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Abstract

This paper investigates the trade migration link within a Ricardian model à la Eaton and Kortum (2002) and it quantifies the pro-trade effects of immigrants for 18 manufacturing sectors in a sample of 19 OECD countries. The results are robust across different econometric specifications and they indicate *pulp, paper, paper products, printing and publishing* as the sector where immigration has the greatest impact on trade. The analysis shows that accounting for ethnic networks in the trade share equation has important implications for the estimation of trade cost elasticity parameter across all manufacturing sectors. By following a two-step approach to estimate trade cost elasticity at sector level where θ is proportional to the effect of wages on exporter fixed effects, I find that in *total manufacturing* θ decreases by 1.03 when ethnic networks are included among the determinants of trade. This drop of trade cost elasticity approximately corresponds - on average - to a welfare gain of 4.16% of national income.

Classificazione JEL: F10, F11, F14, F22
Keywords: *migration; trade cost elasticity; gravity model; trade share equation*

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Contents

I. Introduction

The importance of ethnic networks in reducing information costs is more relevant for more differentiated rather than for homogeneous goods. This rather intuitive statement has been tested empirically mostly by dividing the spectrum of traded goods into three broad subclasses that differ with respect to the degree of differentiation according to Rauch (1999) classification.[1] By running a gravity model separately for each aggregated group, Rauch and Trindade (2002) estimate separate elasticities of trade with respect to immigrant stocks for differentiated goods, goods traded on organized exchanges, and goods that display some reference price. However, as argued by Anderson (2011) and Anderson and Wincoop (2004), these elasticities are likely to vary across sectors: the ability of migrant-based networks to help overcoming informal trade barriers may be more effective in *textiles* rather than *chemicals*; immigrants may derive relatively higher utility in purchasing from their native countries *food products* rather than *basic metals*. The three macro categories proposed by Rauch (1999) are way too large - and therefore inadequate - to capture the sectoral variability of the pro-trade effect of immigrants.

The first part of this paper addresses this issue by estimating the elaticity of trade flows with respect to the stock of immigrants for 18 ISIC Rev.3 manufacturing sectors in a sample of 19 OECD countries.[2] I assume that in a context where trade is disaggregated at industry level, the pro-trade effect of immigrants for industry k not only depends on bilateral stock of immigrants employed in sector k, but rather on the overall bilateral stock of immigrants. The results show that the elasticity of trade flows with respect to immigrant stocks depends largely on sector's characteristics and they indicate *pulp, paper, paper products, printing and publishing* as the industry where migrants-based networks have the greatest impact on trade.

The gravity equation which incorporates the total number of immigrants as trade determinant is derived from a supply-side perfect competition Ricardian model of trade à la Eaton and Kortum (2002) (henceforth EK) where I extend Fieler (2011) to characterize the demand side. I let the number of types of goods to coincide with the number of sectors in the economy: this assumption allows to treat different levels of hetero-

[1]Peri and Requena-Silvente (2010) use Broda and Weinstein (2006) classification to characterize the degree of differentiability of traded products according to their elasticity of substitution across varieties. Althogh Peri and Requena-Silvente (2010) use a different classification of goods to characterize the degree of differentiability of products, they follow the same procedure of grouping these products into three broad categories: highly differentiated, moderately differentiated and less differentiated

[2]The first paper to show empirically the variability of the pro-trade effect of migrants at sector level is Tai (2009) who studies the trade migration link within a monopolistic competition multisector economy. However, in Tai (2009) the sectoral migration effect on trade largely depends on the (proxies of) elasticity of substitution parameters. The use of proxies for σ may create distortions in the resulting migration impact on trade. Tai (2009) focuses on the case of Switzerland and it uses sector level elasticities of substitution based on the United States elasticities estimated by Broda and Weinstein (2006): the choice of US values of σ is motivated by the lack of data on the elasticities of substitution for each country and by the country's representability in the world economy

geneity across goods in the model at a sufficiently small level of aggregation. In this framework I also develop an alternative two-step methodology to estimate trade cost elasticity at sector level which builds on the EK trade share approach. Other than estimating θ at sector level and comparing the outcomes with the benchmark results of EK and Caliendo and Parro (2011), this methodology allows to measure the impact of migrants-based networks on trade cost elasticity, which is the other main contribution of this paper. The results show that accounting for ethnic networks in the first step has a significant negative impact on trade cost elasticity parameter: in total manufacturing, θ decreases by 1.03 when migration is included among the determinants of trade. Since - as argued by Arkolakis et al. (2012) and Costinot and Rodriguez-Clare (2013) - θ is the fundamental statistic needed to conduct welfare analysis, including or not a proxy for migrant-based networks into a gravity specification has dramatic implications also on the resulting gains from trade.

The paper is organized as follows. Section II.A. outlines the model whereas section II.B. describes how the migration channel enters the final supply-side gravity expression. Sections III.A. and III.B. illustrate some key definitions useful for a better understanding of the model, the data needed for the estimations and the resulting econometric specifications. Section IV. describes the results and section V. summarizes my findings.

II. The model

II.A. Extension of Fieler (2011)

The model builds on the Ricardian setup of Eaton and Kortum (2002) and follows Fieler (2011) to characterize the demand side. On the supply side the setup reduces to the Ricardian EK framework: labor is the unique factor of production, markets are perfectly competitive and the source of comparative advantage lies in countries differential access to technology, so that efficiency varies across countries and industries. On the demand side I depart from the standard EK model by abandoning the homothetic preferences assumption with constant elasticity of substitution as in Fieler (2011). Based on the evidence that the income elasticity of demand varies across goods and that this variation is economically significant, Fieler (2011) divides goods into two types (A and B) which may differ in demand and technology. I extend Fieler (2011) by including a higher number of types: I assume that the number of types (and the correspondent elasticities of substitution) will coincide to the number of industries in the economy.[3] This assumption allows (i) to treat different levels of heterogeneity across goods in the model at a sufficiently small level of aggregation and (ii) to estimate trade cost elasticity at sector level.[4] Without loss of generality I consider a multisector economy where each industry k of country i produces a continuum of goods $j_k \in [0,1]$ with productivity $z_i(j_k)$. All consumers in the world choose the quantities of goods $j_k, (Q(j_k))_{j_k \in [0,1]}$ to maximize the same utility function

$$U_n = \sum_{k=1}^{K} \left\{ \frac{\sigma_k}{\sigma_k - 1} \left[\int_0^1 Q(j_k)^{\frac{(\sigma_k - 1)}{\sigma_k}} dj_k \right] \right\}, \tag{1}$$

where σ_k is the elasticity of substitution across goods within the same industry and the income elasticity of demand for those goods. The country i's productivity in industry k is a realization of a random variable (drawn independently for each j_k) from its specific Fréchet probability distribution $F_i(j_k) = \exp^{-T_i z^{-\theta_k}}$, where $\theta_k > 1$ and $T_i > 0$. The industry specific parameter θ_k governs comparative advantage within industries and it is common across countries. As Fieler (2011) points out, the Fréchet distribution gives a dual role to type or industry specific trade elasticity θ_k. First, the variability of technology across commodities governs comparative advantage within industries. A smaller θ_k, indicating more heterogeneity across goods within industry k (hence a greater dispersion in price distribution) exerts a stronger force for trade against the

[3] Broda and Weinstein (2006) estimate the elasticities of substitution for each available category at the same level of aggregation, and describe their behavior across SITC industries. By disaggregating at 3 digit level they end up with 256 categories with the correspondent values of sigma.

