The Network of Migrants and International Trade

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Abstract

This paper investigates the relationship between international trade and migration with the specific aim of estimating direct and indirect effect of the latter on cross-border flows of both homogeneous and differentiated goods. Adopting a spatial econometric approach along with a gravity model set-up, we account for the role of ethnic communities in *neighbouring* countries on trade, and we propose a new way to define neighbours based on the intensity of links in the migration network. Our approach is particularly well suited to measure the indirect effect stemming from the presence of significant ethnic communities on trade through a "market familiarization" effect. Using data covering all countries between 1970 and 2000, we find a significant indirect effect of migration on trade, that depends on the chosen weight matrix.

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1 Introduction

Since the mid 1990s a growing body of research has investigated the relation between migration and international trade. Whereas the standard Heckscher-Ohlin model suggests that the movement of goods across borders can substitute for the movement of production factors such as labour, the most recent empirical works show that the two movements complement each other. In particular, a large body of literature finds that the presence of migrant communities enhances trade between their home countries and the new place of residence: this holds for different countries (e.g United States, Canada, Spain, Italy and France, see respectively Gould 1994, Head & Ries 1998, Peri & Requena-Silvente 2010, Bratti et al. 2014, Briant et al. 2014) and has recently been confirmed by a meta-analysis covering 48 different studies (Genc et al. 2012).

As it often happens, empirical findings have percolated to economic theory, with recent models being able to accommodate the complementarity between migration and trade (Felbermayr et al. 2015). One of the main findings in the literature is that the pro-trade effect of migration is stronger in the case of differentiated goods, for which specific knowledge is particularly valuable (Rauch & Trindade 2002).[1]

Similar results have been replicated by a number of later works, using a variety of datasets and techniques. Peri & Requena-Silvente (2010), for instance, analysed the Spanish case and found that doubling the number of immigrants from a given country increases exports to the same destination by 10 percent. This effect is higher for firms selling differentiated products and for more distant countries (geographically or culturally). Aleksynska & Peri (2013) focused on the share of migrants involved in business activities rather than the total migrant population, and found a significant effect, even after controlling for the overall bilateral stock of migrants.

Briant et al. (2014) used a fine geographical disaggregation based on French departments to investigate the effect of migration on trade in goods with different degrees of complexity, as well as across countries with various levels of institutional quality: regardless of the quality of institutions in the partner country, migration is more pertinent for complex goods, whereas it matters also for simple products only when the institutional quality of the source country is low. A similar substitution effect between migrants and institutions is found in Ehrhart et al. (2014), who focused on African countries.

The core of the argument is that formal and informal links among co-ethnic migrants in other countries and at home facilitate trade by providing potential trading partners with access to valuable information. The pro-trade effect thus stems from the reduction

[1] Although subsequent work has shown that the actual magnitude of this pro-trade effect is smaller than originally estimated (see Felbermayr et al. 2010), its existence and its specific importance for differentiated goods has always been confirmed.

of trade barriers and search costs associated with market transactions. Since these costs are likely to be larger for international trade due to distance, language and cultural differences, legal provisions and the like, ethnic networks end up being especially relevant in facilitating cross-border transactions.

Most of the empirical literature shares a common strategy, based on the estimation of a log-linear gravity model where bilateral trade flows are regressed over standard explanatory variables (economic "mass" and distance), the stock of migrants from specific partner countries, and other controls aimed at capturing various types of trade costs (e.g. common language, colonial relationships). The two main strands of research that have emerged investigate the direct relation between trade and migration (i.e. the impact of migration from i to j on import/export flows between the same countries, see for instance Gould 1994 and Genc et al. 2012), and the existence of an indirect effect. For example, Rauch & Trindade (2002) investigated the role of ethnic Chinese communities, whereas Felbermayr et al. (2010) extended the analysis to several other diasporas.

In parallel to these developments in the trade-migration literature, the past decade has witnessed important advances in the theoretical foundations of the gravity model (Anderson 1979, Eaton & Kortum 2002, Anderson & van Wincoop 2003, Feenstra 2003, Helpman et al. 2008), as well as in its estimation methods (Glick & Rose 2002, Egger 2004, Head & Mayer 2014). The literature has suggested that special care is necessary in the empirical analysis to account for the interdependencies between trade flows which are inherent in the estimation of a general equilibrium model. In fact, Anderson & van Wincoop (2003) showed that bilateral export does not only depend on bilateral trade costs, the size of the trading economies and other dyad-specific characteristics, but also on *multilateral trade resistance* (MTR) i.e. the overall set of trade barriers that exporter and importer countries face. Several ways to account for MTR have been proposed: these involve the use of country-specific fixed effects (Feenstra 2003), export- and import-specific dummies (Anderson & van Wincoop 2004), measures of geographic remoteness (Helliwell 1998), origin and destination-specific spatial filters (Patuelli et al. 2016, Metulini et al. 2018) as well as more sophisticated methods (see Head & Mayer 2014, for an excellent survey). With regards to spatial econometric approaches, Behrens et al. (2012) claimed that a consistent estimation of the gravity equation can be obtained by adopting a spatial autoregressive moving average specification and using it as a proxy for MTR.

The main approach to analyze the indirect effect of migration on trade, is to look at migration from a common source country i to countries j and h (see for instance the seminal contribution by Rauch & Trindade 2002). The empirical evidence shows that migration does have a positive effect on trade between j and h, on top of the direct effect on trade from i to j and from i to h. In this paper we take a different standpoint to investigate how migration reduces trade barriers through a "market familiarization effect". We argue that trade from j to h can increase because of direct trade effects from j to h as well as indirect effects due to migration from j to i and from i to h. In our case country i is not a common source country, like in Rauch & Trindade (2002), but an intermediate country in the migration network. For instance Italians (i) are familiar with the Albanian trade opportunities, as there is a large Albanian community in Italy. When Italians migrate to France (h) they bring their knowledge with them, thus facilitating trade between Albania (j) and France (h).

