yields insignificant results. Furthermore, endogeneity might arise due to a correlation between imported intermediates and unobserved shocks in product demand. Employing an instrumental variable strategy, we observe a positive and partly significant relationship between manufacturing employment growth and different measures of import penetration which is in line with the findings from the baseline regression. When accounting for the origin of the imported intermediates, inputs from China and the EU-12 exert a negative influence on employment prospects in rich economies which is significant in most of the specifications.

Methodologically, the unique dataset allows for the application of a three-level mixed model with random intercepts at the country and the sector level, therefore incorporating the hierarchical structure of the data. Incorporating this information is important, as observations from the same country and the same industry are not independent from each other. To exclude the possibility that the findings are primarily driven by the selected estimation strategy, we provide an extensive sensitivity analysis, including several alterations of the baseline technique.

The paper is structured as follows. Section 2 provides a short literature review and discusses some theoretical aspects. Section 3 offers a description of the data and outlines the underlying empirical strategy. Section 4 presents the main findings for various model specifications, different measures of import penetration and alternate estimation strategies. The final section concludes.

²EU-12 comprises the countries that gained accession to the European Union in 2004/07, including Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Lithuania, Latvia, Malta, Poland, Romania, Slovakia, and Slovenia.

2 Literature review and theoretical considerations

2.1 Literature review

A vigorous scientific debate on the relationship between import competition and labor market outcomes is in progress with a bunch of studies focusing on the effects for a single country. The findings indicate a positive and mostly significant relationship between offshoring and relative labor demand of the high-skilled across different countries ([Geishecker, 2006](#), [Feenstra and Hanson, 1996](#), and [Hsieh and Woo, 2005](#)). According to these studies, offshoring can explain 10 to 50 percent of the rise in employment and wage shares of the high-skilled, promoting the process of skill upgrading (see e.g. [Berman et al., 1994](#) and [Autor et al., 1998](#)).³ While most investigations observe a positive relationship between offshoring and labor demand of the high-skilled, the effect is significantly negative for low-skilled workers ([Bloom et al., 2016](#), [Falk and Koebel, 2002](#) and [Morrison Paul and Siegel, 2001](#)).

Further research focuses on the production transfer within multinational enterprises and the impact on wages and relative labor demand. The relevant articles find a positive and significant effect, explaining up to 15 percent of the increase in wage-bill shares of the high-skilled ([Becker et al., 2013](#) and [Head and Ries, 2002](#)). [Baumgarten et al. \(2013\)](#) point to the degree of interactivity and non-routine content of occupations that have an influence on the wage effects of offshoring. They observe that low-skilled workers carrying out tasks with the lowest degree of non-routine content experienced the most distinct wage losses due to offshoring between 1991-2006. [Harrison and McMillan \(2011\)](#) emphasize that in the MNE context it is the underlying motive of offshoring which affects the impact on parent employment. In firms that do significantly different tasks at home and abroad, domestic and foreign labor are complements, while offshoring to low-wage countries often substitutes for domestic labor. As a result, they observe a quantitatively small effect of wage changes in foreign affiliates on manufacturing employment in US-based parent companies for the 1980s and 1990s. These results are in line with findings of [Marin \(2011\)](#) and [Autor et al. \(2015\)](#), implying that offshoring is not the primary driver of declining manufacturing employment in this period.⁴ The article of [Ebenstein et al. \(2014\)](#) analyzes the impact of changes in trade and offshoring on wages of U.S. employees with regard to the location of offshoring. Again, they show that offshoring to low-wage countries substitutes for domestic employment, while offshoring to high-income countries coincides with higher employment levels in the parent

³The skill upgrading hypothesis originates from the discussion about the impact of technological progress on labor market outcomes, but can also be observed in the offshoring context. [Spitz-Oener \(2006\)](#) emphasizes that occupations require more complex skills today than in 1979, showing that changes in occupational content account for one third of the recent educational upgrading in employment.

⁴A recent paper by [Blinder and Krueger \(2013\)](#) examines the amount and the characteristics of jobs in the United States with regard to their level of offshorability. According to their findings roughly 25 percent of the jobs are potentially offshorable with higher educated workers holding somewhat more offshorable jobs. However, they emphasize that differences in offshorability by race, sex, age, or geographic region are minor, as it is the case with respect to the routinizability of jobs as developed by [Autor et al. \(2003\)](#).

company. The authors also reveal that occupational exposure to globalization exerts more pronounced effects on wages than sector exposure. Therefore, leaving the manufacturing sector implies wage losses of 2 to 4 percent, while individuals additionally switching their occupation incur an extra wage loss of 4 to 11 percent.

An early study by [Revenge \(1992\)](#) points to the negative influence of increased import competition, measured by changes in import prices between 1977-1987, on employment and wages in manufacturing industries. In a similar line, rising exposure to low-wage country imports negatively affects plant survival and growth as indicated by [Bernard et al. \(2006\)](#). This paper applies a measure of offshoring, which defines low-wage countries as those with a per capita GDP that is less than 5 percent of the U.S. per capita GDP between 1972 and 1992, including China or India.⁵

A recent strand of literature investigates the effects of growing international trade on employment outcomes in local labor markets. [Autor et al. \(2013\)](#) examine the impact of rising import competition from China on the employment prospects in local labor markets in the U.S. and find a significantly negative relationship. With regard to local labor markets the paper relies on the concept of Commuting Zones (CZ) developed by [Tolbert and Sizer \(1996\)](#), which are characterized by strong commuting ties within CZs, and weak ties across CZs. The authors observe that local labor markets being confronted with import competition from China more intensively are those that suffer most from it. They conclude that one-quarter of the aggregate decline in US manufacturing employment can be attributed to rising import competition with China while offsetting gains in employment through a higher demand for US exports cannot be observed. The investigation of [Dauth et al. \(2014\)](#) yields rather nuanced results examining the role of rising trade with China and Eastern Europe on German local labor markets. Using local administrative units as local labor markets, this study omits commuting ties between the regions. While local labor markets that specialized in import-competing industries experience severe job losses, other regions with a focus on export-oriented industries exhibit substantial employment gains, outweighing the negative employment impact of import competition. While Chinese imports only play a minor role in explaining labor market outcomes of German trade integration, the effects are mostly driven by trade with Eastern Europe.

In a recent paper, [Bloom et al. \(2016\)](#) investigate the impact of import competition from China on employment and innovation for a panel of 12 European countries, suggesting that Chinese imports are associated with falling levels of manufacturing employment and reallocations of employment towards more technologically advanced firms.

⁵As per capita GDP has risen substantially in China and India (from 9 to 19 percent of the U.S. per capita GDP between 1995 and 2011 in China, and 4.3 to 8.4 percent in India, respectively), this measurement approach does not appear to be suitable for our analysis.

2.2 Theoretical considerations

A standard Heckscher-Ohlin approach of trade implies that growing trade between countries with different factor endowment would encourage both countries to specialize in the export of those commodities produced with relatively large quantities of the country's relatively abundant factor. Relatively capital- and skill-abundant countries like the United States or Germany are expected to accommodate a more capital- and skill-intensive mix of industries than relatively labor-abundant countries like China. While this model may hold for the trade of commodities between countries of different development levels, it is not suitable for drawing conclusions on trade between countries of the same development level. [Melitz \(2003\)](#) provides a theoretical model explaining why large amounts of resource allocations occur across firms in the same industry in similarly developed economies. Due to initial uncertainty regarding its productivity before entering the industry, firms with different levels of productivity coexist in an industry. In fact, only the most productive firms engage in export activities, which is costly but allows to realize gains from trade, while the least efficient firms are forced out of the industry.

Moreover, the nature of trade has changed dramatically during recent decades illustrating more subtle patterns of specialization between countries. In the past, trade was thought of as the exchange of final goods while current international trade focuses on intermediates as production is increasingly fragmented across borders. Measuring final goods trade ignores the role of intermediate inputs and therefore underestimates the real trade intensity. Three main causes have been detected for this development as emphasized by [Kleinert \(2003\)](#): outsourcing, global sourcing, and increasing importance of networks of multinational enterprises (MNE). According to the outsourcing hypothesis, increasing intermediate inputs are the result of firms' strategies to relocate parts of their production to foreign countries with comparative advantages in the production of particular products. While the outsourcing motive requires foreign direct investment (FDI) in less-developed economies, the MNE networks hypothesis rather focuses on inward FDI. In this case, an increasing number of imported intermediate inputs occurs due to growing trade between MNEs' affiliates across the world. The global sourcing motive is based on decreasing transportation costs, resulting in decreasing prices of imported intermediates. As our sample is based on macro data, we are not interested in capturing the role of particular motives, but rather in ascertaining the aggregate impact of growing intermediate inputs on employment.

There are various channels through which higher import competition affects the labor market. An increasing number of imports may reduce domestic employment since the foreign production of goods or certain stages of production makes domestic jobs redundant. In particular, this might be the case if the goods produced abroad are substitutes to those produced domestically. Otherwise, growing trade integration provides

larger opportunities for the distribution of domestic products, allowing to break into new markets. Furthermore, if imported goods are complements to domestically produced ones, growing trade may foster domestic production. While the first aspect is employment growth reducing, the latter issues enhance employment growth. As a result, the impact of growing import penetration on employment growth depends on which channel is relevant for the current topic.

In a seminal paper, [Grossman and Rossi-Hansberg \(2008\)](#) account for the changing nature of trade through global value chains, thereby introducing the concept of *task trade*. According to the concept, a reduction in the cost of task trade has effects which are similar to factor-augmenting technological progress, boosting the productivity of the factor whose tasks become easier to offshore. Apart from this productivity effect the model incorporates two other effects: the relative-price effect and the labor-supply effect. The relative-price effect results from changes in relative prices via a mechanism that is familiar from [Stolper and Samuelson \(1941\)](#). Since improvements in the technology for offshoring generate greater cost-savings in labor-intensive industries than in skill-intensive ones, a fall in the relative price of the labor-intensive good will exert downward pressure on low-skill wages. The labor-supply effect implies that a reduction in trade costs through technological progress causes offshoring which frees up domestic low-skilled labor. As these workers must be reabsorbed by the labor market, this leads to a decline in their wages. While the relative-price effect and the labor-supply effect typically works to the disadvantage of low-skilled labor, the productivity effect tends to inflate their wages. Assuming the adjustment in relative prices to be not too large, all domestic parties, i.e. high-skilled and low-skilled labor, may gain from offshoring, which is in contrast to some traditional trade theories. Hence, the theoretical impact of offshoring on labor market outcomes is unclear a priori.

3 Empirical strategy

3.1 Data on offshoring

This analysis is particularly interested in data on international trade relations. To measure offshoring, we employ the share of imported intermediates in total non-energy input purchases for industry i and country j at time t (inp_{ijt}) as promoted by [Feenstra and Hanson \(1999\)](#). This can be described via a two-step procedure where

$$inp_{ijt} = \sum_{h=1}^H [\text{input purchases of good } h \text{ by industry } i \text{ in country } j]_t \quad (1)$$

$$* \left[\frac{\text{imports of good } h}{\text{apparent consumption of good } h} \right]_t.$$

Table 1 Imported intermediate inputs in total manufacturing in 2010.