[4] Given the ample evidence of significant variation in the trade elasticity across sectors, Costinot and Rodriguez-Clare (2013) argue that a natural way to incorporate formally the heterogeneity in trade elasticities across sectors is to write down multiple-sector models.

resistance imposed by the geographic barriers d_{ni}. Trade is more intense where θ_k is small. Second, the variability of labor efficiencies across countries governs comparative advantage across industries.
T_i governs the location of the distribution and it reflects country i's absolute advantage: a bigger T_i indicates that a higher efficiency draw for any good j is more likely. As in Fieler (2011) I assume that T_i does not depend on type-industry k, which implies that a country that is generally efficient at making goods in one industry is also efficient at making goods in all industries. I follow EK by treating the cost of a bundle of inputs as the same across commodities (and therefore industries) within a country.[5] They denote input cost in country i as c_i, which is defined as follows:

$$c_i = w_i^{\beta} p_i^{1-\beta} \tag{2}$$

Since it's a Cobb-Douglas-type cost function β stands for the constant labor share; w_i is wage in country i, while p_i is the overall price index of intermediates in country i. Having drawn a particular productivity level, the cost of producing a unit of good j in country i in industry k is then $\frac{c_i}{z_i(j_k)}$. The Samuelson iceberg assumption implies that shipping the good from country i to country n requires a per-unit iceberg trade cost of $d_{ni} > 1$ for $n \neq i$, with $d_{ii} = 1$. It is assumed that cross-border arbitrage forces effective geographic barriers to obey the triangle inequality: for any three countries i , h , and n, $d_{ni} \leq d_{nh} d_{hi}$. With the assumption of perfect competition and triangle inequality, the price of a good imported from country i into country n is the unit production cost multiplied by the geographic barriers:

$$p_{ni}(j_k) = \frac{d_{ni} c_i}{z_i(j_k)} = \frac{d_{ni} w_i^{\beta} p_i^{1-\beta}}{z_i(j_k)} \tag{3}$$

Substituting equation (3) into the distribution of efficiency $F_i(j_k)$ implies that country i presents country n with a distribution of prices $G_{ni}(p_k) = 1 - \exp^{-\left[T_i (d_{ni} c_i)^{-\theta_k}\right] p_k^{\theta_k}}$. Since the Ricardian assumptions imply that country i will search for the better deal around the world (pricing rule), the price of good j will be $p_{n,k}(j) = min\left[p_{ni,k}(j); i = 1, ..., N\right]$ i.e. the lowest across all countries i. Following EK the pricing rule and the productivity distribution give the price index for every destination n: $p_{n,k} = \left[\Gamma\left(\frac{1+\theta_k - \sigma_k}{\theta_k}\right)\right]^{\frac{1}{1-\sigma_k}} \Phi_n^{-\frac{1}{\theta_k}}$, where $\Phi_n^k = \sum_{n=1}^{N} T_i (c_i d_{ni})^{-\theta_k}$ and Γ is the Gamma function. Parameters are restricted such that $\theta_k > \sigma_k - 1$. By exploiting the properties of price distribution the fraction of goods that country n buys from country i is also the fraction of its expenditure on goods from country i. As EK pointed out, computing the fraction of income spent on imports from i, $\frac{X_{ni,k}}{X_{n,k}}$ can be shown to be equivalent to finding the probability that

[5] As in Ricardo and EK within a country inputs are mobile across activities and because activities do not differ in their input shares the cost of a bundle of inputs is the same across commodities.

country i is the low-cost supplier to country n given the joint distribution of efficiency levels, prices, and trade costs for any good j_k. The trade share $\pi_{ni,k}$ is given by $X_{ni,k} = X_{n,k} T_i \left(\frac{d_{ni} c_i}{p_{n,k}}\right)^{-\theta_k}$[6]. By following Fieler (2011), in order to show the importance of the dual role of θ_k in this framework I re-express the gravity equation as the imports of country n's from country i relative to its domestic consumption:

$$\frac{X_{ni,k}}{X_{nn,k}} = \frac{T_i}{T_n} \left(\frac{d_{ni} c_i}{c_n}\right)^{-\theta_k} = \frac{T_i}{T_n} \left(\frac{d_{ni} w_i^{\beta} p_i^{1-\beta}}{w_n^{\beta} p_n^{1-\beta}}\right)^{-\theta_k} \tag{4}$$

Equation (4) can be simplified in log term to $\ln X_{ni,k} = S_{i,k} + S_{n,k} - \theta_k \ln d_{ni}$, where $S_{i,k}$ stands for the competitiveness of country i, which is function of technology, wages and prices. As Head and Mayer (2013) pointed out, using the EK input cost assumption that $c_i = w_i^{\beta} p_i^{1-\beta}$ where the price index P_i is proportional to $\Phi_n^{-\theta_k}$ implies that the two structural gravity terms in log terms are given by $S_i = \ln T_i - \beta \theta_k \ln w_i - (1-\beta) \ln p_i$. The trade cost elasticity, $-\theta_k$ is is equal to the input cost elasticity but the wage elasticity will be smaller since $\beta < 1$.

In equation (4) two factors control the proportion of goods imported from country i to country n with respect to the domestic consumption of country n in industry k: the ratio of their effective wages and the ratio of technology parameters.[7]. The industry-specific trade elasticity parameter θ_k controls the relative importance of these two factors. If θ_k is large, the variability in production technologies across goods and countries in industry k is small, and consumers place more emphasis on the effective cost of labor $\frac{d_{ni} w_i^{\beta} p_i^{1-\beta}}{w_n^{\beta} p_n^{1-\beta}}$ than on technology parameter $\frac{T_i}{T_n}$.

II.B. Inserting migration into the picture

Migration enters the Ricardian EK model by affecting the distribution of prices $G_{ni}(p_k)$ that country i presents to country n. Migrants' networks mitigate the negative effect of geographic barriers by attenuating incomplete and asymmetric information in international transactions. This positive migration effect on trade is likely to vary across industries k and it is proportional to the stocks of bilateral migration between country

[6]Under some parametric assumptions Simonovska and Waugh (2013) show that the trade share is the common expression for trade flows in five models characterized by different micro-level margins. The class of models includes Armington, Krugman (1980), EK, Bernard et al. (2003), and Melitz (2003)

[7]Which is to say two factors control the cost of producing goods in country i relative to producing them in country n. Fieler (2011) noticed that the right hand side of equation (4) is the expectation over j_k of the mean of the Fréchet distribution elevated to the power of $-\theta_k$. The cost of delivering one unit of good j_k from country i to country n relative to the cost of producing it domestically is $\frac{p_{ni\,j(k)}}{p_{nn\,j(k)}} = \frac{z_{n\,j(k)}}{z_{i\,j(k)}} \frac{d_{ni} w_i^{\beta} p_i^{1-\beta}}{w_n^{\beta} p_n^{1-\beta}}$. By taking the expectation over j_k the expression reduces to $\frac{E(p_{ni\,j(k)})}{E(p_{nn\,j(k)})} = \frac{T_i}{T_n}^{1/\theta} \frac{d_{ni} w_i^{\beta} p_i^{1-\beta}}{w_n^{\beta} p_n^{1-\beta}}$.