The empirical methodology is similar to that of Behrens et al. (2012): we estimate a spatial autoregressive model in a gravity setup to account for MTR. Instead of adopting a standard *geographic* metric based on proximity, we define a weight matrix in which neighbours are countries with strong migration ties. The main novelty of our approach is to use network analysis to identify significant migration links. Namely, the weight matrix is build upon the worldwide migration network that connects countries based on the share of fellow citizens of the same nationality they host. Our approach allows us to properly identify the indirect effect of migration by considering at the same time the interdependencies among trade flows that would otherwise lead to inconsistent estimates (Behrens et al. 2012).

In a nutshell, this paper studies the indirect effect of migrants on trade due to ethnic communities abroad, combining network analysis and spatial econometrics. We define a weight matrix based on the migration network to properly assess the indirect effect of all ethnic communities by means of a single estimated coefficient, whereas the related literature generally estimates a coefficient for each ethnicity.[2]

The rest of the paper is structured as follows: our empirical strategy is laid down in Section 2, where we illustrate the rationale of our approach, the model specification, and the data we use. Section 3 discusses our main results, while Section 4 concludes.

[2]Rauch & Trindade (2002) evaluated the effect of the Chinese network alone, while Felbermayr et al. (2010) extended the analysis to all potential ethnic group, but one at a time.

2 Empirical strategy

In line with the literature, we model the indirect effect of migration on trade as a (spatial) spillover.[3] More precisely, we assume that export from i to j depends on variables specific to the country-pair (e.g distance, stock of bilateral migrants) as well as on their neighbours (the so called *third countries*). In particular, we focus on the potential impact that migrants from third countries (say h) may have on bilateral trade between countries i and j (see Figure 1). Countries h and i are neighbours in the migration network if there is a significant number of people born in i who are residents in h.[4] Migrants from h to j is what gives rise to the indirect (third-countries) effect we take into account in our analysis. In other words, we investigate whether migration from h to j affects exports from i to j, given the existence of a strong migration link from i to h.[5]

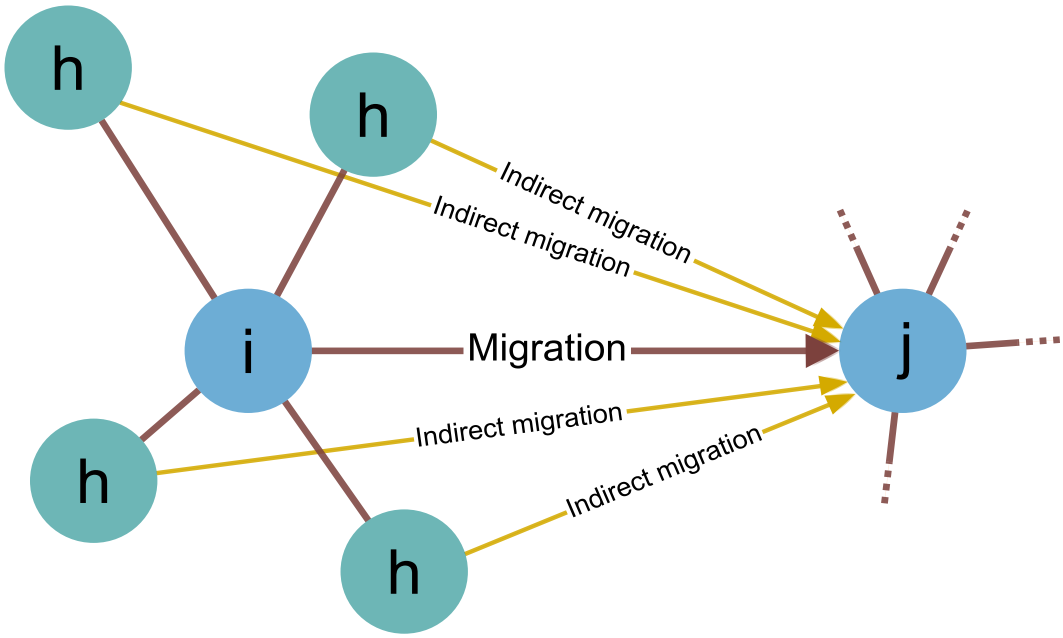

Figure 1: Direct and indirect migration channels in the network.

In our setup both direct and indirect network effects through third countries are considered. For instance, Italy hosts one of the largest Albanian community abroad. As a result, migration from Italy to France, can boost trade between Albania and France thanks to the fact that Italians are likely to be familiar with the Albanian market and/or

[3]In this context a spatial spillover is defined as the relationship between a characteristic of a country and the outcome of another country located in its neighbourhood (LeSage 2014).

[4]The exact meaning of *significant number* of migrants is explained in Section 2.1.

[5]Similarly, one could let k be a migration neighbour of the destination country j. In such a case migrants from i to k should represents another indirect channel affecting trade from i to j. However, we have no theoretical and empirical reason to model this second type of network dependence.

to have business contacts in Albania.[6] This approach, as opposed to a standard weighting matrix based on geography (such as contiguity, inverse distance or nearest neighbours), allows for a more precise identification of the indirect effect since "proximity" is determined by the actual strength of migration ties. Back to our example, many of the countries that have strong migration ties with Italy, like for instance Argentina, are neither close nor do share borders with Italy.

2.1 Gravity model and spatial interaction

As mentioned above, we follow the standard approach in the empirical studies on migration and trade which entails the estimation of a gravity model augmented with the stock of migrants. Besides migrants, we consider per capita GDP of both origin and destination countries to control for their purchasing power, plus a number of other standard controls such as geographic contiguity, common language, common currency, colonial ties and participation into regional trade agreements. All these factors are expected to lower the costs of international transactions (Anderson & van Wincoop 2004).

Since the seminal contribution by Anderson & van Wincoop (2003), various methods have been proposed to deal with MTR, i.e. interdependencies among trade flows, that stem from the estimation of a model in a general equilibrium framework (Baier & Bergstrand 2009, Feenstra 2003, Behrens et al. 2012, Patuelli et al. 2016). Among them, one approach entails augmenting the gravity model with importer and exporter time-varying fixed effects whereas a second method is based on a spatial autoregressive model. Behrens et al. (2012) argued that the fixed effects specification does not fully succeed in capturing the MTR dependencies in the error structure, and indeed find that the residuals still display a significant amount of autocorrelation.[7] Therefore, Behrens et al. (2012) derived a gravity equation from the quantity-based version of the constant elasticity of substitution (CES) model, where MTR take the form of a spatial autoregressive moving average term, which yields a consistent estimation of the parameters. Spatial autoregressive models are particularly interesting to us since they account for MTR in estimating the direct and indirect effects of migration.