Country	III_R	III_B	III_N	III_B^{CHN}	III_B^{BRIC}	III_B^{EU27}	III_B^{EU12}
SWE	.374	.615	.514	.013	.052	.313	.026
FIN	.334	.594	.413	.017	.129	.197	.019
BEL	.578	1.477	2.161	.022	.050	.818	.020
JPN	.129	.154	.073	.019	.026	.008	.000
USA	.208	.243	.148	.024	.035	.033	.001
NLD	.539	1.284	3.11	.026	.103	.491	.014
GBR	.343	.552	.541	.022	.037	.244	.018
DEU	.338	.562	.518	.027	.050	.274	.050
ITA	.251	.325	.215	.014	.044	.135	.015
AUT	.423	.858	.953	.016	.034	.525	.078
FRA	.274	.356	.293	.013	.034	.198	.012
ESP	.274	.357	.236	.009	.025	.172	.012

In a second step, we normalize inp_{ijt} with the total purchases on non-energy intermediates in each industry i and country j at time t :

$$iii_{ijt} = \frac{inp_{ijt}}{NE_{ijt}}. \quad (2)$$

This measure not only allows for imports, but also takes export activities of industry i in country j at time t into account, which may be offsetting to some extent. Additionally, this measure permits the application of a broad and a narrow concept of offshoring. The broad concept includes imported intermediates from all industries (III_B), whereas the narrow concept of offshoring (III_N) comprises imported intermediate inputs from the same industry. Since we conduct an aggregate analysis of the impact of offshoring on employment, we mainly focus on the broad concept of offshoring. To cross-check the findings, the results of the narrow concept are routinely reported. Furthermore, we apply a rough measure of import penetration denoted III_R , which is the share of foreign intermediates in total intermediate inputs for industry i and country j at time t . This rough measure only incorporates imports and therefore ignores the role of exports and energy aspects. While III_R serves as a first indicator, III_B and III_N represent more sophisticated measures of offshoring.

The offshoring measures are constructed with data from the World Input-Output Database (WIOD) provided by [Timmer et al. \(2015\)](#), which include input-output tables for 27 EU countries and 13 other major countries in the world for the period from 1995-2011. Due to these recent data advances, we are able to explore the effects of growing import penetration from different countries on manufacturing employment in 12 developed economies. Hence, we quantify the impact of intermediate inputs from China, the BRIC nations (Brazil, Russia, India, and China), a broader set of emerging countries (including the BRIC countries and Indonesia, Mexico, and Turkey), the EU member countries (EU-27), and the new EU member states (EU-12) on employment in 11 manufacturing industries.

Table 1 shows the descriptive statistics for different imported intermediate inputs in total manufacturing in 2010. The share of foreign intermediates in total intermediates (III_R) varies considerably across countries with only 12.9 and 20.8 percent for Japan and the United States, respectively, whereas in small economies more than half of the intermediates in the manufacturing sector stem from abroad (Belgium: 57.8 percent, the Netherlands: 53.9 percent). The differences in imported intermediate inputs become even more distinct when using more sophisticated measures of offshoring, ranging from .154 in Japan to 1.477 in Belgium for III_B and from .073 in Japan to 3.11 in the Netherlands for III_N . With respect to intermediates from different countries one can observe that intermediate inputs from China matter in each of the 12 countries at analysis while this is not valid concerning inputs from the new EU member states. The EU-12 are major trade partners for other EU members, whereas imported intermediate inputs from these countries hardly play any role for the U.S. and the Japanese economy. This can also be seen in Figure 2 which displays the development of intermediate inputs from China and the EU-12 for the period 1995-2011. The ubiquitous role of Chinese intermediates is in stark contrast to a rather regional impact of growing trade with the new EU member states with a special focus on European neighbor countries, like Austria and Germany.

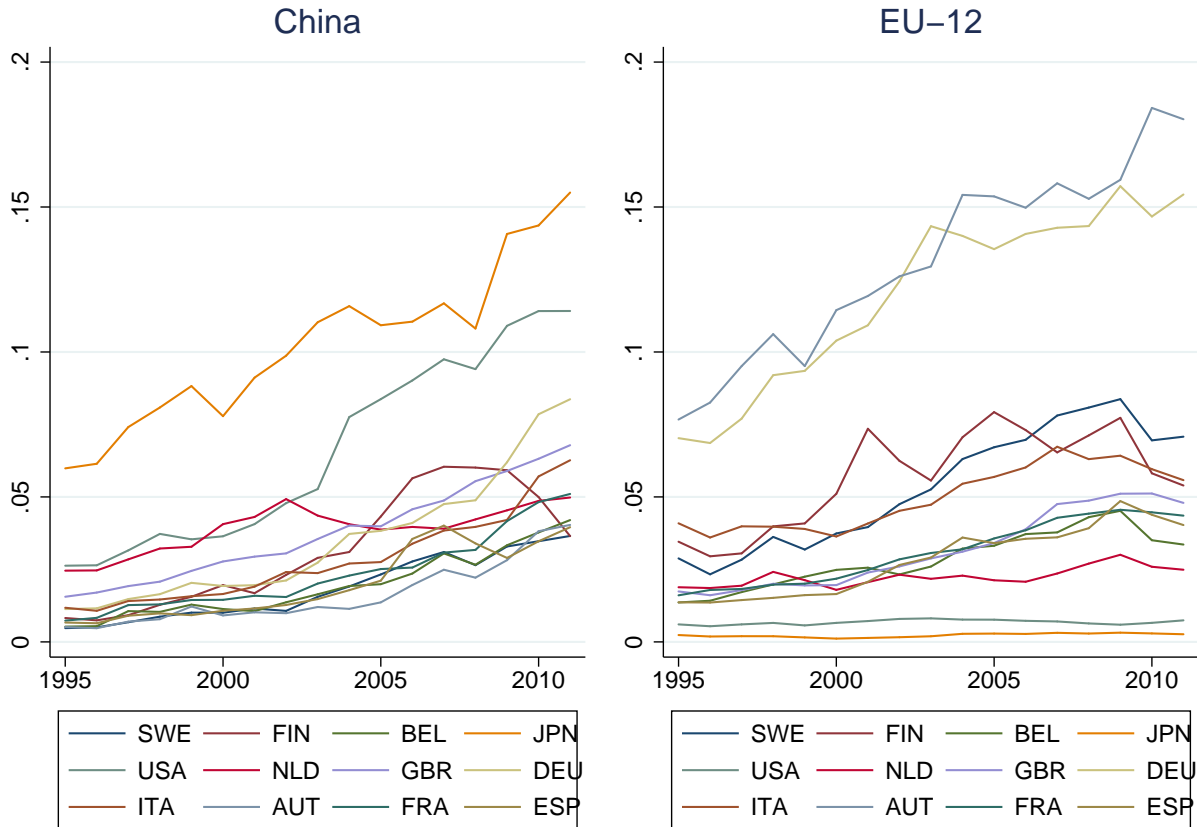


Figure 2 Imported intermediate inputs from China and the EU-12 as share of all foreign inputs.

Since the more sophisticated measures of offshoring include several outliers, we restrict the sample to values of III_B between -6 and 13 and values of III_N between -10 and 10. This procedure is valid, as the outliers relate to mainly small countries, where in some sectors the denominator of the second part of Equation 1 is nearly zero, resulting in an extraordinarily large or low level of imported intermediate inputs. As the observations excluded by application of the broad measure of offshoring are different to those when using the narrow measure of offshoring, we mitigate problems with the choice of data. Nevertheless, to ensure that the results are not affected by data issues, we re-estimate the baseline regressions with the rough measure (III_R), which does not require any data exclusions.

3.2 Empirical model

To estimate the impact of import penetration on employment prospects and to achieve a more in-depth understanding of this relationship, we assume EMP_GR , the growth of the employment-to-working age population ratio, to be a function

$$EMP_GR_{ijt} = F(IP_{ijt}, \mathbf{X}_{ijt}, \xi_t), \quad (3)$$

where $i = 1, \dots, N$ denotes industries, $j = 1, \dots, M$ denotes countries, $t = 1, \dots, T$ is the time index, and ξ_t is a specific effect of period t . \mathbf{X}_{ijt} captures a variety of control and environment variables and includes a number of determinants that we assume to have an effect on manufacturing employment growth. These determinants comprise the development level of the economy, which we include via the logarithmic value of real per capita GDP on the expenditure side, denoted by $Log(GDP_{pc})$. We further incorporate an index of the educational level (HC) to account for differences in the qualification of workers across countries. The analysis also includes the fertility rate, denoted by $FERT$. Although the analysis comprises 12 highly developed economies from the OECD, there is sufficient variation in fertility rates across the countries to employ them as a covariate (mean: 1.61, sd: .259, Min: 1.16, Max: 2.12). We assume the coefficient of $FERT$ to be negative, since a higher number of children requires more time spent on parenting which negatively affects individual labor supply.

Governmental activities enter into the regression using public social expenditures (PUB_SOCEXP). We assume that a more generous welfare state hampers employment growth, since work incentives, particularly for low-skilled workers, are negatively affected by higher public social expenditures. In a further step, we incorporate the logarithm of the employment level in 1996 ($EMP96$), which is the start of our analysis as calculating growth rates leads to a loss of one observation in time. We apply the TFP growth rate to control for technological change which is one of the main drivers of employment changes. Several robustness checks

extend the analysis and allow for the re-estimation of the baseline model incorporating a wide variety of covariates serving as a proxy for technological development, labor market institutions, and socio-economic circumstances. Similar to the existing branch of literature, we apply different measures of employment as dependent variable. Our main dependent variable is *EMP_GR* while further dependent variables comprise the logarithm of total employment, the employment-to-population ratio, and others.

Data on manufacturing employment and TFP growth is extracted from the EU KLEMS database, including information on output, employment, and growth contributions for 11 manufacturing industries from 1970-2010 for 12 OECD countries (O'Mahony and Timmer, 2009). All data on offshoring stems from the World Input-Output Tables (Timmer et al., 2015). The human capital index is taken from Barro and Lee (2013), while data on fertility, current account balance and the share of natural resource exports is from the World Bank (2014). Data on the development level stems from the Penn World Tables 8.0 (Feenstra et al., 2015). Information on working hours of high-skilled are extracted from the Socio-Economic Accounts of the World Input-Output Database (Timmer et al., 2015), while data on public social expenditures and the employment protection legislation is taken from the OECD. Table A3 in the appendix provides summary statistics of the variables employed in the analysis, including their means, standard deviations, the number of observations, as well as their minima and maxima.

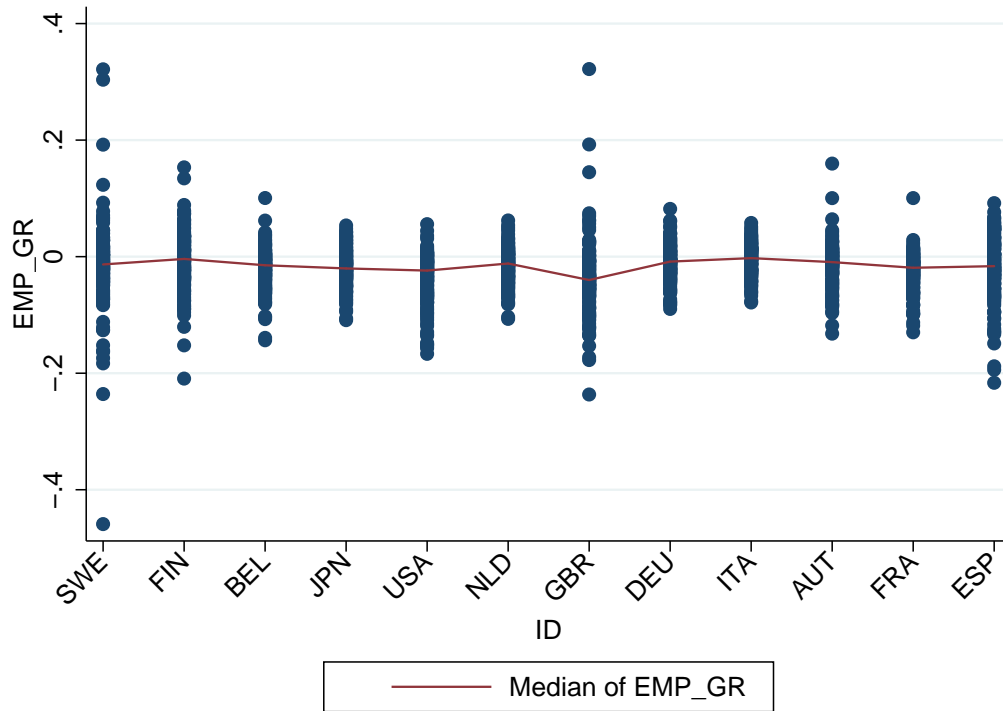


Figure 3 Employment growth across countries, *EMP_GR* ($N = 1,128$, skewness= 1.043, kurtosis= 2.847).