i and country n. This is a *comparative advantage* effect since it impacts directly the level of heterogeneity across goods and countries through the parameter θ_k.
In order to capture the trade cost channel of migration I divide d_{ni} into two components. The first term is the usual EK geographic barriers term which is denoted with ρ, the second one is the information costs I_{ni} which in this model will depend solely (negatively) on migrants' networks. For every $i \neq n$, d_{ni} is defined as follows:

$$\mathrm{d}_{ni} = [\rho_{ni}\mathrm{I}_{ni}] \tag{5}$$

As in EK geographic barriers take the following moltiplicative form $\rho_{ni} = \mathrm{dist}_{ni} \exp^{[\mathrm{l}_{ni}\mathrm{adj}_{ni}\mathrm{EC}_{ni}\mathrm{EFTA}_{ni}]}$, whereas informational frictions I_{ni} are only affected by migrant networks as follows: $\mathrm{I}_{ni} = \frac{1}{[\mathrm{mig}_{ni}]}$ [8] More precisely, m_{ni} is the total number of migrants born in country i resident in country n. By combining equation (3) and equation (5) the price of a good imported from country i into country n then becomes: $p_{ni}(j_k) = \frac{c_i \rho_{ni} \mathrm{I}_{ni}}{z_i(j_k)}$. By substituting this expression into the distribution of efficiency $F_i(j_k)$ and by following the same procedure as in the previous section which leads to the trade equation, we get:

$$\frac{X_{ni,k}}{X_{nn,k}} = \frac{T_i}{T_n} \left(\frac{w_i^{\beta} p_i^{1-\beta} \rho_{ni}}{w_n^{\beta} p_n^{1-\beta} \mathrm{mig}_{ni}} \right)^{-\theta_k} \tag{6}$$

This expression can be simplified in log term to $\ln X_{ni,k} = S_{i,k} + S_{n,k} - \theta_k \ln \rho_{ni} + \theta_k \ln \mathrm{I}_{ni}$, whereas the competitiveness equation remains unaffected $S_{i,k} = \ln T_i - \beta \theta_k \ln w_i - (1-\beta) \ln p_i$.
Equation (6) incorporates the trade cost channel of migration in a supply-side derivation of the gravity expression. Unlike Combes et al. (2005), Tai (2009), Felbermayr and Toubal (2012) and all the demand side gravity equations derived from symmetric Dixit-Stiglitz-Krugman monopolistic competition models, the assumptions behind the Ricardian EK model automatically rule out the preference channel of migration and any role of the elasticity of substitution in determining immigrants' trade effect.[9] In the model demand affects trade only through the allocation of spending across industries because, within industries, the share of each exporter in a countrys imports does not depend on the elasticity of substitution, only on technologies.

[8] This expression follows Combes et al. (2005). However, Combes et al. (2005) include *plant* as an additional determinant of I_{ni}.

[9] Despite the relevance of quantifying the relative importance of the preference channel on the pro-trade effect of migrants for its implications on welfare analysis, according to Felbermayr et al. (2012) several papers attempted to disentangle and separately identify the preference channel from the trade cost channel of migration but so far, no conclusive answer to this identification problem is provided.

III. Data, definitions and econometric specifications

III.A. Data and definitions

My analysis uses data for manufacturing in 1990 for 19 OECD countries.
Trade data and proxies for geographic barriers. Data on imports at disaggregated level in thousand dollars for 20 sectors for 1990 are from an old version of STAN database (2002), where data are collected according to the 2-digit level ISIC Revision 3 industry classification.[10] To perform a robustness-check I also utilize the correspondent trade values for 1991 and 1993 which are from the same source. Since data on Austrian imports are not available, I use the correspondent exports to Austria from a more recent version of STAN (2011). The data are balanced: out of the 6840 observations of the whole sample (20*342), there are only four missing import values for 1990 which I replaced with zeroes.[11] Data on weighted distance and all the geographic barriers used in this paper namely common border, common language are from CEPII gravity database.[12]
Welfare analysis. Arkolakis et al. (2012) showed that within a particular class of trade models, the elasticity of trade and the share of expenditure on domestic goods are the only two parameters needed to calculate welfare gains from trade. I show the welfare implications of including migrants' networks in the first stage of the EK trade share approach in *total manufacturing*: this is equivalent to show the welfare implications in the one-sector EK model using the Arkolakis et al. (2012) expression for G_n. Welfare gains expressed in percentage of country n's GDP are defined as:

$$G_n = 100 * \left[1 - \pi_{nn}{}^{1/\theta}\right] \tag{7}$$

where π_{nn} is country n's home share and it is defined as $\frac{\text{prod}_n - \text{exp}_n}{\text{prod}_n - \text{exp}_n + \text{imp}_n}$. prod_n and exp_n are total manufacturing production and exports of country n whereas imp_n is the sum of manufacturing imports from all countries in the sample. Data on manufacturing production and total manufacturing exports are from STAN (2011). Since production

[10] Along with the 18 manufacturing sectors I also estimate pro-trade elasticities of immigrants for *agriculture* and *mining*. List and description of the 20 ISIC Rev.3 sectors are outlined in Table 6

[11] Specifically, these values are imports of Austria from Australia in *petroleum* and from New Zealand in *minerals*, *basic metals* and *transport*. In addition, there are negligible numbers of missing observations for trade data in 1991 and 1993 replaced by zeroes. Again, missing values are all Austrian imports. Specifically, for 1991 these are *wood* and *petroleum* from Australia and *minerals* and *transport* from New Zealand. For 1993 these values are *petroleum* from Australia and Portugal and *basic metals* from New Zealand

[12] Weighted distance calculates the distance between two countries based on bilateral distances between the biggest cities of those two countries: those inter-city distances are weighted by the share of the city in the overall countrys population. The CEPII gravity database includes data on distance between n and i based on the following formula from Head and Mayer (2002): $\text{dist}_{ni} = \left(\sum_{k \in n} \frac{\text{pop}_k}{\text{pop}_n}\right) * \left(\sum_{l \in i} \frac{\text{pop}_l}{\text{pop}_i}\right) * \text{dist}_{kl}$, where pop_k stands for the population of agglomeration k belonging to country n while pop_l is the population of agglomeration l belonging to country i.

and total exports in manufacturing are expressed in national currency they have been converted in current US dollars by using 1990 exchange rates (euro converted historical data for US dollars) from OECD database.

Determinants of competitiveness. As in EK annual compensation in total manufacturing in national currency are from STAN database. Compensation of employees LABR encompasses wages and salaries of employees paid by producers as well as supplements such as contributions to social security, private pensions, health insurance, life insurance and similar schemes. Compensation of employees are then translated into US current dollars by using OECD exchange rates; in order to obtain the annual compensation per worker, annual compensation is divided by the number of employees in total manufacturing EMPE. Number of employees in total manufacturing are from STAN for large part of my sample; for Australia, Belgium, Greece, Portugal and Sweden I use UNIDO data from the recent INDSTAT2 2012 database. In both INDSTAT2 and STAN databases data are collected using the 2-digit level ISIC Revision 3 industry classification. Compensation per worker data are then adjusted by worker quality, setting $\mathrm{w}_i = (\mathrm{comp}_i)\exp^{-gH_i}$, where h is average years of total schooling of population aged 15 and over in 1985 and g is the return to education which is set to 0.06 as in EK. Average years of schooling and R&D expenditures in current US dollars are the proxies for technology. Average years of schooling of adults (aged 15+) for 1985 are obtained from Barro and Lee (2010) data. All country's R&D shares of GDP are from the CANA database, a panel dataset for cross-country analyses of national systems;[13] GDP data in billions of current US dollars are from IMF.