However, it is still largely debated how to choose the most appropriate weight matrix to define the neighbouring structure in spatial autoregressive models. The most common choice is geographic contiguity: country i and j are neighbours if and only if they share a

[6] Second-generation Albanians also play a role, since some of the Italian migrants abroad can have family ties to Albania.

[7] Also Anselin & Arribas-Bel (2013) demonstrated by simulation experiments that fixed effects correctly remove autocorrelation only in some specific cases.

border. A second possibility is to fix number of nearest countries, so that every country has the same number of neighbours. This approach is generally used for islands with no contiguous countries. Another traditional formulation is based on inverse distance.

More recent solutions entail a combination of geographic, economic and demographic aspects, instead of spatial metrics, even though those matrices may suffer from endogeneity (LeSage & Pace 2011, Kelejian & Piras 2014). To address this issue, Case et al. (1993) and Cohen & Paul (2004) averaged the variable used to construct the weight matrix over time, claiming that the resulting weights are orthogonal to the other explanatory variables. Behrens et al. (2012) used 5-years lagged values to control for the endogeneity of wages and populations with respect to potential trade shocks. Kelejian & Piras (2014) have recently proposed another estimation method to overcome the problem of endogeneity in the weight matrix, whereas LeSage & Ha (2012) and Parent & LeSage (2008) estimated their model as if their weight matrices were exogenous. Another potential solution is to analyse the effect of network-propagation, viewed both as an alternative and a complement to the spatial effect. LeSage & Pace (2011) discuss the possibility of jointly modelling spatial and non-spatial dependence through a double autoregressive component that makes use of two different weight matrix specifications. However, Elhorst et al. (2012) warns against using high-order spatial autoregressive terms, because this can lead to incorrect estimation of the spatial parameters, as long as we ignore the parameters' feasible region.

In this paper we use the migration network to build the weight matrix, in addition to the traditional spatial approach. To motivate our choice consider the relationships between China, India and the United States. Chinese migration to India is limited, whereas migration from India to the United States is strong. Whenever exports from China to USA turns out to be strong, this is unlikely be due to Chinese migration to India, but for some goods it can take advantage of spatial proximity of China to India. Using the network of migrants, the indirect effect is computed exclusively on country pairs with strong migration ties, thus avoiding any confusion between the indirect effect of migration and other geographical factors.

To identify the most significant migrants links, we use the hypergeometric distribution as a benchmark (Riccaboni et al. 2013, Sgrignoli et al. 2015). We compare actual migration links with a null hypothesis of migrants choosing destination countries at random.

More precisely, for each pair of countries, we compute the probability that the observed stock of migrants from country i residing in country h is extracted from an hypergeometric distribution with parameters given by the total number of migrants from country i, the total stock of migrants in country h (from all possible source countries), and the stock of world migrants. We consider the acceptance or rejection of the null hypothesis that the actual number of migrants is stronger than a random allocation of migrants according to the hypergeometric distribution.[8]

The specification of the weight matrix then becomes

$$\mathbf{W}^M : \begin{cases} w^M_{i,h} = 1, & \text{if } i \text{ has a significant migration relationship with } h \\ & \text{(null hypothesis rejected);} \\ w^M_{i,h} = 0, & \text{otherwise.} \end{cases}$$

Therefore, only statistically significant migration links are considered in the weight matrix. Fagiolo & Mastrorillo (2014) found that, with some exceptions, a strong link in the trade network is typically associated to a strong link in the migration network, and they observed an increasing overlap between the two networks over time.[9] This evidence justifies the use of a matrix based on the strongest migration links to account for MTR without violating the economic equilibrium in the structural gravity model discussed in Anderson & van Wincoop (2003). As a robustness check, we also use the original migration flows, without any filtering procedure, to compute the weight matrix. This matrix is denser than the matrix of bilateral trade flows and the estimated impact of migration turns out to be even stronger than in the case of the filtered weight matrix. This confirms that reducing the density of the weight matrix does not overestimate the effect of migration due to the possible exclusion of some MTR terms.

The matrix $\mathbf{W}^M$ is then transformed by means of a Kronecker product in order to extract neighbours for each country-pair and specifically the neighbours of the exporter (origin) country (LeSage & Pace 2008).[10]

[8] Assuming two countries, i and h, let N_i be the total number of migrants from country i, N_h the total number of migrants to country h, N_k the overall total number of migrants and N_{ih} the observed number of migrants from i to h. Under the null hypothesis of random co-occurrence, i.e. country h hosts indifferently migrants from every origin country, the probability of observing X migrants is given by the hypergeometric distribution

$$H(X|N_k, N_i, N_h) = \frac{\binom{N_i}{X}\binom{N_k - N_i}{N_h - X}}{\binom{N_k}{N_h}}$$

and we can associate a p-value with the observed N_{ih} as

$$p(N_{ih}) = 1 - \sum_{X=0}^{N_{ih}-1} H(X|N_k, N_i, N_h)$$

.

[9] The share of links present in both networks has grown from 65% in 1960 to more than 70% in 2000. Sgrignoli et al. (2015) provides evidence pointing in the same direction.

[10] More in details, since we also need to account for the time index in the pooled model specification (see section 3) the matrix that defines the set of our origin countries' neighbours has dimension $n^2 * t \times n^2 * t$ and it is constructed as follows: $\mathbf{W}^M_{Kr,t} = I_t \otimes \mathbf{W}^M_{Kr}$, where $\mathbf{W}^M_{Kr} = \mathbf{W}^M \otimes I_n$.

2.2 Model specification, estimation and interpretation

We use traditional parametric spatial econometrics (i.e. spatial autoregressive models, see Anselin 1988) to estimate the indirect effect of migration on trade. The presence of a spatial lag of the dependent (and independent) variables among the explanatories, in this family of models makes ordinary least squares (OLS) estimation inconsistent, due to the presence of intrinsic endogeneity.