How much variation can be observed across countries and industries? The following figures illustrate employment growth across countries (Figure 3) and industries (Figure 4). The findings show a negative manufacturing employment growth in each country and display only little variation across countries with a relatively bad performance being observed in Great Britain and a median employment growth of around 0 for the Finnish, German, and the Italian manufacturing sector. Similarly, we observe little variation between the industries where the textile sector underperforms. In general, much of the variation occurs within countries or within industries. Notwithstanding, there are considerable differences regarding the variation within countries, e.g. Japan vs. the United Kingdom, as well as within industries. While there is only little variation in employment growth in the food sector, it is much higher in other industries like coke and refined petroleum products or transportation equipment.

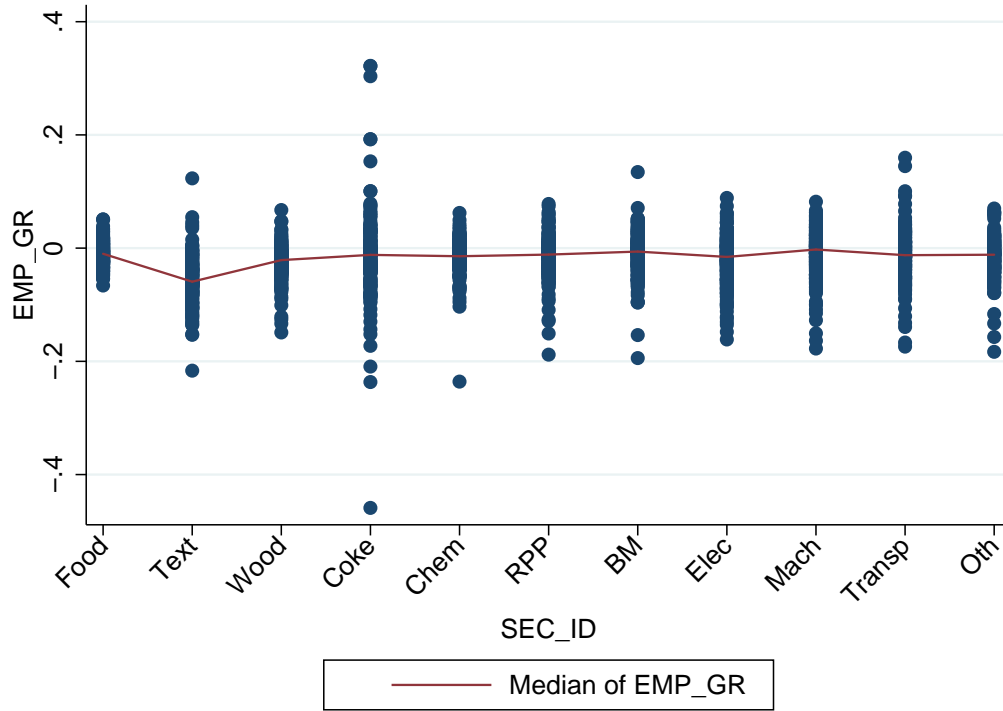


Figure 4 Employment growth across industries, *EMP_GR* ($N = 1,128$, skewness= 1.043, kurtosis= 2.847).

3.3 Estimation technique

A common and widely-used approach to investigate the trade-employment nexus is the two-stage least squares (2SLS) estimator (Autor et al. (2013), Dauth et al. (2014), and Bloom et al. (2016)). Consider a linear model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_K x_K + u \quad (4)$$

where x_K might be correlated with u . In this case, imported intermediate inputs are not independent from unobserved shocks in product demand, misestimating the true impact of imported intermediates on employment growth. The basic idea of the 2SLS estimator includes that in the first stage endogenous covariates are regressed on the exogenous regressors and the instruments where we obtain the fitted values \hat{x}_K :

$$x_K = \delta_0 + \delta_1 x_1 + \dots + \delta_{K-1} x_{K-1} + \theta_1 z_1 + \dots + \theta_M z_M + r_K. \quad (5)$$

By definition, r_K has zero mean and is uncorrelated with the right-hand-side variables, so that any linear combination of \mathbf{z} is uncorrelated with u . Additionally, \mathbf{z} must be correlated with x_K . In the second stage, regressing y on $1, x_1, \dots, x_{K-1}, \hat{x}_K$ yields:

$$y = \beta_0 + \beta_1 x_1 + \dots + \beta_{K-1} x_{K-1} + \beta_K \hat{x}_K + v \quad (6)$$

where v is a composite error term that is uncorrelated with x_1, \dots, x_{K-1} , and \hat{x}_K .

While the 2SLS approach allows for endogeneity issues, it does not sufficiently incorporate the hierarchical structure of the data stemming from 12 countries and 11 manufacturing industries. This approach differs from previous research, which focused on the relationship between trade and employment in a single country context. Hence, a linear three-level model provides the opportunity to adequately account for the hierarchical structure of the data. For any observation in country j and industry i at time t , we consider a three-level random-intercept model with the variables to be linked additively yielding

$$EMP_GR_{ijt} = \beta_1 + \beta_2 \mathbf{X}_{ijt} + \beta_3 \mathbf{X}_{ij} + \beta_4 \mathbf{X}_j + \zeta_j^{(3)} + \zeta_{ij}^{(2)} + \epsilon_{ijt}, \quad (7)$$

where $\beta_1 + \beta_2 \mathbf{X}_{ijt} + \beta_3 \mathbf{X}_{ij} + \beta_4 \mathbf{X}_j$ is the fixed part of the model and $\zeta_j^{(3)} + \zeta_{ij}^{(2)} + \epsilon_{ijt}$ is the random part of the model. While the fixed part of the model specifies the overall mean relationship between the dependent variable and the covariates, the random part of the model specifies how country and sector-specific relationships differ from the overall mean relationship. In the fixed part of the model, \mathbf{X}_{ijt} is a set of controls at level 1 with slope coefficient β_2 , \mathbf{X}_{ij} is a set of covariates at the sector level (level 2) with slope coefficient β_3 , and \mathbf{X}_j is a set of control variables at the country level (level 3) with slope coefficient β_4 .

The random part consists of a country-level random intercept $\zeta_j^{(3)}$ with zero mean and variance $\psi^{(3)}$, given the covariates \mathbf{X}_j , \mathbf{X}_{ij} , and \mathbf{X}_{ijt} , which represents the combined effects of omitted country characteristics. $\zeta_{ij}^{(2)}$ is a sector-level random intercept with zero mean and variance $\psi^{(2)}$, given $\zeta_j^{(3)}$, \mathbf{X}_j , \mathbf{X}_{ij} , and \mathbf{X}_{ijt} , representing unobserved heterogeneity at the sector level. The level-1 error term ϵ_{ijt} has zero mean and

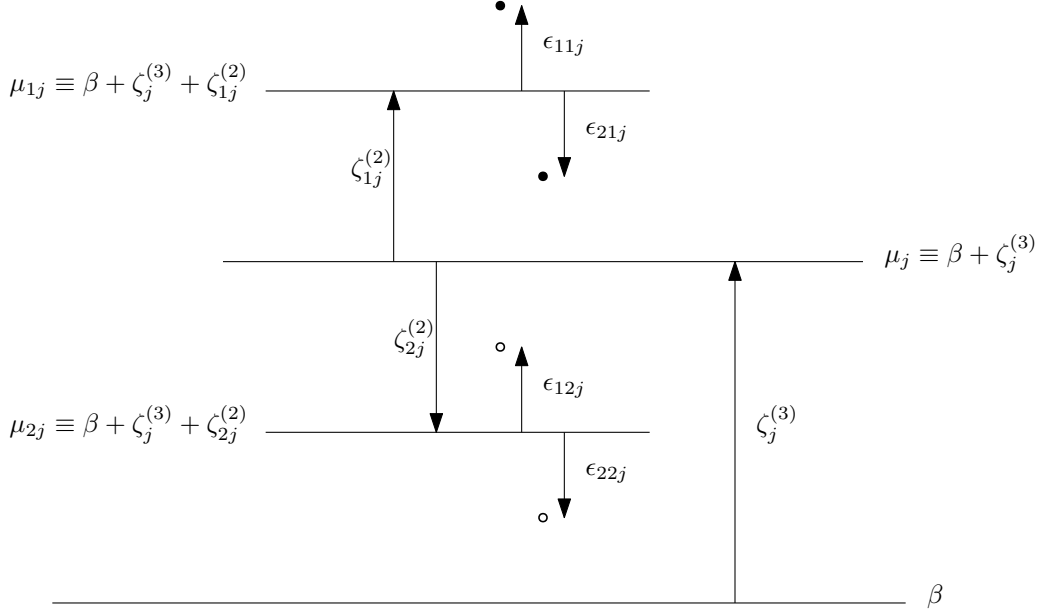


Figure 5 Illustration of error components for the three-level variance-components model (Rabe-Hesketh and Skrondal, 2012)

variance θ , given $\zeta_j^{(3)}$, $\zeta_{ij}^{(2)}$, \mathbf{X}_j , \mathbf{X}_{ij} , and \mathbf{X}_{ijt} , and varies between different points in time t as well as countries j and sectors i . The $\zeta_j^{(3)}$ are uncorrelated across countries, the $\zeta_{ij}^{(2)}$ are uncorrelated across countries and sectors, the ϵ_{ijt} are uncorrelated across countries, sectors, and observations in time, and the three error components are uncorrelated with each other (Rabe-Hesketh and Skrondal, 2012).

Figure 5 illustrates the error components for a three-level variance-components model. It can be observed that the error term is a composed error with $\zeta_j^{(3)}$ being shared between observations of the same country, $\zeta_{ij}^{(2)}$ being shared between observations of the same country and the same sector, and ϵ_{ijt} , which is unique for each observation in time. While β represents the overall mean, the mean employment growth of country j is equal to $\mu_j \equiv E(y_{ijt}|\zeta_j^{(3)}) = \beta + \zeta_j^{(3)}$. In the second stage, a sector-specific random intercept $\zeta_{1j}^{(2)}$ produces a sector-specific mean employment growth for country j which is equal to $\mu_{1j} \equiv E(y_{ijt}|\zeta_j^{(3)}, \zeta_{1j}^{(2)}) = \beta + \zeta_j^{(3)} + \zeta_{1j}^{(2)}$. Finally, residuals ϵ_{11j} and ϵ_{21j} are drawn from a distribution with zero mean and variance θ .

Maximum Likelihood (ML) appears to be an appropriate estimation strategy, allowing for the hierarchical structure of the data. ML estimation yields the parameters of a statistical model given a set of data, by finding the parameter values that maximize the likelihood of obtaining that particular set of data given the chosen probability distribution model. The probability density function $f(y|\theta)$ identifies the data-generating process that underlies an observed sample of data and provides a mathematical description of the data that the process will produce. The joint density of n independent and identically distributed observations from the process is the likelihood function

$$f(y_1, \dots, y_n | \theta) = \prod_{i=1}^n f(y_i | \theta) = L(\theta | \mathbf{y}), \quad (8)$$

which is defined as a function of the unknown parameter vector, θ , where \mathbf{y} is used to indicate the collection of sample data. For reasons of lucidity, the log of the likelihood function is employed:

$$\ln L(\theta | \mathbf{y}) = \sum_{i=1}^n \ln f(y_i | \theta). \quad (9)$$

While maximizing the log-likelihood function, Maximum-Likelihood estimators have very desirable large sample properties. If the density is correctly specified, the ML estimator is consistent for θ and asymptotically more efficient than other estimators, implying that no other estimator has a smaller asymptotic variance-covariance matrix of the estimator. (Greene, 2012 and Wooldridge, 2010).

The literature contains two major estimation methods for estimating the statistical parameters, under the assumption that the random part of the model is normally distributed: Maximum-Likelihood or restricted Maximum-Likelihood (REML). The expectation-maximization (EM) algorithm treats the random effects as missing data and allows to determine the ML or REML estimates via an iterative process, in which a provisional estimate converges to the ML or REML estimate. Both methods differ little with regard to the regression coefficients, but they vary substantially with respect to the variance components. When estimating the variance components REML takes into account the loss of degrees of freedom which results from the estimation of the regression parameters, while ML does not. As a result, ML estimators of the variance components have a downward bias, which is why the REML method is preferable concerning the estimation of the variance parameters. Additionally, in cases of small sample sizes at the highest level REML produces more reliable standard errors (Snijders and Bosker, 2012). As our sample consists of 12 countries at the highest level, we apply the REML method. However, REML does not allow for heteroskedasticity-robust standard errors. A Breusch-Pagan test indicates that heteroskedasticity is an issue, which is why we re-estimate the baseline specification via ML and include robust standard errors as a robustness check.