Total labour force and the inverse of population density are the instruments for wage costs. The inverse of population density is obtained as the inverse of the ratio of country's total labour force over land area. Total labour force data in thousands of workers are obtained from the annual labor force statistics OECD database. Like wages, total employment is corrected for education, setting $\mathrm{L}_i = (\mathrm{work}_i)\exp^{gH_i}$.

Labour share. The β parameter stands for the average labor share in gross manufacturing production in the sample and is calculated as follows: $\beta = \frac{\mathrm{Wage} * \sum_n^N \mathrm{Employment}_n}{\sum_n^N \mathrm{Production}_n}$. Also data on total manufacturing production are from STAN (2011). In line with EK results I obtain $\hat{\beta} = 0.21$.

Migrants. The proxy for migrants-based networks is the bilateral stock of immigrants born in country i and resident in country n. Data are from World Bank which provides a balanced dataset for the years 1960, 1970, 1980, 1990 and 2000. Data on the bilateral stocks of immigrants for 1990 are employed in the estimation of equation (6), whereas the correspondent stocks for 1980 and 1970 are used as instruments in the 2SLS and IV-Poisson estimations.

[13] Available at http://english.nupi.no/Activities/Projects/CANA

III.B. Econometric specifications

In the first stage a transformed version of bilateral trade is regressed on measures of bilateral trade costs (geographic barriers), informational frictions, importer and exporter fixed effects. The estimated exporter fixed effects obtained in the first stage are then regressed on two proxies for technology (R&D expenditures and human capital) and wages corrected for worker quality. From equation (6), the first stage regression becomes:

$$\ln X_{ni,k} = S_{i,k} - S_{n,k} - \theta_k \text{dist}_{ni} - \theta_k \text{lang}_{ni} - \theta_k \text{contig}_{ni} - \theta_k \text{RTA}_{ni} + \theta_k \ln \text{mig}_{ni} + \theta_k \delta_{ni}$$

This gravity equation is estimated separately for all sectors outlined in Table 6. For our purposes estimating this alternative version of equation (6) is equivalent to estimating the standard EK trade share expression: competitiveness of country i $\hat{S}_{i,k}$ remains unaffected whether or not the denominator of the trade share $X_{nn,k}$ is taken to the right hand side.

Estimating this gravity expression presents three major econometric concerns. The first concern deals with the treatment of zero flows since the log-linearized specification can only be estimated on strictly positive flows. Table 9 in the Appendix reports the percentage of zeroes for trade flows in each sector. As it emerges from Table 9 the percentage is very low across sectors: the zero flows issue is relatively problematic in *petroleum* sector where the zeroes are 8% of the total number of observations. A second issue concerns the heteroskedasticity of error terms in levels. Santos Silva and Tenreyro (2006) argue that OLS with log of trade as dependent variable becomes an inconsistent estimator in the presence of Poisson-type heteroskedasticity. Santos Silva and Tenreyro (2006) suggested Poisson pseudo-MLE as a valid alternative to linear-in-logs OLS for multiplicative models like the gravity equation. The Poisson PML (PPML) estimator allows to tackle simultaneously the zero-flows and the heteroscedastic issues, by guaranteeing consistent estimates regardless of the distribution of the error term, as long as $E\left[X_{ni}|z_{ni}\right] = \exp\left(z_{ni}^{'}\upsilon\right)$, where $z_{ni}^{'}$ is the transpose of a vector of the trade cost variables and υ is the correspondent vector of coefficients.

Despite these issues in estimating the gravity model in log form, recent studies still propose OLS as the preferred gravity models' estimator. Aleksynska and Peri (2012) selected OLS estimates as the benchmark results regardless the relatively high percentage of zero trade flows in their sample: they motivate their choice arguing that the conditions which must be satisfied to produce consistent estimates with PPML - namely log normality and homoskedasticity conditions - are indeed very strong assumptions.[14] Peri and Requena-Silvente (2010) use PPML to explore how sensitive the estimated pro-trade effect of immigrants is to the exclusion of zero-trade observations: they show the estimated effects with or without the inclusion of zero observations are

[14]In Aleksynska and Peri (2012) for imports, the coefficient on the logarithm of the share of business network immigrants almost doubles in magnitude the correspondent OLS coefficient, whereas for exports the estimates are very similar.

very close. On the contrary, Tai (2009) obtain PPML estimates of the pro-trade effect of immigrants which more than double the correspondent OLS results. Tai (2009) argues that while the OLS estimator is appropriate for comparisons with other studies and it provides a view of the gravitational determinants of trade, it is not the best estimator for identifying the impact of immigrants and therefore Poisson PML estimates should be preferred. Rather than selecting Poisson PML as the single workhorse estimator of gravity equations I follow Head and Mayer (2013) by including PPML as part of a robustness-exploring ensemble that also includes OLS and Gamma PML.
The third issue is the endogeneity bias that may arise from measurement errors, omitted variables or potential reverse causality between the dependent variable, imports from country i to country n and the variable of interest, the stock of immigrants from country i and resident in country n. I follow Briant et al. (2009) and Combes et al. (2005) by instrumenting the 1990 stock of immigrants with past stocks, specifically in 1980 and 1970. Section AA. in the Appendix tests the validity of the lagged stocks of immigrants as instruments: they both satisfy the conditions of relevance and exogeneity.
To further address the issue of potential joint determination of migration and trade I check the robustness of the pro-trade elasticity results by using trade data in period t+1 and t+3. By so doing, the stock of immigrants is further predetermined with respect to trade.

From equation (6) the second stage regression becomes:

$$\hat{S}_{i,k} = \alpha_{0,k} + \alpha_{R,k} \ln \mathrm{R\&D}_i + \alpha_{H,k} \ln \mathrm{H}_i - \theta_k \beta \ln \mathrm{w}_i + u_{i,k}$$

where $\mathrm{R\&D}_i$ is country i's R&D expenditure, H_i is the average years of education, w_i is country i wages adjusted for education and $u_{i,k}$ is the error term assumed orthogonal to all regressors. This specification differs with respect to the EK expression since wage elasticity and trade cost elasticity doesn't coincide. By substituting β with the actual value of the labour share (0.21) the effect of wage variation on estimated exporter fixed effects gives an alternative source of identification for the same key parameter.
Equation (6) is estimated solely for manufacturing sectors. Agriculture and mining are not considered because of lack of available data for labour costs and employment in those sectors.
Since in the Ricardian framework of Fieler (2011) the cost of an input bundle in country i is constant across types, in the following estimations of θ_k the compensation of employees in total manufacturing w_i will be the proxy of labour costs in each manufacturing industry. This is equivalent to assume that in the EK sample of 19 OECD countries $\forall k$ the variance of $\mathrm{w}_{i,k}$ is equal to the variance of $\sum_{k=1}^{K} \mathrm{w}_{i,k}$.
As Head and Mayer (2013) point out, wages are likely to be simultaneously determined with trade patterns; thus, in order to correct for endogeneity I instrument for wages using 2SLS. The instruments are the same as in EK: total labor force and the inverse of population density which proxy respectively for labour supply and for productivity

outside manufacturing.

IV. Results

Column 1 of Table 1 reports the OLS estimates of the pro-trade effects of immigrants for each industry.[15] The elasticities of ethnic networks are all statistically significant and the magnitude of the coefficients is in line with the main results of the trade-migration literature summarized in Bratti et al. (2012). The results reveal that the pro-trade effect of immigrants varies significantly by sector. The statistics indicate *petroleum* as the industry where immigration has the highest impact on trade and *basic metals* as the sector where immigrants have the lowest pro-trade effect.