The standard alternative in the literature is the concentrated maximum likelihood estimator (CML) proposed by Anselin (1988) and revised for gravity models by LeSage & Pace (2008), while a class of spatial instrumental variable generalized method of moments (IV/GMM) estimators has been proposed by Kelejian & Prucha (1998) and Kelejian & Prucha (1999) as an alternative when particular assumptions on the model need to be relaxed. Fitting a CML estimator on a linear-in-log gravity model disregards the presence of zero trade flows, which represent around 20 percent of country pairs in our sample. The standard literature has addressed it by considering trade flows as count processes and fitting Poisson or negative binomial models (Santos Silva & Tenreyro 2006, Burger et al. 2009). However, to the best of our knowledge, no extension of this approach exists for spatial autoregressive models. The choice of fitting a Poisson model, in which the spatial effect is captured by spatial-filtering eigenvectors (see Patuelli et al. 2016), prevents from distinguishing between direct and indirect effects; whereas the other option, using spatial generalized linear models (Lambert et al. 2010, Sellner et al. 2013), prevents from using a spatial autoregressive specification and thus from explicitly estimating indirect effects.

The most widely used spatial autoregressive models include the lagged dependent variable (SAR models) or the lagged error terms as regressors (spatial error model, SEM). We use a spatial Durbin model (SDM) to consider the lagged independent variables among the regressors (including lagged migration) and to explicitly model the indirect effect of migrants. Such specification is also known to correct for parameter misspecification deriving from autocorrelated omitted variables, even when the true model is not a SDM (Elhorst 2010). The SDM model reads as follow

$$\text{SDM:} \qquad \mathbf{Y} = \rho \mathbf{W}^M_{Kr,t}\mathbf{Y} + \mathbf{X}\beta + \mathbf{W}^M_{Kr,t}\mathbf{X}\gamma + \epsilon, \tag{1}$$

where $\mathbf{Y}$ is the dependent variable, i.e. the exports; ρ is the scalar coefficient of the spatial autoregressive term to be estimated; β is the $k \times 1$ vector of coefficients to be estimated for the explanatory variables in matrix $\mathbf{X}$, which are distance, origin and destination per capita GDP and population, migration, contiguity, common currency, common language, colony and regional trade agreements dummies; γ is the $k \times 1$ vector of coefficients to be estimated for the lagged explanatories in the matrix $\mathbf{W}^M_{Kr,t}$, which is defined above.[11]

The presence of a rich set of interactions implies a special care in the interpretation of the results: trade flows from i to j are likely to react to the presence of ethnic communities in j (coming both from i and from third countries h). Recent literature on the subject (LeSage & Pace 2008, LeSage & Thomas-Agnan 2015, LeSage & Fischer 2016) suggests how to compute the different types of impact: SDM's direct and indirect impacts for the rth explanatory variable are defined using a partial derivative expression.[12]

2.3 Data

Migration data come from the World Bank's Global Bilateral Migration dataset (Özden et al. 2011). It is composed of matrices of bilateral migrant stocks spanning five decades from 1960 to 2000 (five census rounds), and it is based primarily on the foreign-born definition of migrants. The World Bank's dataset provides a comprehensive picture of bilateral global migration over the second half of the 20th century for a total of 232 countries. The data reveals that the global migrant stock increased from 92 million in 1960 to 165 million in 2000. Migration between developing countries dominates, constituting half of all international migration in 2000, whereas flows from developing to developed countries represent the fastest growing component of international migration in both absolute and relative terms.

For international trade, we use the NBER-UN dataset described by Feenstra et al. (2005), disaggregated according to the Standardized International Trade Code at the four-digit level (SITC-4). For each country it provides the value exported to all other countries, expressed in thousands of US dollars, for 775 product classes. In our analysis, we focus on the years 1970, 1980, 1990 and 2000.[13]

Looking at the SITC product code of goods traded between each country pair we apply Rauch's (1999) classification to distinguish between homogeneous and differentiated goods. Trade in the latter type of products are more heavily influenced by the presence

[11] All the data (except for the dummies) are in $\log_{10}$.

[12] To compute direct and indirect impacts in the SDM specification for the rth explanatory variable, we compute the following partial derivative expression: $\frac{\partial \mathbf{T}_{ij}}{\partial \mathbf{X}_{k,hk}} = S_r(\mathbf{W}^M_{Kr})_{ij,hk}, \forall k = 1, ..., K$, where $S_r(\mathbf{W}^M_{Kr}) = V(\mathbf{W}^M_{Kr})(I_{n^2}\beta_k + \mathbf{W}^M_{Kr}\gamma_k)$ is a $n^2 \times n^2$ matrix, with $V(\mathbf{W}^M_{Kr}) = (I_{n^2} - \rho\mathbf{W}^M_{Kr})^{-1}$. The presence of global spillovers can be seen by recognizing that $(I_{n^2} - \rho\mathbf{W}^M_{Kr})^{-1} = I_{n^2} + \rho\mathbf{W}^M_{Kr} + \rho^2\mathbf{W}^{M,2}_{Kr} + ...$ For each explanatory variable in the model, the direct impact is the average of the values in the main diagonal of $S_r(\mathbf{W}^M_{Kr})$, while the total impact is determined as the sum of all the elements of the matrix, divided by n^2. The indirect impact is simply the difference between the total and the direct effect: $Indirect = Total - Direct = \frac{\sum_{ij}\sum_{hk}(S_r(\mathbf{W}^M_{Kr}))_{ij,hk}}{n^2} - \frac{\sum_{ij}\sum_{hk} diag(S_r(\mathbf{W}^M_{Kr})_{ij,hk})}{n^2}$.

[13] We use nominal values for trade data, as well as for GDP per capita. Besides being customary in the literature (see for instance Head et al. 2010), the choice is motivated by the fact that price levels are part of the multilateral trade resistance term: hence, by properly taking into account the MTR, there is no need for any additional deflation.

of migrant networks, as buyers and sellers need to look for relevant information that is not easily embedded in prices.