4 Results

4.1 Baseline results

Table 2 displays the results of the baseline estimation. Column (1) presents a model which only incorporates the effect of TFP growth, the employment level at the start of our observation period, and a broad measure of import penetration. We observe a positive and weakly significant effect of import penetration on manufactur-

Table 2 Baseline regressions. Dependent variable is employment growth *EMP_GR*.

	(1)	(2)	(3)	(4)	(5)
TFP	-0.0178** (0.00746)	-0.0176** (0.00742)	-0.0168** (0.00740)	-0.0171** (0.00736)	-0.0163** (0.00749)
EMP96	-0.00202 (0.00188)	0.00217 (0.00287)	0.00191 (0.00292)	0.00362 (0.00306)	0.00253 (0.00297)
III _B	0.00196* (0.00108)	0.00183* (0.00108)	0.00191* (0.00109)		
Log(GDP _{pc})		-0.00820** (0.00346)	-0.0181*** (0.00516)	-0.0182*** (0.00529)	-0.0170*** (0.00485)
FERT		-0.0398*** (0.00877)	-0.0616*** (0.0127)	-0.0611*** (0.0128)	-0.0556*** (0.0122)
HC		0.0164 (0.0102)	0.0130 (0.0148)	0.00954 (0.0149)	0.0133 (0.0144)
PUB.SOCEXP			-0.00261*** (0.000777)	-0.00274*** (0.000778)	-0.00228*** (0.000759)
RES_EXP			0.489*** (0.126)	0.476*** (0.126)	0.497*** (0.128)
III _R				0.0377** (0.0150)	
III _N					-0.0000213 (0.000817)
N	1905	1905	1905	1925	1903
Time Dummies	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

ing employment growth indicating a positive contribution of increased trade on employment prospects in the 12 OECD countries. The results support the findings of [Dauth et al. \(2014\)](#), pointing to job losses through growing imports which are more than offset by increasing export prospects and the complementarity of the imported intermediates. Additionally, we find a negative and significant impact of TFP growth on manufacturing employment growth, indicating an employment growth reducing impact of technological change in the manufacturing sector. The coefficient of the employment level in 1996 is not significant implying that initial employment does not play a crucial role in explaining future employment prospects.

Column (2) introduces the level of development, fertility, and the level of human capital in the model. The import penetration variable remains positive and significant, supporting the overall employment enhancing impact of intermediate inputs on employment growth in the OECD countries. The effect of *TFP* remains negative and significant, while the coefficient of the initial employment level becomes positive, but

remains insignificant. The development level itself is negatively related to employment growth, indicating that growing prosperity negatively affects the manufacturing sector. The reason is that demand for manufacturing products is steadily decreasing in developed economies relative to the demand for services, although manufacturing industries, on average, have a higher productivity. As goods are internationally tradable, manufacturing firms have to pass along technological improvements and lower prices to the consumer resulting in a constantly declining market share of the manufacturing sector. Fertility exerts a significantly negative impact on employment growth as rearing children negatively affects the employment probability of women in particular. The coefficient of the human capital index has the expected positive sign. However, the impact is not significant since human capital operates on a long-term basis leaving the coefficient insignificant in a year-to-year consideration.

Column (3) includes public social expenditures to allow for the generosity of the social security system and possible implications on labor supply. The results reveal a robust negative relationship between public social expenditures and employment growth, indicating that more generous welfare states negatively affect the individual's decision to work. Additionally, the variable *RES_EXP* is incorporated, which is the share of exports of raw materials on all merchandise exports of a country or region of origin. This covariate accounts for the exports of raw materials which often have a positive impact on employment growth as they serve as a prerequisite for manufacturing production in highly developed economies. As we are interested in the link between imported intermediate inputs and employment prospects beyond the export of raw materials, inclusion of *RES_EXP* is highly advantageous. All other regressors remain unchanged confirming the stability of the baseline model. All specifications include time and sector dummies as our observation period includes a variety of shocks, like the dot-com bubble or the Great Recession, as well as so diverse sectors as e.g. food and beverages, textiles, or machinery equipment.

In Columns (4)–(5), we replace III_B with a rough (III_R) and a narrow (III_N) measure of import penetration and re-estimate the preferred baseline specification (Column 3). with a rough (III_R , Column (4)) and a narrow (III_N , Column (5)) measure of import penetration. Although the rough measure omits export activities as well as energy aspects, the coefficient points to a positive and significant impact on manufacturing employment growth in 12 OECD countries, supporting the findings of our preferred measure III_B . Obviously, a majority of foreign intermediate inputs serves as a complement to domestic production in manufacturing, fostering employment growth rather than impeding it. Applying a narrow measure of globalization (III_N), one cannot observe a significant influence of the import variable. This might be due to the construction of the indicator that measures the impact of imported intermediate inputs from the same industry, which in some cases only play a minor role. The coefficient of *TFP* remains negative and robust in all specifications, indicating that different import penetration measures does not change the influence of

technological progress on employment growth in manufacturing.

Furthermore, we re-estimate our baseline model altering the model fit from REML to ML which allows for the application of heteroskedasticity-robust standard errors. Table A4 in the appendix displays the results. In line with the findings in our baseline regression, imported intermediate inputs are positively related to employment growth, while technological progress is not. Though the signs of the coefficients remain stable, both effects become insignificant. The results emphasize that the employment reducing effect of growing import competition is offset by employment enhancing effects as imported intermediates rather act as complements to domestic production in the 12 OECD countries.

Our mixed model includes random intercepts at the country and sector level as the impact of our import penetration measure on employment growth may vary between countries and sectors. A likelihood-ratio test rejects the null hypothesis that a random intercept at the country level and at the sector level is 0. Thus, a country-specific and a sector-specific random intercept are added to the population mean, while the null hypothesis of a random slope at the country and the sector level cannot be rejected.

4.2 Sensitivity analysis

We are persuaded that our baseline estimation technique is the most appropriate approach for analyzing the impact of imported intermediate inputs on manufacturing employment growth. Yet it is essential to explore whether the results are robust to alternative estimation techniques and additional variables. In a first step, we include several exogenous variables, which we think may additionally influence employment outcomes.

Table 3 replicates the baseline model of Column (3) in Table 2 and provides results of the impact of the additional exogenous variables. Column (1) adds an interaction term $TFP \times III_B$ as we assume the import penetration measure to differ in the intensity how it affects employment growth conditional on the total factor productivity. The results indicate that TFP still exerts a negative and significant influence on employment growth for an import penetration of 0, while the coefficient of III_B remains positive but insignificant when TFP is 0. The coefficient of the interaction term reveals a positive and significant relationship implying that the positive effect of import penetration on manufacturing employment growth is stronger for higher TFP growth rates. These findings highlight that the more productive country-sector combinations benefit most from increasing import penetration. The remaining covariates do not alter across the different model specifications, underlining the stability of the baseline results.

Column (2) incorporates a country's one-period lagged current account balance in the estimation (CAS_{t-1}). The results indicate that countries with a current account deficit in the previous period have a lower manufacturing employment growth than those with a surplus. As the majority of manufacturing goods is highly

Table 3 Sensitivity analysis, additional exogenous variables. Dependent variable is employment growth EMP_GR .

	(1)	(2)	(3)	(4)	(5)	(6)
TFP	-0.0185** (0.00742)	-0.0171** (0.00781)	-0.0169** (0.00739)	-0.0172** (0.00738)	-0.0167** (0.00739)	-0.0169** (0.00739)
EMP96	0.00199 (0.00291)	0.00153 (0.00290)	0.00159 (0.00291)	0.00130 (0.00293)	0.00176 (0.00293)	0.00153 (0.00293)
III_B	0.00141 (0.00110)	0.00184 (0.00122)	0.00198* (0.00109)	0.00188* (0.00108)	0.00187* (0.00109)	-0.00763 (0.00567)
$\text{Log}(\text{GDP}_{pc})$	-0.0176*** (0.00504)	-0.00270 (0.00410)	-0.0185*** (0.00522)	-0.0279*** (0.00643)	-0.0247*** (0.00633)	-0.0170*** (0.00506)
FERT	-0.0602*** (0.0125)	-0.0329*** (0.00902)	-0.0631*** (0.0128)	-0.0678*** (0.0140)	-0.0700*** (0.0138)	-0.0616*** (0.0125)
HC	0.0123 (0.0146)	-0.00134 (0.0110)	0.0121 (0.0149)	0.00685 (0.0162)	0.0104 (0.0159)	0.0154 (0.0147)
PUB_SOCEXP	-0.00252*** (0.000769)	-0.000197 (0.000606)	-0.00264*** (0.000781)	-0.00267*** (0.000847)	-0.00301*** (0.000816)	-0.00244*** (0.000771)
RES_EXP	0.482*** (0.126)	0.435*** (0.125)	0.495*** (0.127)	0.498*** (0.130)	0.512*** (0.129)	0.421*** (0.131)
$\text{TFP} \times III_B$	0.0358** (0.0151)					
$\text{CAS}_{(t-1)}$		0.00227*** (0.000473)				
HS96			0.0433 (0.0304)			
EPL				-0.0224*** (0.00826)		
MANUF96					-0.249 (0.215)	
$\text{RES_EXP} \times III_B$						0.0606* (0.0354)
N	1905	1712	1905	1905	1905	1905
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

tradable across the world, current account deficits can be interpreted as a lack of competitiveness resulting in worse manufacturing employment prospects for those countries. Column (3) includes the share of hours worked by high-skilled workers in 1996 ($HS96$) to account for skill differences between the country-sector-combinations. We obtain a positive and barely insignificant relationship with a p-value of 0.14, supporting the theoretical view that the availability of high-skilled workers increases labor demand and therefore employment growth. While the technology variable (TFP) remains robust across all specifications, the import penetration measure (III_B) is positive and weakly significant in 3 of 5 cases.

Column (4) incorporates the employment protection legislation index for regular workers (EPL) from the OECD database as proposed by [Crinò \(2009\)](#), which serves as a proxy for the rigidity of the labor market. The results reveal that a higher employment protection negatively affects employment growth in manufacturing industries. The reason is that higher employment protection legislation impedes firms' willingness to hire new workers which is adverse for the job creation in times of economic recovery. Controlling for our standard covariates, more vital employment prospects can be observed for country-sector combinations with lower employment protection legislation.

In a next step, we reassess whether there is evidence for an *unevitable* structural change from the industry sector to the service sector (Column 5). In concrete terms, we employ the share in manufacturing value added in percent of GDP in 1996 ($MANUF96$) to examine whether countries with a strong manufacturing sector in 1996 are more intensively exposed to manufacturing employment decline than countries where manufacturing only plays a minor role. The former economies are expected to undergo serious transformations with adverse employment effects as they do not have experienced this structural change, yet. The results indicate that countries with a broad industrial basis have not been subject to stronger manufacturing employment decline between 1996 and 2011 than countries with a smaller industrial sector. As our observation period comprises only one and a half decades, we cannot conclusively answer the question of the inevitability of structural change which depicts a long-term development.

Column (6) of Table 3 includes the interaction term $RES_EXP \times III_B$ into the estimation as we expect the imported intermediate inputs to affect employment growth dependent on the extent of exports of raw materials. We assume a higher impact of imported intermediates on manufacturing employment growth when the share of exports of raw materials is larger. As exports of raw materials are a prerequisite of manufacturing production in highly developed economies, we assume the interaction term to be positive. The results confirm the theoretical predictions, implying a positive and significant coefficient for $RES_EXP \times III_B$. The coefficient of III_B itself is insignificant, indicating that imported intermediates exert no significant influence on manufacturing employment when the export of raw materials is 0. However, with an increasing share of exports of raw materials the influence of imported intermediate inputs on employment growth becomes

positive and significant. All other variables remain unchanged.