Column 3 of Table 1 reports the pro-trade elasticities of immigrants estimated using PPML. In some sectors such as *mining*, *office* and *transport* the gap with the correspondent OLS estimates is particularly significant which may indicate the presence of heteroskedasticity-type-of-bias. Table 3 and Table 2 report the comparison between OLS with Poisson PML and Gamma PML: as a robustness test I have included the pro-trade elasticity coefficients of migrants-based networks along with other proxies of gravity trade costs such as distance and EC. The OLS coefficients are very similar to Gamma PML whereas Poisson PML estimates are very close to OLS only for *total manufacturing*, *chemicals*, *metal products*, *office*,*electrical* and *com*.[16] However, since the gap between OLS and PPML is particularly evident only for some specific sectors and the direction of the bias is not clear, for the arguments expressed in Head and Mayer (2013) it is safer to keep OLS estimates as benchmark results.[17]

Columns 2 and 4 of Table 1 show the pro-trade elasticities of immigrants obtained with 2SLS and IV Poisson. As in Combes et al. (2005) endogeneity appears to introduce a downward bias. All 2SLS network coefficients are larger, even if slightly so in most cases, when instrumented.[18] To further address the issue of endogeneity due to potential joint determination of migration and trade I check the robustness of the pro-trade elasticity results by using trade data in period t+1 and t+3. Table 4 reports the estimates: the results indicate that sectoral pro-trade elasticities are robust to this

[15] The whole set of first stage coefficients is available upon request. Table 9 reports some key statistics such as R^2 and RMSE.

[16] The only differences between Gamma PML and OLS estimates are in sectors such as *mining* and *petroleum* where there's a significant number of zeroes.

[17] The results do not exhibit the characteristics of any of the four scenarios suggested by Head and Mayer (2013) after conducting a Monte Carlo simulation. Gamma and OLS coefficients on trade cost proxies are similar and the Poisson coefficients are sometimes smaller and sometimes greater in absolute magnitude. Head and Mayer (2013) suggest that in sectors where there's significant divergence between Gamma and Poisson can signal model mis-specification. However, the results of the RESET test for regressions with presumed model mis-specification issues (such as *petroleum*, *textiles*, *agriculture* and *mining*)suggest otherwise. The results of the Ramsey test are available upon request.

[18] The only exception is *textiles* where the elasticity decreases by 0.04 when instrumented using 2SLS.

correction.
Table 5 compares the sectoral trade cost elasticities $\theta_{MIG,k}$ obtained from Equation (6) with the correspondent estimates $\theta_{EK,k}$ obtained from the same model which doesn't incorporate migrants' networks among trade determinants. The second step is estimated using $\hat{S}_{i,k}$ as dependent variable both from PPML (column 1 and 3) and OLS (column 2 and 4). I successfully replicated the one-sector EK competitiveness equation benchmark result of θ: the trade elasticity of *total manufacturing* in the second column is very close to 3.60. The evidence shows that sectoral trade cost elasticities vary quite dramatically across sectors and the resulting estimates of θ_k substantially differ with respect to the correspondent elasticities obtained by Caliendo and Parro (2011). Also, the majority of θ_k coefficients are not statistically significant. Out of the 19 sector-level-elasticities reported in Table 5, only 6 coefficients are statistically significant (column 2). The number of coefficients statistically significant increases to 9 when θ_k is obtained from a first stage estimated with Poisson PML (column 1). This unsatisfactory results are partly explained by Costinot and Rodriguez-Clare (2013) who claim that the precision with which each of those elasticities are estimated decreases as the number of θ_k that needs to be estimated raises.
The impact of migrants-based networks on trade cost elasticity is remarkable. Column 4 shows that the inclusion of migrants-based-networks in the first stage on average raises the estimate of $-\theta_k$ by 1.94 in manufacturing. The one-sector EK benchmark estimate of θ decreases by 1.03 when the standard trade share equation is augmented with migrants-based-networks. Table 7 quantifies the impact of the variation of θ due to the inclusion of migrants' networks on welfare gains in *total manufacturing*. The calculations have been made utilising Arkolakis et al. (2012) methodology (equation (7)); the gains are expressed in percentage of national GDP. Column 1 reports the share of expenditures on domestic goods in manufacturing, column 2 and 3 shows the welfare gains from trade estimated with $\theta = 3.58$ and $\theta = 2.55$, respectively. A drop of trade elasticity of 1.03 in *total manufacturing* on average increases welfare gains by 4.16% of country *n*'s income.

V. Summary

The first contribution of this paper is the estimation of the pro-trade effects of immigrants for 18 manufacturing sectors in a sample of 19 OECD countries. To do so trade data are divided by sector according to ISIC Rev.3 industry classification. As in Rauch and Trindade (2002) I run the same gravity model separately for each aggregated group using different econometric techniques. The evidence shows that the pro-trade effect of immigrants varies significantly by sector: the statistics indicate *pulp, paper, paper products, printing and publishing* as the industry where immigration has the highest impact on trade.
The gravity equation is obtained from a perfect competition Ricardian model à la Eaton and Kortum (2002) where I followed Fieler (2011) to characterize the demand side. I let the number of types of goods to coincide with the number of sectors in the econ-

omy: this assumption allows to incorporate formally the heterogeneity in trade elasticities across sectors and to estimate θ_k at sector level.
The alternative two-step methodology for the estimation of θ_k provides contrasting results. On the one hand the trade cost elasticity of total manufacturing coincides with the one-sector EK *competitiveness equation* benchmark result of 3.60, which I view as reassuring. On the other hand most of the sectoral trade cost elasticities are not statistically significant, which implies the irrealistic scenario of infinite gains from trade. This unsatisfactory results are partly explained by Costinot and Rodriguez-Clare (2013) who claim that the estimation of θ_k in a multiple-sector model is a natural way to address the issue of sectors' heterogeneity, but the precision with which each of those elasticities are estimated is inversely related to the number of elasticities that needs to be estimated.
Finally, the impact of migrants-based networks on the estimation of θ_k is quite strong. The statistics show that accounting for ethnic networks in the first step has a significant negative impact on trade cost elasticity parameter in all sectors: in *total manufacturing* θ decreases by 1.03 when migration is included among the determinants of trade. Since θ is the fundamental statistic needed to conduct welfare analysis, including or not a proxy for migrant-based networks into a gravity specification has dramatic implications on the resulting benefits from trade. I quantify the welfare effect of ethnic networks in *total manufacturing*: the calculations indicate that a drop of trade elasticity of 1.03 due to the inclusion of migrants' networks on average increases welfare gains by 4.16% of GDP.