All the other controls used in the regressions have been retrieved from the CEPII dataset, documented in Mayer & Zignago (2011). Specifically, we extract from this dataset per-capita GDP (GDPpc_orig and GDPpc_dest), population (population_orig, population_dest), geographical distance between the most important cities of each country pair (distance) and dummy variables for contiguity (contig), common language (comlang), colonial ties (colony), common currency (comcur) and free trade agreement (fta). In all the analysis, we only consider dyads with an active link in both trade and migration datasets.

3 Results

We adopt an estimation strategy pooling data for the years 1970, 1980, 1990 and 2000, and using three different dependent variables: (*i*) total exports; (*ii*) export of differentiated goods; and (*iii*) export of homogeneous goods. To correct standard errors we resort to two approaches that are commonly used in related literature: the first is the Huber-White correction for heteroskedasticity in the error terms (White 1980): this choice is motivated by a Breusch-Pagan test (Table 1), that rejects the null hypothesis of homoskedasticity at a 1% level in every specification (see the upper panel of Table 2). The second is the one-way clustering correction as proposed by Cameron et al. (2011), i.e. setting country-pair as identifiers, to control for autocorrelation and heteroskedasticity.

Table 1: Breusch Pagan test for heteroskedasticity for the models in table 1, without instrumenting migration

Non instrumented	base	total trade		diff. goods		homog. goods	
	ols	ols	fe	ols	fe	ols	fe
BPtest		1033.3	4777.8	493.6	3480.8	979.87	4406.7
df	11	11	1147	11	1147	11	1147
p-value	$< 2.2e^{-16}$	$< 2.2e^{-16}$	$< 2.2e^{-16}$	$< 2.2e^{-16}$	$< 2.2e^{-16}$	$< 2.2e^{-16}$	$< 2.2e^{-16}$

We start by estimating a gravity model for total exports without migration and using pooled OLS.[14] Results, presented in the first column of Table 2, with Huber-White cor-

[14]Santos Silva & Tenreyro (2006) warn against the use of log-linearized gravity models, because of the loss of information associated with discarding country-pairs with zero trade flows. For this reason, we have also performed a Poisson Pseudo Maximum Likelihood (PPML) estimation: we find that both OLS and PPML yield a significant effect of migration on trade.

rected standard errors, are in line with the previous literature.[15] We find that geographical distance has a negative effect on trade, while country size (GDPpc_orig, GDPpc_dest, population_orig, population_dest) plays a positive role. Furthermore, being contiguous (contig), speaking the same language (comlang), being a former colony (colony), using the same currency (comcur) and being in regional trade agreement (rta), all have a positive effect on total trade. In column 2 we add the stock of migrants to the model, and we note that the migration coefficient (0.150) is in line with the meta-analysis by Genc et al. (2012), which reports coefficients varying between 0.13–0.15. Moreover, we find that adding migration to the explanatory variables reduces the impact of distance.[16]

A specification that includes origin- and destination-specific fixed effect has been widely applied in estimating the gravity equation for international trade, in order to account for MTR. Here we opt for importer and exporter time-varying fixed effects (FE) as suggested by the most recent literature (Felbermayr et al. 2015, Head & Mayer 2014) and find a similar migration coefficient (0.150 with OLS, 0.128 with FE). Columns 4–7 of Table 2 report OLS and FE results for exports of differentiated and homogeneous goods: the migration coefficient is higher in the former case (0.189 with OLS and 0.140 with FE for differentiated goods, versus 0.114 with OLS and 0.113 with FE for homogeneous goods), in line with expectations. A statistical confirmation comes from the z-test for the difference between the two coefficients, which delivers p-values very close to zero for the null hypothesis of equality of the coefficients across the two specifications. However, since the causal relationship between trade and migration can hold both ways, the estimated coefficients may suffer from endogeneity bias, and an instrumental variable approach is warranted. We therefore follow an approach which was first suggested by Altonji & Card (1991) and it is now commonly used (e.g. Peri & Requena-Silvente 2010 and Bratti et al. 2014). This entails using an imputed stock of migrants ($mig\_imp^t_{ij}$) obtained by multiplying the share of migrants from country j residing in country i in 1960 (s^{1960}_{ij}) by the total stock of migrants of nationality j at time t: $mig\_imp^t_{ij} = s^{1960}_{ij} \cdot migration^t_j$. Hence, the imputed stock of migrants (mig_imp) varies both over time and across country pairs, but is not affected by contemporaneous trade flows.

To deal with the reverse causality problem with regards to migration, we adopt the traditional instrumental variable two stage least squares (IV-2SLS) approach (Greene 2003). We assume that only one predictor is endogenous, namely, migration, and use as instrument the imputed stock of migrants ($mig\_imp^t_{ij}$).

[15]Table 8 in the appendix reports the standard errors from a one-way clustering approach on country pairs to control for auto-correlation and heteroskedasticity. The two different alternatives for correcting standard errors yield qualitatively similar results in terms of significance of the coefficients.

[16]This is in good agreement with the literature (see for instance Felbermayr et al. 2015) and suggests that distance picks up the effect of formal and informal knowledge barriers.

Table 2: Gravity results with OLS and FE models, with and without instrumenting migration for reverse causality. Huber-White standard errors in parenthesis.

Non instrumented	base	total trade		diff. goods		homog. goods	
	ols	ols	fe	ols	fe	ols	fe
intercept	-10.414***	- 9.782***	6.191 ***	-10.635 ***	4.920 ***	-8.981 ***	5.977 ***
	(.103)	(.116)	(.193)	(.122)	(.192)	(.122)	(.218)
distance	-.858***	-.687***	-1.002***	-.630***	-1.055***	-.728***	-1.011***
	(.018)	(0.020)	(.021)	(.021)	(.020)	(.021)	(.021)
GDPpc_orig	.905***	.908***	-	1.116***	-	.751***	-
	(.007)	(.008)	-	(.008)	-	(.008)	-
GDPpc_dest	.846***	.737***	-	.610***	-	.739***	-
	(.007)	(.009)	-	(.009)	-	(.009)	-
population_orig	1.751***	1.668***	-	1.992***	-	1.421***	-
	(.011)	(.013)	-	(.013)	-	(.013)	-
population_dest	1.616***	1.427***	-	1.140***	-	1.486***	-
	(.010)	(.013)	-	(.014)	-	(.014)	-
contig	.284***	.163***	.079*	.126***	.144***	.139***	.017
	(.036)	(.033)	(.032)	(.037)	(.031)	(.033)	(.032)
comlang	.190***	.074***	.129***	.099***	.244***	.103***	.093***
	(.014)	(.016)	(.015)	(.016)	(.014)	(.016)	(.016)
colony	.608***	.451***	.455***	.332***	.313***	.390***	.443***
	(.033)	(.027)	(.025)	(.031)	(.025)	(.028)	(.025)
comcur	.373***	.293***	.298***	.357***	.270***	.256***	.300***
	(.048)	(.054)	(.047)	(.051)	(.047)	(.056)	(.047)
rta	.192***	.149***	.005	.286***	.009	.100**	0.041
	(.028)	(.022)	(.023)	(.024)	(.023)	(.023)	(.023)
migration	-	.150***	.128***	.189***	.140***	.114***	.113***
	-	(.006)	(.006)	(.006)	(0.006)	(.006)	(.006)
R^2 adj	.640	.643	.752	.672	.820	.6043	.716
obs	29784	24105	27217	20908	23467	22256	24813