The analysis up to this point supposed an immediate effect of the covariates on manufacturing employment growth. Yet it may take some time for the variables to come into effect at the labor market. With regard to the baseline specification this may apply to fertility, the human capital index, and import penetration. Fertility qualifies since individuals enter the labor market one and a half to two decades after birth. We therefore use fertility rates in 1996 ($FERT96$), the start of our observation period, to account for fertility differentials between the countries. Changes in human capital endowment only gradually influence labor demand, so that we include one-period lagged human capital ($HC_{(t-1)}$). Similarly, growing import penetration might not have an immediate impact on employment growth since negative consequences on employment may be temporarily impeded through public funds. Employing one-period lagged imported intermediate inputs and other lagged covariates, Table A5 in the appendix re-estimates the baseline specifications. The results remain relatively stable with a significantly negative effect of $FERT96$ and a positive, but insignificant impact of human capital. While $III_{B(t-1)}$ becomes insignificant, this is not the case for the rough measure of import penetration ($III_{R(t-1)}$).

In a further step, we test whether the baseline results are robust to different measures of employment. Table A6 in the appendix provides the findings of the preferred baseline specification for different dependent variables implying a high robustness of the results. The impact of TFP , $Log(GDP_{pc})$, and $PUB.SOCEXP$ on employment remains negative and significant in most of the cases, while observing a positive and slightly significant effect of the import penetration measure for all specifications. The coefficient of HC is positive and highly significant only when using employment levels as dependent variables while it is positive, albeit insignificant for employment growth. The share of exports of raw materials on all merchandise exports is significantly positive for employment growth as dependent variable whereas a significant and negative relationship can be observed when using employment levels as endogenous variable. The latter could be due to the fact that the extraction of raw materials is highly mechanized, creating relatively few jobs compared to other sectors.

Yet the analysis focused on the aggregate impact of increasing import competition on manufacturing employment growth. Subsequently, the baseline specification is applied to imports from specific countries to quantify whether the effects of imported intermediates on employment growth differ by country of origin. Column (1) of Table 4 replicates the preferred model specification from Column (3) of Table 2 and serves as a reference category. All other columns in Table 4 use a similar model specification.

Column (2) investigates the specific impact of intermediates from China on employment prospects in the 12 OECD countries. The results point to a negative, though insignificant effect, leaving other covariates unchanged. The findings suggest that Chinese intermediate inputs are rather substitutes to domestic produc-

Table 4 Sensitivity analysis, import penetration measures from different countries of origin. Dependent variable is employment growth EMP_GR .

	(1)	(2)	(3)	(4)	(5)
TFP	-0.0168** (0.00740)	-0.0166** (0.00740)	-0.0171** (0.00742)	-0.0166** (0.00740)	-0.0165** (0.00741)
Log(GDP _{pc})	-0.0181*** (0.00516)	-0.0180*** (0.00514)	-0.0178*** (0.00514)	-0.0185*** (0.00519)	-0.0192*** (0.00538)
FERT	-0.0616*** (0.0127)	-0.0616*** (0.0127)	-0.0615*** (0.0126)	-0.0618*** (0.0127)	-0.0630*** (0.0129)
HC	0.0130 (0.0148)	0.0130 (0.0148)	0.0132 (0.0147)	0.0124 (0.0149)	0.0125 (0.0151)
PUB.SOCEXP	-0.00261*** (0.000777)	-0.00263*** (0.000775)	-0.00257*** (0.000773)	-0.00266*** (0.000778)	-0.00275*** (0.000795)
EMP96	0.00191 (0.00292)	0.00143 (0.00294)	0.00152 (0.00298)	0.00164 (0.00293)	0.00159 (0.00293)
RES_EXP	0.489*** (0.126)				
III _B	0.00191* (0.00109)				
RES_EXP ^{CHN}		-1.353*** (0.335)			
III _B ^{CHN}		-0.0824 (0.115)			
RES_EXP ^{BRIC}			0.239*** (0.0629)		
III _B ^{BRIC}			0.0222 (0.0209)		
RES_EXP ^{EU27}				0.750*** (0.188)	
III _B ^{EU27}				0.000378 (0.00282)	
RES_EXP ^{EU12}					0.401*** (0.100)
III _B ^{EU12}					-0.0252 (0.110)
N	1905	1905	1905	1905	1905
Time Dummies	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

tion in the highly developed economies. As III_B^{CHN} also includes export activities from OECD countries to China those may mitigate the negative impact on manufacturing employment growth. While a higher share of exports of raw materials generally fosters employment growth in the manufacturing sector, this cannot be observed with regard to exports from China. The reason might be that China is the only country in the analysis where the share of exports of raw materials has been declining during the observation period. The rise of manufacturing production in China has dramatically changed the structure of exports with increasing relevance on goods exports.

Column (3) examines the influence of imported intermediate inputs from the BRIC countries on manufacturing employment growth observing a positive but insignificant relationship. It appears that imported intermediates from Brazil or Russia are rather complements to manufacturing production in the developed economies, which is in contrast to Chinese imports, resulting in an insignificant overall effect. While imports from Brazil and Russia are to a large extent raw materials a positive and significant impact can be observed with respect to RES_EXP^{BRIC} . Therefore, it is crucial to distinguish between imports of raw materials which serve as prerequisite for manufacturing production and those that substitute for domestic production which is the case for most of the Chinese imports.⁶

The analysis has a special focus on European nations, with 10 in 12 of the countries at analysis being member of the European Union. For this reason, we investigate the role of the single European Market on employment prospects in the member countries. The results are shown in Column (4) indicating a positive but insignificant relationship between intermediate inputs from the EU-27 and employment growth in the OECD countries. The findings point to a positive influence of deeper economic integration within the EU. Additionally, we separately account for the role of the new EU member states (EU-12). As can be seen from Figure 2 and noted by Dauth et al. (2014), the EU-12 are highly relevant for some of the countries in the analysis, like e.g. Austria or Germany, where a non-trivial part of foreign inputs originates from Eastern Europe. Column (5) displays a negative but insignificant impact of intermediates from the EU-12 which do not foster employment growth in the OECD countries. Higher export shares of raw materials in the EU-12 as well as the EU-27 positively contribute to manufacturing employment growth. All other covariates remain robust across all specifications.

Thus far, the analysis describes the impact of imported intermediate inputs on employment growth for 12 OECD countries. Since the effects may differ across countries, Table A7 in the appendix provides mixed evidence of the influence of intermediates from China and the EU-12 on employment prospects in Germany, France, Spain, and Italy. While German and Italian manufacturing employment is not negatively affected

⁶Harding and Venables (2016) point to the different nature of revenues from natural resource exports and non-resource exports, indicating that a one dollar increase in revenues from resource exports leads to a decrease in non-resource exports revenues of three quarters of a dollar.

Table 5 Sensitivity analysis, 4-year averages and 2 periods (1996-2003, 2004-2011), import penetration measures from different countries of origin. Dependent variable is employment growth EMP_GR .

	4-year averages			2 periods		
	(1)	(2)	(3)	(4)	(5)	(6)
III_B	0.000792 (0.000915)			0.000207 (0.000857)		
III_B^{CHN}		0.0302 (0.115)			-0.00647 (0.130)	
III_B^{EU12}			-0.0930 (0.0746)			-0.213** (0.0942)
N	523	523	523	262	262	262
Time Dummies	Yes	Yes	Yes	No	No	No
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

by intermediate inputs from China or the EU-12, adverse effects can be observed for France and Spain. Imports from China and the new EU member states substitute for domestic manufacturing production in these countries, indicating that neither exports to China and the EU-12 nor a higher share of exports of raw materials can compensate for the employment losses.

The previous findings are estimated on a year-to-year basis, ignoring cyclical influences which may play a role for employment prospects. We therefore create 4-year averages, resulting in four observations of each country-sector combination which cover the following time periods: 1996-1999, 2000-2003, 2004-2007, and 2008-2011. Columns (1)–(3) of Table 5 display the results suggesting an insignificant relationship between imported intermediates and employment growth when accounting for time and sector dummies. For reasons of lucidity, we only report the results of the import penetration variable as the other covariates remain unchanged. In Columns (4)–(6) of Table 5 the time interval between 1996 and 2011 is split into two periods, 1996 to 2003 and 2004 to 2011. The main variable of interest (III_B) remains insignificant, indicating that imported intermediate inputs do not impede employment growth in the 12 OECD countries. When accounting for the country of origin of intermediate inputs, a negative though insignificant coefficient is obtained for inputs from China, while the relationship is significantly negative for intermediates from the EU-12. The results imply that the impact of imported intermediate inputs on manufacturing employment growth depends on the origin of the inputs.

4.3 Endogeneity

The robustness checks from Section 4.2 discard cyclical fluctuations and include several additional covariates in the estimation which we think may play a role in explaining employment prospects in manufacturing.

In general, we observe a slightly positive and partly significant impact of imported intermediate inputs on manufacturing employment growth which is fairly robust across the different specifications. However, the results are more nuanced when accounting for the intermediates' country of origin. Although we are convinced that our baseline estimation technique is the most promising approach for the analysis at hand, it is essential to explore whether the findings reveal a robust relationship regardless of the applied technique. A major empirical challenge in determining the causal effect of trade on employment is the presence of industry import demand shocks which may be correlated with realized imports raising issues of endogeneity (Autor et al. (2013), Dauth et al. (2014), and Bloom et al. (2016)). Manufacturing employment and imported intermediates may be correlated with unobserved shocks in product demand, misestimating the true impact of imported intermediate inputs on employment growth.

To avoid potential weaknesses which may arise due to endogeneity we employ an instrumental variable (IV) strategy, alleviating the problem of correlation between both variables. We apply two instruments for the import penetration measure which we suppose to be endogenous. In the first case, imported intermediate inputs are instrumented with the intermediates of all other 11 OECD countries in the analysis. This procedure is in line with suggestions by Autor et al. (2013) instrumenting Chinese imports to the United States with Chinese imports to eight other developed economies. However, this may not ultimately solve issues of endogeneity since supply and demand shocks in neighboring countries as well as other member states of the European Monetary Union are likely to be correlated with those in the country at hand (Dauth et al., 2014). Additionally, in highly integrated regions trade shocks which change trade flows between neighboring countries and China or the EU-12 may directly affect regional performance in the country at analysis, thus violating the exclusion restriction. As the sample includes 12 OECD countries, 10 of which are located in Europe, and the underlying database (WIOD) provides data on imported intermediate inputs for 40 countries, the instrument group allowing for the correlation and the exclusion restriction only consists of Australia. While trade flows of Australia with China or the BRIC nations are relevant instruments for the trade exposure of the 12 OECD countries, caution is advised with regard to trade flows with the new EU member states.

Table 6 reports results of two modifications of the baseline estimations for the three preferred import penetration measures. Columns (1)—(3) provide evidence of the OLS estimation which is often seen as a reference estimation strategy in the literature. The OLS results display an insignificant relationship between import penetration and manufacturing employment growth. However, caution is recommended when interpreting the results as OLS does not allow for the hierarchical structure of the data, ignoring the correlation of two observations of the same country-sector combination. Thus, OLS discards the information at the country and the sector level. Additionally, potential endogeneity may cause biased estimates which is why

Table 6 Regression with alternative estimation methods, different instrumental variables. Dependent variable is employment growth *EMP_GR*.

	OLS			IV-2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
III _R	-0.00156 (0.0129)			0.319*** (0.111)		
III _B		0.000551 (0.000649)			0.207 (0.320)	
III _N			-0.000530 (0.000542)			0.0201 (0.102)
N	1925	1905	1903	1925	1905	1903
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Columns (4)–(6) display the findings of the IV estimation where the instrumentation follows the concept of [Dauth et al. \(2014\)](#). The IV strategy does not adequately control for the hierarchical structure of the data either. The results confirm the findings of the baseline regressions in [Table 2](#) indicating a rather positive and partly significant impact of imported intermediate inputs on manufacturing employment growth. A Durbin-Wu-Hausman test and a [Wooldridge \(2010\)](#) test reject the null hypothesis of exogeneity in most cases which is why we rely on the IV results rather than the OLS estimates.