Table 1: Pro-trade effects of immigrants

Estimator	OLS	2SLS	PPML	IV-PPML
Dependent variable	$\ln X_{ni,k}$	$\ln X_{ni,k}$	$X_{ni,k}$	$X_{ni,k}$
ISIC Rev.3	mig_{ni}	mig_{ni}	mig_{ni}	mig_{ni}
01-05	0.23^a	0.26^a	0.25^a	0.32^a
	(0.05)	(0.06)	(0.05)	(0.06)
10-14	0.20^a	0.27^a	0.44^a	0.49^a
	(0.07)	(0.09)	(0.10)	(0.11)
15-37	0.10^a	0.13^a	0.14^a	0.14^a
	(0.03)	(0.03)	(0.17)	(0.02)
15-16	0.14^a	0.16^a	0.24^a	0.27^a
	(0.04)	(0.04)	(0.04)	(0.04)
17-19	0.18^a	0.13^b	0.20^a	0.18^a
	(0.04)	(0.06)	(0.03)	(0.04)
20	0.23^a	0.35^a	0.22^a	0.33^a
	(0.06)	(0.07)	(0.05)	(0.07)
21-22	0.22^a	0.33^a	0.19^a	0.22^a
	(0.05)	(0.06)	(0.03)	(0.04)
23	0.21^b	0.29^b	0.11^c	0.15^a
	(0.11)	(0.12)	(0.06)	(0.06)
24	0.17^b	0.23^a	0.11^a	0.10^a
	(0.05)	(0.06)	(0.02)	(0.03)
25	0.17^a	0.17^a	0.16^a	0.16^a
	(0.04)	(0.05)	(0.03)	(0.03)
26	0.17^a	0.23^a	0.17^a	0.17^a
	(0.05)	(0.05)	(0.03)	(0.03)
27	0.10^b	0.18^b	0.19^a	0.25^a
	(0.05)	(0.07)	(0.03)	(0.04)
28	0.19^a	0.23^a	0.21^a	0.21^a
	(0.40)	(0.05)	(0.02)	(0.02)
29	0.14^a	0.17^a	0.13^b	0.12^a
	(0.03)	(0.04)	(0.03)	(0.03)
30	0.15^a	0.18^a	0.06	0.07
	(0.05)	(0.06)	(0.05)	(0.09)
31	0.19^a	0.27^a	0.25^a	0.27^a
	(0.05)	(0.06)	(0.03)	(0.03)
32	0.16^a	0.19^a	0.18^a	0.20^a
	(0.05)	(0.07)	(0.04)	(0.06)
33	0.19^a	0.23^a	0.16^a	0.18^a
	(0.03)	(0.04)	(0.02)	(0.03)
34	0.18^b	0.27^a	0.13^b	
	(0.08)	(0.09)	(0.06)	
35	0.15^b	0.16	-0.05	-0.02
	(0.78)	(0.10)	(0.08)	(0.08)
36-37	0.18^a	0.17^a	0.20^a	0.20^a
	(0.04)	(0.05)	(0.04)	(0.04)

a, b, c denotes statistical significance at the 1%, 5%, 10% levels of significance, respectively.

Standard errors in parenthesis are heteroscedasticity-robust and clustered by trading-pair

The IV Poisson regression for sector *auto* does not converge and therefore no results are displayed

Table 2: First stage OLS - PPML

Estimator	OLS				PPML			
ISIC Rev.3	dist	EC	mig_{ni}	n	dist	EC	mig_{ni}	n
01-05	-1.50^{a}	-0.33	0.23^{a}	341	-0.99^{a}	0.79^{a}	0.25^{a}	342
10-14	-1.88^{a}	-1.32^{a}	0.20^{a}	328	-1.18^{a}	-1.32^{a}	0.44^{a}	342
15-37	-1.00^{a}	0.11	0.10^{a}	342	-1.00^{a}	0.05	0.14^{a}	342
15-16	-0.95^{a}	0.27	0.14^{a}	342	-0.65^{a}	1.25^{a}	0.24^{a}	342
17-19	-1.32^{a}	-0.76^{a}	0.18^{a}	342	-0.92^{a}	-0.28	0.20^{a}	342
20	-2.05^{a}	-1.88^{a}	0.23^{a}	338	-1.65^{a}	-1.38^{a}	0.22^{a}	342
21-22	-1.43^{a}	-0.38^{c}	0.22^{a}	341	-1.26^{a}	-0.81^{a}	0.19^{a}	342
23	-2.52^{a}	-0.79	0.21^{a}	313	-1.72^{a}	-1.34^{a}	0.11^{a}	342
24	-1.06^{a}	0.10	0.17^{a}	342	-0.96^{a}	-0.09	0.11^{a}	342
25	-1.37^{a}	0.05	0.17^{a}	342	-1.20^{a}	0.09	0.16^{a}	342
26	-1.27^{a}	0.17	0.17^{a}	334	-1.20^{a}	-0.24	0.17^{a}	342
27	-1.61^{a}	0.54^{b}	0.10^{a}	339	-1.02^{a}	0.19	0.19^{a}	342
28	-1.24^{a}	0.35^{b}	0.19^{a}	342	-1.12^{a}	0.27^{b}	0.21^{a}	342
29	-0.83^{a}	0.50^{b}	0.14^{a}	341	-0.94^{a}	-0.06	0.13^{a}	342
30	-0.97^{a}	0.50^{b}	0.15^{a}	332	-0.98^{a}	0.53^{b}	0.06	342
31	-0.94^{a}	0.03	0.19^{a}	341	-0.94^{a}	0.03	0.25^{a}	342
32	-0.91^{a}	0.67^{b}	0.16^{a}	338	-1.01^{a}	0.42^{b}	0.18^{a}	342
33	-0.58^{a}	0.48^{a}	0.19^{a}	342	-0.65^{a}	-0.10	0.16^{a}	342
34	-1.35^{a}	1.48^{a}	0.18^{a}	337	-1.29^{a}	-0.62	0.13^{a}	342
35	-0.97^{a}	0.02	0.15^{a}	334	-0.35^{b}	0.24	-0.05	342
36-37	-1.02^{a}	0.05	0.18^{a}	341	-0.92^{a}	-0.44^{b}	0.20^{a}	342

a, b, c denotes statistical significance at the 1%, 5%, 10% levels of significance, respectively.
Standard errors are heteroscedasticity-robust and clustered by trading-pair

Table 3: First stage OLS - GPML

Estimator	OLS				GPML			
ISIC Rev.3	dist	EC	mig_{ni}	n	dist	EC	mig_{ni}	n
01-05	-1.50^a	-0.33	0.23^a	341	-1.45^a	-0.39	0.22^a	342
10-14	-1.88^a	-1.32^a	0.20^a	328	-1.69^a	-0.83^a	0.26^a	342
15-37	-1.00^a	0.11	0.10^a	342	-0.99^a	0.13	0.11^a	342
15-16	-0.95^a	0.27	0.14^a	342	-0.92^a	0.28^c	0.14^a	342
17-19	-1.32^a	-0.76^a	0.18^a	342	-1.25^a	-0.81^a	0.14^a	342
20	-2.05^a	-1.88^a	0.23^a	338	-2.06^a	-1.92^a	0.23^a	342
21-22	-1.43^a	-0.38^c	0.22^a	341	-1.48^a	-0.54^a	0.21^a	342
23	-2.52^a	-0.79	0.21^a	313	-2.96^a	-1.11^a	0.27^a	342
24	-1.06^a	0.10	0.17^a	342	-1.10^a	-0.04	0.15^a	342
25	-1.37^a	0.05	0.17^a	342	-1.33^a	0.14	0.15^a	342
26	-1.27^a	0.17	0.17^a	334	-1.24^a	0.17	0.19^c	342
27	-1.61^a	0.54^b	0.10^a	339	-1.53^a	0.40^c	0.12^a	342
28	-1.24^a	0.35^b	0.19^a	342	-1.23^a	0.28^b	0.21^a	342
29	-0.83^a	0.50^b	0.14^a	341	-0.83^a	0.51^a	0.14^a	342
30	-0.97^a	0.50^b	0.15^a	332	-0.91^a	0.81^a	0.19^a	342
31	-0.94^a	0.03	0.19^a	341	-0.90^a	0.62^a	0.17^a	342
32	-0.91^a	0.67^b	0.16^a	338	-0.90^a	0.84^b	0.19^a	342
33	-0.58^a	0.48^a	0.19^a	342	-0.61^a	0.50^a	0.20^a	342
34	-1.35^a	1.48^a	0.18^a	337	-1.19^a	1.41^a	0.12^b	342
35	-0.97^a	0.02	0.15^a	334	-0.74^b	0.37	-0.13^b	342
36-37	-1.02^a	0.05	0.18^a	341	-1.08^a	0.07	0.19^a	342

a, b, c denotes statistical significance at the 1%, 5%, 10% levels of significance, respectively.
Standard errors are heteroscedasticity-robust and clustered by trading-pair