Instrum. (Altonji-Card)	total trade		diff. goods		homog. goods	
	ols	fe	ols	fe	ols	fe
intercept	-10.200 ***	6.323 ***	-11.18***	5.088 ***	-9.409 ***	6.087 ***
	(.127)	(0.200)	(.127)	(.200)	(.200)	(.232)
distance	-.710***	-1.037***	-0.644***	-1.105***	-0.761***	-1.036***
	(.023)	(.022)	(.023)	(.021)	(.022)	(.023)
GDPpc_orig	0.901***	-	1.109***	-	.750***	-
	(.009)	-	(.009)	-	(.009)	-
GDPpc_dest	.788***	-	.655***	-	.784***	-
	(.010)	-	(.010)	-	(.009)	-
population_orig	1.685***	-	2.013***	-	1.451***	-
	(.014)	-	(.014)	-	(.015)	-
population_dest	1.509***	-	1.224***	-	1.564***	-
	(.014)	-	(.014)	-	(.014)	-
contig	.187***	.099***	.133***	.155***	.162***	.028
	(.037)	(.033)	(.037)	(.032)	(.033)	(.032)
comlang	.100***	.148***	.127***	.269***	.131***	.110***
	(.017)	(.016)	(.017)	(.015)	(.017)	(.017)
colony	.448***	.466***	.317***	.343***	.394***	.443***
	(.032)	(.026)	(.032)	(.026)	(.029)	(.026)
comcur	.302**	.310***	.363**	.284***	.279***	.320***
	(.052)	(.048)	(.052)	(.048)	(.058)	(.048)
rta	.150***	-.020	.299***	-.000	.096***	.013
	(.025)	(.025)	(.025)	(.024)	(.024)	(.025)
iv.migration	.131***	.111***	.189***	.120***	.092***	.103***
	(.007)	(.008)	(.007)	(.007)	(.007)	(.008)
R^2 adj	.653	.761	.680	.824	.614	.728
obs	20052	22492	17781	19782	18720	20715

Table 3: First stage regression results from the IV-2SLS where the endogenous variable is migration and the instrumental variable is the imputed stock of migrants (mig_imp) with the Altonji-Card approach. Standard errors in parenthesis.

	IV-2SLS (1th Stage)
Intercept	0.500 ***
	(.006)
mig_imp	0.843 ***
	(.003)
R^2	.710
obs	36828

Results of the F-test for the validity of the instrument and the Durbin-Wu-Hausmann test for the endogeneity are reported in Table 4, as well as the correlation measure of the instrument with the dependent variable: for all the three dependent variables they confirm the presence of endogeneity and the necessity of using instrumental variables, as well as the validity of the IV strategy adopted. The instrument turns out to be very strong, with an F-test well above the threshold of 10 suggested by Staiger & Stock (1997) to detect a potential weak instrument problem. Results are also in line with previous works (Peri & Requena-Silvente 2010, Bratti et al. 2014) which found really large first stage F-test values and significant Durbin-Wu-Hausman tests. The migration coefficients using the IV model, as reported at the bottom of Table 2, are generally lower than in the non-instrumented model, but nevertheless the positive effect of migration on trade persists and remains larger in the case of trade in differentiated goods.

Table 4: Tests for migration endogeneity and instruments with Altonji-Card approach

	total trade	diff. goods	homog. goods
Correlation between trade and migration	.351	.368	.287
Correlation between trade and mig_imp	.331	.325	.311
First stage test for the validity of the instrument	4495.7	4400.3	4400.3
Durbin-Wu-Hausman for the endogeneity in the model	3.937	22.12	3.20

Although a non-spatial weight matrix could also lead to endogeneity issues (using migration to construct the weight matrix could generate reverse causality of migration on trade), we estimate our model as if the matrix were exogenous, as done by LeSage & Ha (2012) and Parent & LeSage (2008).[17] In our setting, the potential endogeneity of the migration network with respect to trade is greatly diminished by the fact that we

[17]The estimation approach proposed in Kelejian & Piras (2014) to remove endogeneity applies only to SAR models.

use the stock of migrants rather than the annual flows. In fact, while economic theory suggests that the presence of large ethnic communities lowers informational barriers and trade costs, there is little reason to expect that a change in bilateral trade affects the stock of migrants from any country. However, to tackle this problem, we generate the matrix using migration data from 1960, that is prior to any period we use in our analysis.

We now estimate the migration network effect using spatial autoregressive models. Referring to section 2.1, we can say that spatial autoregressive models are a better alternative to FE models to account for MTR (Behrens et al. 2012).[18] To justify the introduction of spatial econometrics, we analyse the residual autocorrelation in the estimated error terms of the non-spatial models in Table 2. To this aim we perform a Moran I test (Cliff & Ord 1973, 1981) based on the network of migrants matrix.[19]

Table 5: Moran I test on the residuals of the OLS and FE models

	OLS	FE
total	.035	- .008
z-score (p-val)	8.49 (.000)	-3.49 (.000)
differentiated	.016	-.009
z-score (p-val)	3.34 (.000)	-3.43 (.000)
homogeneous	.035	-.011
z-score (p-val)	7.84 (.000)	-4.16 (.000)

The first two columns of Table 5 report the test results for the OLS and FE models, and they confirm the presence of residual autocorrelation for all the classifications (total trade, differentiated and homogeneous goods). To choose the best model specification we perform a likelihood ratio (LR) test and Lagrange Multiplier (LM) diagnostic tests (Elhorst 2010, Anselin et al. 1996, Florax et al. 2003), which point us to the SDM specification. Following the results of these tests, we perform our analysis using the SDM model with a CML estimator.