Moreover, we test whether additional covariates are endogenous and re-estimate the IV specification by instrumenting further variables. We instrument the development level and public social expenditures with a one-period lag obtaining $\text{Log}(GDP_{pc})_{(t-1)}$ and $PUB_SOCEXP_{(t-1)}$, respectively. The results do not change considerably supporting the robustness of the baseline results. In a next step, we split our endogenous variables into a cluster mean for a specific country-sector combination (MN_*) and the deviation from this cluster mean (DEV_*) and employ these variables as covariates in the estimation. The cluster mean variable represents the between effect of different country-sector combinations, whereas the deviation depicts the within effect, comparing two observations of the same country-sector combination. While all the cluster mean variables are insignificant the deviations from the cluster mean are significantly different from zero for $DEV_Log(GDP_{pc})$ and DEV_PUB_SOCEXP implying that country-sector combinations with a higher development level or higher levels of public social expenditures experience lower employment growth given the other covariates. The results also illustrate that most of the variation lies within a country-sector combination rather than between different countries and sectors.

Additionally, we account for the origin of the intermediate inputs and re-estimate the IV-2SLS specifications. Column (1) of [Table 7](#) is the exact replication of Column (5) from [Table 6](#) and serves as a reference

Table 7 IV-2SLS results for import penetration measures from different countries of origin. Dependent variable is employment growth EMP_GR . Instrumental variables are created according to [Dauth et al. \(2014\)](#).

	(1)	(2)	(3)	(4)	(5)
III_B	0.207 (0.320)				
III_B^{CHN}		-0.664* (0.347)			
III_B^{BRIC}			-1.164 (1.285)		
III_B^{EU27}				0.203* (0.114)	
III_B^{EU12}					-0.966* (0.561)
N	1905	1905	1905	1905	1905
Time Dummies	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

category. The results suggest different effects of import penetration on manufacturing employment growth depending on the country of origin. Chinese intermediates impede employment growth, supporting notions that inputs from China are substitutes to manufacturing production in the 12 OECD countries as promoted by [Autor et al. \(2013\)](#). This pattern cannot be observed for intermediates from the BRIC countries. Imports from nations other than China partly compensate for the employment losses which can be seen in Column (2), resulting in an overall insignificant effect. Column (5) indicates that higher import penetration from the EU-12 hampers manufacturing employment growth in the highly developed economies. In contrast, intermediate inputs from the EU-27 have a positive influence on employment growth in manufacturing. These findings illustrate that trade with the old members of the European Union (EU-15)⁷ overcompensates the negative employment impact from trade with the new member states (EU-12). Accordingly, while inputs from the EU-15 act as complements to manufacturing production, thereby increasing domestic manufacturing employment growth, intermediates from the EU-12 are rather substitutes to employment growth. The results are in line with those from Table 4, indicating a negative impact of inputs from China and the EU-12, while observing a slightly positive influence for III_B as well as intermediates from the EU-27.

Finally, we allow for cyclical fluctuations which may play a role in explaining employment prospects. Table 8 replicates the estimations from Table 5, now applying an IV strategy which accounts for endogeneity. Columns (1)–(3) use 4-year averages as described in Section 4.2, while Columns (4)–(6) split the sample

⁷The EU-15 comprises all members of the European Union, which gained accession before the enlargement of the EU in 2004.

Table 8 IV-2SLS estimations, 4-year averages and 2 periods (1996-2003, 2004-2011), import penetration measures from different countries of origin. Dependent variable is employment growth EMP_GR .

	4-year averages			2 periods		
	(1)	(2)	(3)	(4)	(5)	(6)
III_B	-0.00315 (0.0471)			-0.0289 (0.0899)		
III_B^{CHN}		-0.697** (0.306)			-0.491 (0.299)	
III_B^{EU12}			-1.296* (0.710)			-1.084 (0.826)
N	523	523	523	262	262	262
Time Dummies	Yes	Yes	Yes	No	No	No
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

into two periods, resulting in a strong reduction in the number of observations. The findings display an insignificant impact of III_B on manufacturing employment growth. However, a negative and significant relationship between intermediates and employment growth can be observed for inputs from China and the EU-12. The results are in line with those in Table 7 pointing to a substitutive impact of these intermediates on domestic manufacturing production. In Columns (4)–(6) the coefficients remain negative though slightly insignificant implying that the robustness of the trade-employment link to some extent depends on the country of origin, the measure of import penetration, and the model specification.

4.4 Residual diagnostics

In the following section some residual diagnostics should assess the model fit and the stability of our results. First, we want to address the question whether there is sufficient variation at the higher levels to justify the application of a multilevel mixed approach. Although likelihood-ratio tests underline the appropriateness of including random intercepts at the country and the industry level we partition the variance into its components to assess the level at which the variation occurs. A variance components model indicates that only 4 percent of the variation in employment growth stems from differences between countries. Another 9.3 percent of the variation appears at the sector level, while most of the variation, 86.7 percent, is explained by differences between observations within a country-sector combination. These results challenge the application of a three-level hierarchical model as the variation at the country level is below the rule of thumb of about 10 percent. The intraclass correlation of the model which is the correlation between two observations t and t' from the same country j and the same industry i is about 13.3 percent implying that only this share of the variation of EMP_GR can be attributed to country and sector-specific characteristics. However, as

likelihood-ratio tests argue in favor of the three-level hierarchical model we retain this specification.

The inclusion of a random intercept (ζ_j) at the country and the sector level allows to determine the random intercepts for each country and sector, respectively. Maximum-Likelihood estimation and empirical Bayes prediction provide two possibilities in doing so. While Maximum-Likelihood estimation treats ζ_j as a fixed parameter, it is treated as a random variable in the empirical Bayes prediction. Moreover, ML estimation uses the responses y_{ijt} for country j as the only information about ζ_j by maximizing the likelihood of observing these particular values (Rabe-Hesketh and Skrondal, 2012):

$$\text{Likelihood}(y_{i1t}, \dots, y_{i12t} | \zeta_j). \quad (10)$$

Empirical Bayes prediction also uses the prior distribution of ζ_j as additional information for predicting values of ζ_j before having seen the data. The prior distribution assumes a normal distribution for the random intercept with zero mean and estimated variance $\hat{\psi}$. Given the observed responses y_{i1t}, \dots, y_{i12t} , we can then combine the prior distribution with the likelihood to obtain the posterior distribution of ζ_j leading to

$$\text{Posterior}(\zeta_j | y_{i1t}, \dots, y_{i12t}) \propto \text{Prior}(\zeta_j) \times \text{Likelihood}(y_{i1t}, \dots, y_{i12t} | \zeta_j) \quad (11)$$

where the posterior distribution of ζ_j represents the updated knowledge of the random intercept after having seen the data.

Figure 6 plots empirical Bayes predictions for random intercepts at the country and the sector level as well as the level-1 residuals at the time level. As the random intercepts at the different levels and the level-1 residuals are all on the same scale, one can observe that there is much more variability within countries and sectors than between them, challenging the three-level hierarchical model. As emphasized by Rabe-Hesketh and Skrondal (2012), the prediction error of the empirical Bayes prediction has zero mean over repeated samples of ζ_j and ϵ_{ijt} when model parameters are treated as fixed and known. Moreover, empirical Bayes predictions also have the smallest possible variance for given model parameters, making them the best linear unbiased predictor (BLUP) in linear models.

Table 9 displays the empirical Bayes predictions for the country-specific ($\zeta_j^{(3)}$) and the sector-specific ($\zeta_{ij}^{(2)}$) random effects for a generic subset of our sample, including 5 countries and 4 sectors. Column ($\zeta_j^{(3)}$) depicts the country-specific differences in manufacturing employment growth. While the United States and Great Britain exhibit a country-specific downward deviation of the population mean, the opposite can be observed for Germany. However, the country-specific deviations from the population mean are moderate, ranging from -.014 for Great Britain to .010 for Italy. The differences concerning the sector-specific random effects are somewhat larger, ranging from -.038 in the British textiles sector to .023 in the Swedish coke and refined

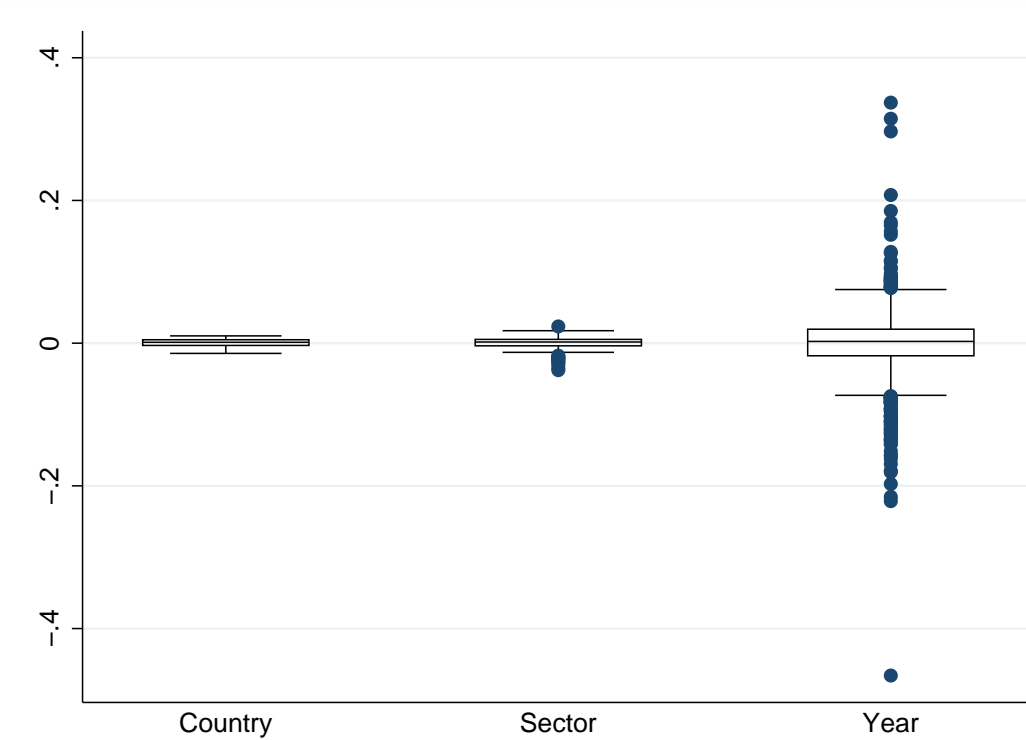


Figure 6 Box plots of empirical Bayes predictions for random intercepts at the country and the sector level, and level-1 residuals at the time level.

petroleum products sector. Employment growth generally underperforms in the textiles sector, resulting in a negative sector-specific random intercept in each country of the analysis. Other sectors, e.g. food, beverages and tobacco or machinery and equipment, usually outperform with regard to the sector-specific mean.

Figure 7 illustrates the empirical Bayes predictions for the random effects at the country (level-3) and the sector (level-2) level as well as the predicted level-1 residuals. Each figure includes a normal sampling distribution being assumed in linear mixed models. The distribution for the predicted level-1 residuals (ϵ_{ijt}) seems to be leptokurtic since the peak of the distribution is higher than expected for a normal distribution. The distribution of the predicted level-2 random intercepts ($\zeta_{ij}^{(2)}$) shows signs of left skewness while a Jarque-Bera test rejects the null of normality. The predicted country-level random effects ($\zeta_j^{(3)}$) do not follow a normal distribution either although a Jarque-Bera test does not reject the null hypothesis. However, this may be due to the low number of 12 observations at the country level, while the test is only valid asymptotically, relying on a large sample size. As normality cannot generally be assured, it may be useful to employ robust standard errors that do not rely on the model being correctly specified. As REML is not supported with robust variance estimation, ML estimations allow for robust standard errors (see Table A4 in the appendix).