Table 4: Pro-trade effects of immigrants - t+1 and t+3

Estimator	OLS	PPML	OLS	PPML
Dependent variable	$\ln X_{ni,k}$	$X_{ni,k}$	$\ln X_{ni,k}$	$X_{ni,k}$
	$(t+1)$	$(t+1)$	$(t+3)$	$(t+3)$
ISIC Rev.3	mig_{ni}	mig_{ni}	mig_{ni}	mig_{ni}
01-05	0.23^a	0.29^a	0.24^a	0.31^a
	(0.05)	(0.05)	(0.05)	(0.04)
10-14	0.25^a	0.44^a	0.17^b	0.56^a
	(0.07)	(0.11)	(0.07)	(0.09)
15-37	0.11^a	0.14^a	0.11^a	0.16^a
	(0.03)	(0.02)	(0.03)	(0.02)
15-16	0.14^a	0.22^a	0.11^a	0.22^a
	(0.04)	(0.04)	(0.04)	(0.04)
17-19	0.16^a	0.21^a	0.17^a	0.21^a
	(0.04)	(0.03)	(0.04)	(0.04)
20	0.27^a	0.21^a	0.21^a	0.16^a
	(0.06)	(0.05)	(0.07)	(0.05)
21-22	0.15^a	0.18^a	0.16^a	0.19^a
	(0.04)	(0.03)	(0.05)	(0.03)
23	0.21^b	0.11^b	0.29^a	0.21^a
	(0.10)	(0.06)	(0.09)	(0.06)
24	0.16^b	0.11^a	0.13^a	0.09^a
	(0.05)	(0.02)	(0.04)	(0.03)
25	0.13^a	0.16^a	0.14^a	0.16^a
	(0.04)	(0.03)	(0.04)	(0.03)
26	0.19^a	0.16^a	0.17^a	0.18^a
	(0.05)	(0.03)	(0.04)	(0.02)
27	0.13^b	0.20^a	0.06	0.16^a
	(0.05)	(0.03)	(0.05)	(0.03)
28	0.21^a	0.21^a	0.18^a	0.19^a
	(0.03)	(0.02)	(0.04)	(0.02)
29	0.13^a	0.13^a	0.15^a	0.16^a
	(0.03)	(0.03)	(0.03)	(0.03)
30	0.22^a	0.08	0.14^b	0.09^c
	(0.052)	(0.05)	(0.05)	(0.05)
31	0.20^a	0.25^a	0.23^a	0.26^a
	(0.05)	(0.03)	(0.05)	(0.03)
32	0.17^a	0.21^a	0.18^a	0.20^a
	(0.05)	(0.04)	(0.06)	(0.04)
33	0.16^a	0.16^a	0.14^a	0.18^a
	(0.04)	(0.02)	(0.04)	(0.02)
34	0.14^b	0.13^a	0.20^a	0.18^a
	(0.06)	(0.06)	(0.07)	(0.07)
35	0.15^b	-0.09	0.17^b	-0.17^c
	(0.08)	(0.08)	(0.07)	(0.11)
36-37	0.20^a	0.19^a	0.19^a	0.19^a
	(0.04)	(0.04)	(0.04)	(0.04)

a, b, c denotes statistical significance at the 1%, 5%, 10% levels of significance, respectively.

Standard errors in parenthesis are heteroscedasticity-robust and clustered by trading-pair

Table 5: Effect of ethnic networks on trade elasticity

First Stage Estimator	PPML	OLS	PPML	OLS
Dependent variable	$\hat{S}_{i,k}$	$\hat{S}_{i,k}$	$\hat{S}_{i,k}$	$\hat{S}_{i,k}$
ISIC Rev.3	$-\theta_{k,EK}$	$-\theta_{k,EK}$	$-\theta_{k,MIG}$	$-\theta_{k,MIG}$
15-37	-6.86^{a}	-3.58^{a}	-4.89^{a}	-2.55^{b}
	(1.39)	(0.94)	(1.36)	(1.2)
15-16	-7.55^{c}	-7.38^{c}	-3.97	-5.99
	(3.97)	(4.21)	(3.49)	(4.00)
17-19	-13.96^{a}	-13.05^{a}	-10.74^{a}	-11.25^{a}
	(3.57)	(3.47)	(3.01)	(3.19)
20	-21.43^{a}	-18.79^{b}	-17.07^{b}	-16.46^{b}
	(7.65)	(7.38)	(7.22)	(7.63)
21-22	-3.79	-0.64	-1.28	1.58
	(4.37)	(5.22)	(4.74)	(5.68)
23	-12.20^{b}	-21.86^{b}	-10.69^{b}	-19.64^{b}
	(5.03)	(8.88)	(4.80)	(8.48)
24	-0.90	3.38	0.46	5.13
	(2.78)	(4.10)	(2.94)	(4.44)
25	-4.42^{a}	-1.03	-2.37^{c}	0.66
	(1.49)	(1.95)	(1.33)	(1.98)
26	-8.99^{a}	-5.85^{b}	-6.91^{b}	-4.13
	(2.80)	(2.68)	(2.49)	(2.71)
27	-3.49	-0.41	-0.95	0.62
	(5.58)	(5.88)	(5.32)	(5.78)
28	-3.24	0.21	-0.42	2.11
	(1.79)	(2.53)	(2.06)	(2.88)
29	1.26	5.40	2.73	6.81^{c}
	(2.66)	(3.44)	(2.92)	(3.79)
30	-3.15	1.52	-2.32	3.06
	(3.44)	(4.13)	(3.64)	(4.48)
31	-7.15^{a}	1.05	-3.89^{b}	4.14
	(1.77)	(3.08)	(1.91)	(4.01)
32	-5.22	2.55	-2.69	4.07
	(4.07)	(6.26)	(4.64)	(6.66)
33	-0.98	4.26	1.18	6.20
	(2.36)	(3.64)	(2.60)	(4.07)
34	-2.87	6.20	-1.34	8.05
	(6.45)	(7.34)	(6.81)	(7.84)
35	-4.24^{b}	-3.80	-4.81^{b}	-2.10
	(2.22)	(2.66)	(2.31)	(2.83)
36-37	-2.07	1.15	0.92	2.96
	(3.04)	(3.24)	(3.50)	(3.65)
Observations	19	19	19	19

a, b, c denotes statistical significance at the 1%, 5%, 10% levels of significance, respectively.