The results of our analysis are reported in Table 6. A Breusch-Pagan test has also been performed on SDM models for the introduction of the Huber-White correction of standard errors to overcome a possible heteroskedasticity problem. The migration values are those predicted from the first stage regression reported in Table 3. The first three columns report results from the SDM model with the hypergeometric-filtered migration matrix $\mathbf{W}^{M}_{Kr,t}$. As a comparison, we also report results from the specification with the

[18] It obviously follows that in the spatial autoregressive models we do not include origin- and destination- fixed effects.

[19] $\mathbf{W}^{M}_{Kr,t}$, which is the $n^2 * t \times n^2 * t$ network weight matrix described in section 2.1, constructed on 1960 migration data, and therefore a time invariant matrix where data for 1960 is replicated t=4 times.

spatial weight matrix (columns 4–6) and those obtained with a non-filtered migration matrix (columns 7–9).[20]

Table 6: Results from SDM model with Altonji-Card instrumented migration. With network of migrants (i) and with spatial (inverse distance) weight matrix (ii). Huber White standard errors in parenthesis.

	(i) **Migrants (Filtered)**			(ii) **Inverse distance**			(iii) **Migrants (Non-Filtered)**		
	total trade	diff. goods	homog. goods	total trade	diff. goods	homog. goods	total trade	diff. goods	homog. goods
intercept	-11.013***	-11.718***	-10.188***	-9.012***	-11.581***	-7.401***	-10.734 ***	-12.014***	-9.803***
	(.133)	(.139)	(.138)	(.533)	(.523)	(.533)	(.437)	(.375)	(.413)
distance	-.747***	-.680***	-.792***	-.793***	-.706***	-.837***	-.777***	-.683***	-.824***
	(.022)	(.023)	(.022)	(.021)	(.023)	(.022)	(.021)	(.022)	(.022)
GDPpc_orig	.966***	1.155***	.808***	1.078***	1.240***	.912***	1.065***	1.225***	.897***
	(.009)	(.010)	(.010)	(.010)	(.011)	(.011)	(.010)	(.011)	(.010)
GDPpc_dest	.912***	.743***	.903***	.969***	.782***	.953***	.967***	.781***	.944***
	(.012)	(.013)	(.013)	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
pop_orig	1.785***	2.084***	1.540***	1.969***	2.218***	1.712***	1.944***	2.185***	1.686***
	(.015)	(.015)	(.015)	(.016)	(.017)	(.017)	(.016)	(.017)	(.017)
pop_dest	1.665***	1.336***	1.712***	1.773***	1.403***	1.810***	1.767***	1.401***	1.792***
	(.017)	(.017)	(.018)	(.016)	(.017)	(.017)	(.016)	(.017)	(.017)
contig	.186***	.134***	.163***	.240***	.172**	.214***	.231***	.167***	.205***
	(.034)	(.037)	(.033)	(.034)	(.037)	(.034)	(.034)	(.037)	(.034)
comlang	.126***	.142***	.154***	.176***	.183**	.200***	.193***	.187***	.214***
	(.016)	(.017)	(.017)	(.016)	(.017)	(.017)	(.016)	(.017)	(.017)
colony	.432***	.307***	.381***	.422***	.303***	.374***	.433***	.313***	.382***
	(.028)	(.031)	(.029)	(.028)	(.031)	(.029)	(.028)	(.031)	(.029)
comcur	.303***	.349***	.280***	.314***	.368***	.294***	.293***	.349***	.277***
	(.055)	(.052)	(.057)	(.055)	(.051)	(.057)	(.054)	(.050)	(.056)
rta	.138***	.285***	.091**	.092***	.248***	.048*	.111***	.265***	.065***
	(.023)	(.025)	(.024)	(.023)	(.025)	(.024)	(.023)	(.025)	(.024)
iv.migration	.113***	.176***	.077***	.078***	.150***	.037***	.061***	.129***	.032***
	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)	(.006)	(.006)	(.006)
W.iv.migration	.014	.007	.002	.065	.031	.079*	.102***	.075**	.106***
	(.012)	(.012)	(.012)	(.041)	(.042)	(.041)	(.025)	(.026)	(.025)
ρ	.034***	.020	.032***	-.006*	.059***	.018***	.031***	.017*	.035***
	(.007)	(.011)	(.011)	(.003)	(.011)	(.002)	(.006)	(.009)	(.007)
time FEs	yes	yes	yes	yes	yes	yes	yes	yes	yes

All the coefficients are consistent with the previous literature across the various specifications: geographical distance has negative sign, country size have a positive and significant effect on trade, while being contiguous (contig), speaking the same language (comlang), being a former colony (colony), using the same currency (comcur) and being in regional trade agreement (rta) generally have a positive effect on trade. Moreover,

[20] The spatial weight matrix is computed as the inverse distance metric ($1/dist$). We call this matrix $\mathbf{W}^{S}_{Kr,t}$, that is a $n^2 * t \times n^2 * t$ matrix generated using a Kronecker product on a initial $n * n$ inverse distance weight matrix.

the spatial autoregressive coefficient of the model, ρ, has positive coefficients using the network of migrants matrix specification (significant for total trade and homogeneous goods), whereas it becomes negative (and weakly significant) for total trade, and positive and significant for differentiated and homogeneous goods when we use the weight matrix based on the inverse of geographic distance.[21]

The coefficient of *W.iv.migration* (the lagged migration term in the SDM) represents the magnitude of the indirect effect of migration. This coefficient is positive but not significant when using the filtered migration matrix (columns 1–3). Using the spatial weight matrix (columns 4–6) the indirect effect is bigger (relative to columns 1–3) and statistically significant for the case of homogeneous goods. The same holds when using the non-filtered migration matrix (columns 7–9): the estimated result for the indirect effect is bigger and statistically significant. By using a matrix based on the inverse of distance, a number of different contiguity-related factors are likely to be captured by *W.iv.migration*. The same happens by using the original (non-filtered) migration flows for the weight matrix. These results highlights that a trade-creation effect of the network of migrants depends on the weight matrix adopted.