In a further robustness check, we re-estimate the baseline specification without a country-level random intercept since only a small part of the variation of *EMP.GR* stems from this level. The subsequent model

Table 9 Empirical Bayes predictions for random intercepts at the country ($\zeta_j^{(3)}$) and sector ($\zeta_{ij}^{(2)}$) level for selected countries and sectors.

Country	Sector	$\zeta_j^{(3)}$	$\zeta_{ij}^{(2)}$
JPN	Food products, beverages and tobacco	-.0003729	.0091451
JPN	Textiles, wearing apparel, leather and related prodcuts	-.0003729	-.0270934
JPN	Machinery and equipment n.e.c.	-.0003729	.0098785
JPN	Transport equipment	-.0003729	.0162428
USA	Food products, beverages and tobacco	-.0126817	.0105832
USA	Textiles, wearing apparel, leather and related prodcuts	-.0126817	-.0349687
USA	Machinery and equipment n.e.c.	-.0126817	.0005279
USA	Transport equipment	-.0126817	.000204
GBR	Food products, beverages and tobacco	-.0143465	.0093932
GBR	Textiles, wearing apparel, leather and related prodcuts	-.0143465	-.0378379
GBR	Machinery and equipment n.e.c.	-.0143465	-.0120717
GBR	Transport equipment	-.0143465	.0080854
DEU	Food products, beverages and tobacco	.005646	.0128722
DEU	Textiles, wearing apparel, leather and related prodcuts	.005646	-.0225406
DEU	Machinery and equipment n.e.c.	.005646	.0088118
DEU	Transport equipment	.005646	.0112581
ESP	Food products, beverages and tobacco	.0006859	.0035219
ESP	Textiles, wearing apparel, leather and related prodcuts	.0006859	-.0198551
ESP	Machinery and equipment n.e.c.	.0006859	.0053966
ESP	Transport equipment	.0006859	-.0053132

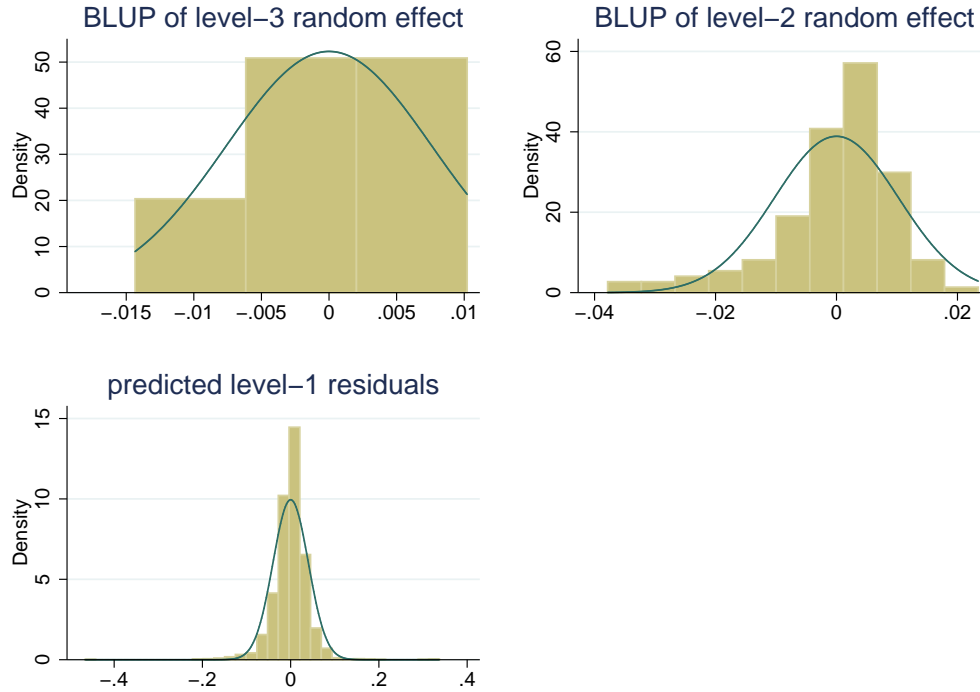


Figure 7 Best linear unbiased predictions for random intercepts at the country and the sector level, and level-1 residuals at the time level.

Table 10 Two-level mixed estimations. Dependent variable is employment growth *EMP_GR*.

	(1)	(2)	(3)	(4)
level-2 random intercept:	SECTOR	COUSEC	SECTOR	COUSEC
TFP	-0.0172** (0.00735)	-0.0164** (0.00749)	-0.0172*** (0.00626)	-0.0165 (0.0126)
Log(GDP _{pc})	-0.0658*** (0.0120)	-0.0658*** (0.0119)	-0.0658*** (0.0116)	-0.0658*** (0.0186)
FERT	-0.0849*** (0.0159)	-0.0850*** (0.0157)	-0.0849*** (0.0165)	-0.0850*** (0.0209)
HC	-0.0195 (0.0190)	-0.0193 (0.0188)	-0.0195* (0.0100)	-0.0193 (0.0229)
PUB_SOCEXP	-0.00388*** (0.000903)	-0.00388*** (0.000893)	-0.00388*** (0.000608)	-0.00388*** (0.00115)
III _B	0.00185* (0.00104)	0.00183 (0.00116)	0.00185** (0.000845)	0.00185** (0.000757)
RES_EXP	0.548*** (0.138)	0.547*** (0.136)	0.548*** (0.196)	0.547*** (0.207)
EMP96	-0.000676 (0.00225)	-0.000268 (0.00163)	-0.000666 (0.00261)	-0.000268 (0.00167)
N	1905	1905	1905	1905
Time Dummies	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *EMP_GR* includes grouped country-sector combinations. Columns (3) and (4) apply ordinary ML estimations and include robust standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

consists of two hierarchical levels with observation periods as level-1 and industries as level-2 while using country dummies to account for differences between countries. Column (1) of Table 10 provides results indicating that the main findings remain unchanged. While imported intermediate inputs foster manufacturing employment growth in the 12 OECD countries the technology variable (*TFP*) exerts a significantly negative influence on employment prospects. Column (2) alters the level-2 random intercept of the hierarchical model employing a newly created variable which groups the country and the sector level (*COUSEC*). The results remain robust, though *III_B* becomes insignificant. However, the grouped country-sector variable does not account for the correlation between country-sector combinations as different industries from one country are treated as independent from one another. This assumption is unrealistic as the Swedish textiles sector is not uncorrelated with the Swedish transportation equipment sector as they share the same country.

Columns (3)–(4) of Table 10 do not use REML, but apply a ML estimation to the two-level hierarchical model including robust standard errors. Column (3) employs the same specification as Column (1), while Column (4) employs *COUSEC* as level-2 random intercept. The findings are similar to those of Columns

(1)—(2) and the baseline results indicating a positive and weakly significant link between import penetration and manufacturing employment growth. Yet the underlying problems concerning the two-level approaches and the likelihood-ratio tests being in favor of a three-level hierarchical model support the choice of the model specification as in the baseline estimation.

5 Conclusion

A vigorous political debate about the role of globalization on labor market outcomes is in progress. The present paper investigates the link between growing import penetration and manufacturing employment growth in 12 OECD countries. Combining a variety of macroeconomic indicators from multiple recently collected datasets that allow to assess the relationship on a two-digit level between 1995 and 2011, the findings point to a positive and weakly significant impact of imported intermediate inputs on employment growth in the manufacturing sector which is robust to various model specifications and alternate estimation strategies. This is also true for different import penetration measures which in some cases account for the export activities of the OECD countries.

Additionally, we disaggregate the imported intermediates according to their country of origin and determine the impact of growing trade with particular countries on manufacturing employment growth. The results support previous findings that increasing import penetration from China exerts a significantly negative influence on employment growth in most specifications. A similar pattern can be observed for inputs from the new EU member states (EU-12) encouraging the view that imports from China or the EU-12 are substitutes to domestic manufacturing production. In contrast, intermediates from the EU-27 appear to act as complements, thereby fostering employment growth in highly developed nations. Thus, whether imported intermediate inputs are conducive or detrimental to manufacturing employment growth in the OECD countries depends on the country of origin.

The analysis allows for the specific impact of the country and the sector level employing a three-level mixed model. While variation at both levels is rather low, a likelihood-ratio test rejects the null that a random intercept at the country and the sector level is 0. When determining the random part of the model, differences in the country and sector-specific random intercepts are moderate with employment growth being relatively weak in the United Kingdom and the United States as well as the textiles sector. Otherwise, employment growth outperforms in the food, beverages and tobacco sector as well as Germany and Italy. The study accounts for potential endogeneity, providing evidence of a positive and partly significant impact of imported intermediates on employment prospects in manufacturing, underlining the stability of the baseline results. The findings are more nuanced when controlling for the origin of the inputs.

This article offers a cross-nationally comparable analysis of the effect of growing import penetration on manufacturing employment growth in 12 OECD countries. The results indicate that there are different channels how trade affects manufacturing employment, illustrating the highly ambiguous attitudes toward globalization. To achieve a more comprehensive view on the trade-employment-nexus from a macroeconomic perspective future research should focus on the enlargement of the sample. Prospective studies may also extend this research question to the services sector, which becomes ever stronger interconnected with manufacturing and whose products are increasingly tradable. This may help to fully assess how countries adjust to growing international trade.

References

- Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review*, 103(6):2121—2168. 6, 13, 26, 28
- Autor, D. H., Dorn, D., and Hanson, G. H. (2015). Untangling trade and technology: Evidence from local labour markets. *The Economic Journal*, 125(584):621—646. 2, 3, 5
- Autor, D. H., Katz, L. F., and Krueger, A. B. (1998). Computing inequality: Have computers changed the labor market? *Quarterly Journal of Economics*, 113(4):1169—1213. 5
- Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, 118(4):1279—1333. 5
- Barro, R. J. and Lee, J. W. (2013). A new data set of educational attainment in the world, 1950–2010. *Journal of Development Economics*, 104:184—198. 12
- Baumgarten, D., Geishecker, I., and Görg, H. (2013). Offshoring, tasks, and the skill-wage pattern. *European Economic Review*, 61:132—152. 5
- Becker, S. O., Ekholm, K., and Muendler, M.-A. (2013). Offshoring and the onshore composition of tasks and skills. *Journal of International Economics*, 90(1):91—106. 5
- Berman, E., Bound, J., and Griliches, Z. (1994). Changes in the demand for skilled labor within U.S. manufacturing: Evidence from the annual survey of manufacturers. *Quarterly Journal of Economics*, 109(2):367—397. 2, 5
- Bernard, A. B., Jensen, J. B., and Schott, P. K. (2006). Survival of the best fit: Exposure to low-wage countries and the (uneven) growth of U.S. manufacturing plants. *Journal of International Economics*, 68(1):219—237. 6
- Blinder, A. S. and Krueger, A. B. (2013). Alternative measures of offshorability: A survey approach. *Journal of Labor Economics*, 31(2):S97—S128. 5
- Bloom, N., Draca, M., and Van Reenen, J. (2016). Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity. *The Review of Economic Studies*, 83(1):87—117. 5, 6, 13, 26
- Crinò, R. (2009). Offshoring, multinationals and labour market: A review of the empirical literature. *Journal of Economic Surveys*, 23(2):197—249. 21
- Dauth, W., Findeisen, S., and Suedekum, J. (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—1675. 6, 13, 17, 24, 26, 27, 28