Standard errors in parenthesis are heteroscedasticity-robust

Table 6: International Standard Industrial Classification (ISIC) Revision 3

ISIC Rev.3	Description	Industry
01-05	Agriculture forestry and fishing	Agriculture
10-14	Mining and Quarrying	Mining
15-37	Total Manufacturing	Manufacturing
15-16	Food products, beverages and tobacco	Food
17-19	Textiles, textile products, leather and footwear	Textiles
20	Wood and products of wood and cork	Wood
21-22	Pulp, paper, paper products, printing and publishing	Paper
23	Coke refined petroleum and nuclear fuel	Petroleum
24	Chemicals	Chemicals
25	Rubber and plastics products	Plastic
26	Other nonmetallic mineral products	Minerals
27	Basic metals	Basic metals
28	Fabricated metal products, except machinery and equipment	Metal products
29	Machinery and equipment n.e.c.	Machinery n.e.c
30	Office, accounting and computing machinery	Office
31	Electrical machinery and apparatus, n.e.c.	Electrical
32	Radio, television and communication equipment	Com
33	Medical, precision and optical instruments, watches and clocks	Medical
34	Motor vehicles trailers and semi-trailers	Auto
35	Other transport equipment	Transport
36-37	Manufacturing n.e.c and recycling	Other

Table 7: Welfare gains from trade

	π_{nn} (%)	$G_{n,EK}$ (%) $\theta = 3.58$	$G_{n,MIG}$ (%) $\theta = 2.55$	$G_{n,MIG} - G_{n,EK}$ (%)
Country				
AUSTRALIA	80.8	5.77	8.01	2.24
AUSTRIA	97.1	0.82	1.16	0.34
BELGIUM	31.3	27.69	36.57	8.88
CANADA	65.7	11.08	15.20	4.12
DENMARK	52.5	16.47	22.32	5.85
FINLAND	73.8	8.12	11.20	3.08
FRANCE	75.5	7.55	10.44	2.89
GERMANY	75.5	7.56	10.44	2.88
GREECE	69.3	9.72	13.37	3.65
ITALY	83.6	4.88	6.78	1.90
JAPAN	2.3	65.06	77.16	12.10
NETHERLANDS	38.9	23.17	30.93	7.76
NEW ZEALAND	67.2	10.50	14.43	3.93
NORWAY	58.9	13.74	18.74	5.00
PORTUGAL	68.1	10.17	13.98	3.81
SPAIN	79.5	6.19	8.58	2.39
SWEDEN	68.0	10.21	14.04	3.83
UNITED KINGDOM	72.4	8.63	11.91	3.28
UNITED STATES	90.5	2.74	3.83	1.09
Mean				4.16

All the values are expressed in (%) of GDP.

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A Appendix

AA. Relevance and exogeneity of the lagged stocks of immigrants as instruments

The instruments I use in the 2SLS estimates reported in Table 1 are the lagged bilateral stocks of immigrants for 1980 and 1970. The bilateral stocks of immigrants in 1980 and 1970 contain 6 zero observations.[19] Since both of instruments are in log form, 2SLS regressions for all industries are performed with 6 observations less compared to OLS.
Table 8 reports the OLS estimates of the traditional first step of the 2-step instrumented regression. As shown by Baum et al. (2003), in the case of a single endogenous explanatory variable, the Partial R^2 and the F-test of the joint significance of excluded instruments are sufficient to assess the relevance of instruments. To further check for the relevance of instruments I also report the Anderson canonical correlations test, a likelihood ratio test of whether the equation is identified (i.e.) that the excluded instruments are correlated with the endogenous regressors.
To check for exogeneity of instruments the Sargan-Hansen test of over-identifying restrictions is reported. The joint null hypothesis is that the additional instrument is uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. Under the null, the test statistic is distributed as chi-squared in the number of over-identifying restrictions. A rejection of the null hypothesis implies that the instruments do not fulfill the orthogonality conditions.
The instruments pass both the exogeneity as well as the relevance tests. In the case of a single endogenous explanatory variable, a F-statistic lower than 10 is of concern according to Staiger and Stock (1997) rule of thumb. The results of Partial R^2 and F-test reported below indicate that the two instruments are relevant. Finally, in the Sargan-Hansen test, I fail to reject the null hypothesis: Chi-sq(1) = 2.109 and P-val = 0.146. The fail of the rejection of the null is a further proof of the validity of instruments.

AB. First stage statistics

Table 9 shows Root MSE and R^2 for all the first stage regressions of which I reported solely the pro-trade effects of immigrants along with distance and EC coeffcients in Table 3. The whole set of first stage coefficients - including exporter and importer fixed effects - of all regressions are available upon request. The fifth column of Table 9 shows the percentage of zero values in each regression. The highest percentage is in *petroleum* and *mining* sectors where zero trade values are the 8% of total observations.

[19] For Australia and New Zealand World Bank reports no immigrants from Spain and Canada in 1980, whereas according to World Bank data Japan has no immigrants from Spain for the same year. In 1970 Spain has no emigrants reported in Australia, New Zealand and Japan; in addition for New Zealand in 1970 World Bank reports no immigrants from Denmark.

Table 8: Relevance and exogeneity of the lagged stocks of immigrants as instruments

Variable		coef	se
Immigrants 80	$\ln(\text{mig80}_{ni})$	0.46^{a}	(0.10)
Immigrants 70	$\ln(\text{mig80}_{ni})$	0.26^{a}	(0.09)
Shared border	contig_{ni}	0.07	(0.10)
Shared language	lang_{ni}	0.24^{b}	(0.11)
EC	EC_{ni}	-0.02	(0.15)
EFTA	EFTA_{ni}	0.46^{a}	(0.16)
Distance	$\ln(\text{Dist}_{ni})$	-0.11^{c}	(0.06)
Observations	336		
Centered R^2	0.94		
Uncentered R^2	0.99		
Shea Partial R^2	0.70		
Partial R^2	0.70		
F Test of Excl. Inst.	F(2,335) = 235.49	P-val = 0.000	
Anderson LR Stat	Chi-sq(2) = 404.14	P-val= 0.000	
Sargan-Hansen J statistic	Chi-sq(1) = 2.109	P-val = 0.146	

a, b, c denotes statistical significance at the 1%, 5%, 10% levels of significance, respectively.

Importer and Exporter fixed effects are included.

Robust country-pair clustered standard errors are in parenthesis.

Table 9: First stage R^2 and Root MSE

Estimator	OLS	OLS	2SLS	2SLS	
ISIC Rev.3	R^2	Root MSE	R^2	Root MSE	zeroes
01-05	0.87	1.01	0.86	1.01	0.03%
10-14	0.78	1.45	0.77	1.45	4.10%
15-37	0.95	0.46	0.95	0.46	0.00%
15-16	0.90	0.67	0.90	0.67	0.00%
17-19	0.88	0.80	0.88	0.80	0.00%
20	0.88	1.02	0.88	1.03	1.17%
21-22	0.92	0.82	0.91	0.82	0.03%
23	0.76	1.79	0.77	1.79	8.50%
24	0.92	0.73	0.92	0.73	0.00%
25	0.94	0.66	0.94	0.66	0.00%
26	0.90	0.80	0.90	0.81	2.34%
27	0.86	1.01	0.86	1.00	0.90%
28	0.94	0.61	0.94	0.60	0.00%
29	0.96	0.51	0.95	0.51	0.03%
30	0.93	0.84	0.93	0.85	3.00%
31	0.90	0.81	0.90	0.82	0.03%
32	0.91	0.86	0.91	0.83	1.17%
33	0.95	0.57	0.95	0.57	0.00%
34	0.87	1.27	0.87	1.27	1.46%
35	0.82	1.35	0.81	1.36	2.34%
36-37	0.92	0.75	0.92	0.75	0.03%