- Ebenstein, A., Harrison, A., McMillan, M., and Phillips, S. (2014). Estimating the impact of trade and offshoring on American workers using the Current Population Surveys. *Review of Economics and Statistics*, 96(4):581—595. 5
- Falk, M. and Koebel, B. (2002). Outsourcing, imports and labour demand. *Scandinavian Journal of Economics*, 104(4):567—586. 5
- Feenstra, R. C. and Hanson, G. H. (1996). Globalization, outsourcing, and wage inequality. *American Economic Review*, 86(2):240—245. 5
- Feenstra, R. C. and Hanson, G. H. (1999). The impact of outsourcing and high-technology capital on wages: Estimates for the United States. *Quarterly Journal of Economics*, 114(3):907—940. 8
- Feenstra, R. C., Inklaar, R., and Timmer, M. P. (2015). The next generation of the Penn World Table. *American Economic Review*, 105(10):3150—82. 12
- Geishecker, I. (2006). Does outsourcing to Central and Eastern Europe really threaten manual workers jobs in Germany? *World Economy*, 29(5):559—583. 5
- Greene, W. H. (2012). *Econometric Analysis*. Pearson, Boston et al., 7th edition. 16
- Grossman, G. M. and Rossi-Hansberg, E. (2008). Trading tasks: A simple theory of offshoring. *American Economic Review*, 98(5):1978—97. 8
- Harding, T. and Venables, J. A. (2016). The implications of natural resource exports for nonresource trade. *IMF Economic Review*, 64(2):268—302. 24
- Harrison, A. and McMillan, M. (2011). Offshoring jobs? Multinationals and U.S. manufacturing employment. *Review of Economics and Statistics*, 93(3):857—875. 5
- Head, K. and Ries, J. (2002). Offshore production and skill upgrading by Japanese manufacturing firms. *Journal of International Economics*, 58(1):81—105. 5
- Hsieh, C.-T. and Woo, K. T. (2005). The impact of outsourcing to China on Hong Kong’s labor market. *American Economic Review*, 95(5):1673—1687. 5
- Katz, L. and Autor, D. (1999). Changes in the wage structure and earnings inequality. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*, volume 3, Part A, pages 1463—1555. Elsevier. 2
- Kleinert, J. (2003). Growing trade in intermediate goods: Outsourcing, global sourcing, or increasing importance of MNE networks? *Review of International Economics*, 11(3):464—482. 7
- Machin, S. and Van Reenen, J. (1998). Technology and changes in skill structure: Evidence from seven OECD countries. *Quarterly Journal of Economics*, 113(4):1215—1244. 2
- Marin, D. (2011). The opening up of Eastern Europe at 20: Jobs, skills and reverse maquiladoras in Austria and Germany. In Jovanović, M., editor, *International Handbook on the Economics of Integration*, volume II, pages 296—323. Edward Elgar Publishing. 5
- Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6):1695—1725. 7
- Morrison Paul, C. J. and Siegel, D. S. (2001). The impacts of technology, trade and outsourcing on employment and labor composition. *Scandinavian Journal of Economics*, 103(2):241—264. 5
- O’Mahony, M. and Timmer, M. P. (2009). Output, input and productivity measures at the industry level: The EU KLEMS database. *The Economic Journal*, 119(538):F374—F403. 12
- Rabe-Hesketh, S. and Skrondal, A. (2012). *Multilevel and Longitudinal Modeling Using Stata*. StataCorp LP, College Station, 3rd edition. 15, 30

- Revenge, A. L. (1992). Exporting jobs? the impact of import competition on employment and wages in U.S. manufacturing. *Quarterly Journal of Economics*, 107(1):255—284. [6](#)
- Snijders, T. A. and Bosker, R. J. (2012). *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*. SAGE, London and Thousand Oaks. [16](#)
- Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of Labor Economics*, 24(2):235—270. [5](#)
- Stolper, W. F. and Samuelson, P. A. (1941). Protection and real wages. *The Review of Economic Studies*, 9(1):58—73. [8](#)
- Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R., and de Vries, G. J. (2015). An illustrated user guide to the World Input-Output Database: The case of global automotive production. *Review of International Economics*, 23(3):575—605. [3](#), [9](#), [12](#)
- Timmer, M. P., Los, B., Stehrer, R., and de Vries, G. J. (2013). Fragmentation, incomes and jobs: An analysis of European competitiveness. *Economic Policy*, 28(76):613—661. [3](#)
- Tolbert, C. M. and Sizer, M. (1996). US commuting zones and labor market areas: A 1990 update. Staff Paper 9614, Economic Research Service. [6](#)
- Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, Mass. and London. [16](#), [27](#)
- World Bank (2014). *World Development Indicators (WDI)*. The World Bank, Washington D.C. [12](#)

Appendix

Table A1 Country labels

ID	Country	Country Label
1	Sweden	SWE
2	Finland	FIN
3	Belgium	BEL
4	Japan	JPN
5	United States	USA
6	Netherlands	NLD
7	United Kingdom	GBR
8	Germany	DEU
9	Italy	ITA
10	Austria	AUT
11	France	FRA
12	Spain	ESP

Table A2 Sector labels

SEC ID	Sector	Sector Label
5	Food products, beverages and tobacco	Food
6	Textiles, wearing apparel, leather and related products	Text
7	Wood and paper products; printing and reproduction of recorded media	Wood
8	Coke and refined petroleum products	Coke
9	Chemicals and chemical products	Chem
10	Rubber and plastics products, and other non-metallic mineral products	RPP
11	Basic metals and fabricated metal products, except machinery and equipment	BM
12	Electrical and optical equipment	Elec
13	Machinery and equipment n.e.c.	Mach
14	Transport equipment	Transp
15	Other manufacturing; repair and installation of machinery and equipment	Oth
40	Total manufacturing	Total

Table A3 Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
ID	6.5	3.453	1	12	2244
SEC_ID	10	3.163	5	15	2244
YEAR	2003	4.9	1995	2011	2244
EMP_GR	-0.018	0.044	-0.459	0.322	2024
TFP	0.019	0.121	-0.857	2.042	2057
Log(GDP _{pc})	13.754	1.253	11.717	16.412	2244
FERT	1.606	0.259	1.16	2.12	2244
HC	2.993	0.251	2.597	3.619	2244
PUB.SOCEXP	24.103	4.592	14.077	32.391	2233
III _B	0.654	0.995	-5.176	12.229	2222
RES_EXP	0.152	0.026	0.11	0.194	2244
EMP96	5.15	1.559	1.053	7.997	2244
III _R	0.315	0.18	0.022	0.981	2244
III _N	0.223	1.076	-9.027	9.842	2219
TFP×III _B	0.008	0.17	-3.456	5.676	2244
CAS _(t-1)	1.225	3.893	-9.676	9.343	1914
HS96	0.143	0.065	0.033	0.402	2244
EPL	2.122	0.74	0.26	2.88	2244
III _B ^{CHN}	0.011	0.014	0	0.111	2244
III _B ^{BRIC}	0.035	0.063	0.003	0.723	2244
III _B ^{EU27}	0.329	0.708	-23.799	8.73	2244
III _B ^{EU12}	0.016	0.024	0	0.595	2244
MANUF96	0.201	0.037	0.15	0.289	2244
RES_EXP×III _B	0.129	1.231	-23.803	47.285	2244
RES_EXP ^{CHN}	0.044	0.009	0.029	0.059	2244
RES_EXP ^{BRIC}	0.244	0.049	0.178	0.318	2112
RES_EXP ^{EU27}	0.068	0.016	0.048	0.101	2244
RES_EXP ^{EU12}	0.103	0.024	0.071	0.168	2244

Table A4 Baseline regressions. Dependent variable is employment growth *EMP_GR*.

	(1)	(2)	(3)	(4)	(5)
TFP	-0.0179 (0.0166)	-0.0179 (0.0165)	-0.0173 (0.0163)	-0.0175 (0.0166)	-0.0172 (0.0163)
EMP96	-0.00206 (0.00209)	0.00201 (0.00340)	0.00195 (0.00358)	0.00342 (0.00384)	0.00211 (0.00356)
III _B	0.00194 (0.00147)	0.00173 (0.00145)	0.00187 (0.00140)		
Log(GDP _{pc})		-0.00746* (0.00418)	-0.0115** (0.00497)	-0.0121** (0.00562)	-0.0105** (0.00460)
FERT		-0.0368*** (0.00917)	-0.0454*** (0.0154)	-0.0472*** (0.0170)	-0.0395*** (0.0128)
HC		0.0145 (0.0142)	0.0152 (0.0190)	0.0130 (0.0208)	0.0144 (0.0169)
PUB_SOCEXP			-0.00138 (0.00114)	-0.00167 (0.00120)	-0.000931 (0.000978)
RES_EXP			0.430 (0.333)	0.427 (0.323)	0.426 (0.349)
III _R				0.0322 (0.0286)	
III _N					-0.000104 (0.000447)
N	1905	1905	1905	1925	1903
Time Dummies	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5 Baseline regressions. Dependent variable is employment growth EMP_GR .

	(1)	(2)	(3)	(4)	(5)
TFP	-0.0176** (0.00746)	-0.0178** (0.00746)	-0.0175** (0.00745)	-0.0171** (0.00740)	-0.0174** (0.00745)
EMP96	-0.00251 (0.00184)	0.00291 (0.00285)	0.00280 (0.00289)	0.00469 (0.00303)	0.00314 (0.00289)
$III_{B(t-1)}$	-0.0000272 (0.000193)	-0.0000194 (0.000193)	-0.0000194 (0.000192)		
$\text{Log}(\text{GDP}_{pc})$		-0.00857*** (0.00329)	-0.0109*** (0.00376)	-0.0115*** (0.00408)	-0.0108*** (0.00369)
FERT96		-0.0297*** (0.00985)	-0.0297** (0.0123)	-0.0283* (0.0148)	-0.0293** (0.0118)
$HC_{(t-1)}$		0.0125 (0.00931)	0.0118 (0.0110)	0.00949 (0.0123)	0.0118 (0.0107)
PUB_SOCEXP			-0.000846 (0.000593)	-0.00115* (0.000646)	-0.000740 (0.000578)
RES_EXP			0.313*** (0.118)	0.293** (0.118)	0.315*** (0.118)
$III_{R(t-1)}$				0.0353** (0.0145)	
$III_{N(t-1)}$					0.00000362 (0.0000304)
N	1905	1905	1905	1925	1903
Time Dummies	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6 Baseline regressions, different dependent variables.

	(1)	(2)	(3)	(4)	(5)	(6)
TFP	-0.0168** (0.00740)	-0.0171** (0.00740)	-0.0174** (0.00723)	-0.0302 (0.0211)	-0.000314** (0.000128)	-0.000471** (0.000194)
Log(GDP _{pc})	-0.0181*** (0.00516)	-0.0146*** (0.00449)	-0.0124*** (0.00384)	-0.0763** (0.0303)	-0.000621*** (0.000162)	-0.00141*** (0.000247)
FERT	-0.0616*** (0.0127)	-0.0360*** (0.0114)	-0.0350*** (0.00939)	0.0800** (0.0406)	-0.0000737 (0.000243)	-0.000772** (0.000369)
HC	0.0130 (0.0148)	0.00729 (0.0134)	0.0194* (0.0109)	0.137*** (0.0484)	0.000839*** (0.000286)	0.00194*** (0.000435)
PUB_SOCEXP	-0.00261*** (0.000777)	-0.00223*** (0.000717)	-0.000481 (0.000577)	-0.0138*** (0.00213)	-0.000119*** (0.0000128)	-0.000148*** (0.0000195)
III _B	0.00191* (0.00109)	0.00199* (0.00109)	0.00190* (0.00104)	0.00614* (0.00343)	0.0000510** (0.0000208)	0.0000722** (0.0000316)
EMP96	0.00191 (0.00292)	0.00208 (0.00292)	0.00329 (0.00286)			
RES_EXP	0.489*** (0.126)	0.446*** (0.123)	0.164* (0.0960)	-2.947*** (0.291)	-0.0209*** (0.00175)	-0.0328*** (0.00267)
N	1905	1905	2015	2037	2037	2037
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. The dependent variables are as follows: *EMP_GR* in Column (1), growth of total employment in Column (2), growth of the employment-to-population ratio in Column (3), the logarithm of total employment in Column (4), the employment-to-population ratio in Column (5), and the employment-to-working age population ratio in Column (6). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7 Sensitivity analysis for single countries, different import penetration measures. Dependent variable is employment growth *EMP_GR*.

	DEU	FRA	ESP	ITA	DEU	FRA	ESP	ITA
III _B ^{CHN}	0.217 (0.207)	-1.427*** (0.538)	-1.722*** (0.583)	-0.630 (0.724)				
III _B ^{EU12}					-0.0798 (0.243)	-1.692** (0.799)	-1.276* (0.657)	0.216 (0.661)
N	154	154	154	154	154	154	154	154

Notes: Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$