The SDM model controls for both the lagged and non-lagged explanatory variables, in order to explicitly allow variations in a given country pair to affect the pair itself and to potentially reverberate (indirectly) across all the other pairs. As a result, the interpretation of the parameters becomes more complicated. We therefore estimate the direct and indirect impacts as defined in section 2.2 (Anselin & Le Gallo 2006, LeSage & Thomas-Agnan 2015, LeSage & Fischer 2016). Results are reported in columns 1–3 of Table 7. In the upper panel, we see that the direct effect of migration is in line with OLS and FE results displayed above (Table 2): a 10% increase in migration stocks increases total export by 1.13%, the export of differentiated goods by 1.76%, and the export of homogeneous goods by 0.77%. Moreover, we find a total coefficient of 0.131, 0.186 and 0.081 for total trade, differentiated goods and homogeneous goods, respectively. Specifically, we find that a 10% increase in migration stocks from a neighbour of the exporter country to the importer one increases total export by 0.18%, export of differentiated goods by 0.10%, and export of homogeneous goods by 0.04%.

Using the spatial weight matrix (columns 4–6 in Table 7) we find different impacts: a 10% increase in migration from a country in the exporter neighborhood to the importer increases exports of differentiated goods by 0.42%, it decreases total exports by 0.64%

[21] In order to make our work comparable with Behrens et al. (2012), who found this parameter to be negative in the Cliff-Ord (SARAR) specification, we also estimated that same model, finding a negative ρ coefficient as well. SARAR regression results are available upon request.

Table 7: Average impacts of migrants on trade, from SDM model with Altonji-Card instrumented migration. Using network of migrants weight matrix (i) and spatial (inverse distance) weight matrix (ii).

	(i) Filtered			**(ii) Inverse distance**			**(iii) Non-Filtered**		
	total trade	**diff goods**	**homog goods**	**total trade**	**diff goods**	**homo goods**	**total trade**	**diff goods**	**homo goods**
direct	.113	.176	.077	.071	.150	.037	.061	.130	.032
indirect	.018	.010	.004	.064	.042	.081	.108	.092	.112
total	.131	.186	.081	.135	.192	.118	.169	.222	.144

and decrease exports of homogeneous goods by 0.81%.

Using the original migration weight matrix (columns 7–9 in Table 7) we find stronger impacts: a 10% increase in migration from a country in the exporter neighborhood to the importer increases exports of differentiated goods by 0.92%, it decreases total exports by 1.08% and decrease exports of homogeneous goods by 1.12%.

In sum, we find a stronger effect of total (direct + indirect) migration on trade in differentiated goods rather than in homogeneous ones, consistently with the previous literature (Rauch & Trindade 2002, Felbermayr et al. 2010). Moreover, we find that the presence of a positive trade-creation effect of migration via market familiarization depends on the specific weight matrix used. In particular, the indirect effect of migration (attributed to market familiarization) turns out to be not significant when we use the filtered migration-network matrix, whereas it finds statistical support when we use alternative weighting schemes. We interpret this difference as an indication that some geographical factors, such as spatial proximity among countries, might be picked up by the migration coefficient when they are not appropriately controlled for. As such, we claim that a spatial-econometrics approach may provide a useful framework of reference for the estimation of the direct and indirect effect of migration on trade.

4 Conclusions

Increased data availability both at national and international levels has triggered a host of research on the relationship between trade and migration, mostly using the gravity equation. Although network effects play a relevant role in shaping world trade patterns, they are not accounted for in the traditional gravity models. Specifically, this contribution aims at testing the argument expressed in Gould (1994) about familiarization of the importer country with the country of origin of migrants.

We contribute to this literature by applying spatial econometric techniques and exploiting the topological distance between countries in the migration network in order to look at indirect effects of migration on trade. Using a Spatial Durbin Model, which adequately accounts for indirect interdependences, we are able to investigate the indirect effect of migration from a global perspective, through a single coefficient, rather than focusing on a single ethnic network as done in the literature so far. Furthermore, the novelty of this paper rests on the fact that the weight matrix is based on network measures rather than geographical distance: building a world-wide network of migration stocks that connects countries by the share of fellow citizens present in both, allows us to include the interaction of countries that, even though geographically distant, have strong migratory links. Thanks to our innovative approach, we are able to correctly estimate the trade-creation effect of migrants via market familiarization: the size and significance of this channel depends on the choice of the weight matrix.

This has developed and applied a novel methodological approach that combines network analysis and spatial econometrics to investigate the network effect of migration on trade. Further research is needed to explore the interaction between migration, trade, and other types of flows such as FDIs, knowledge flows and the like, exploiting the recent methodological advances proposed in the literature (LeSage & Pace 2011, Elhorst et al. 2012).

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Table 8: Gravity results with OLS and FE models, with and without instrumenting migration for reverse causality. One-way clustering standard errors in parenthesis.

Non instrumented	base	total trade		diff. goods		homog. goods	
	ols	ols	fe	ols	fe	ols	fe
intercept	-10.414***	-9.783***	6.191***	-10.636***	4.921 ***	-8.981***	5.977 ***
	(.103)	(.114)	(.194)	(.120)	(.182)	(.119)	(.199)
distance	-.858***	-.687***	-1.002***	-.630***	-1.055***	-.728***	-1.011***
	(.018)	(.020)	(.020)	(.021)	(.019)	(.021)	(.021)
GDPpc_orig	.905***	.908***	-	1.116***	-	.751***	-
	(.007)	(.008)	-	(.008)	-	(.008)	-
GDPpc_dest	.846***	.737***	-	.610***	-	.739***	-
	(.007)	(.009)	-	(.009)	-	(.009)	-
population_orig	1.751***	1.668***	-	1.992***	-	1.421***	-
	(.011)	(.013)	-	(.014)	-	(.013)	-
population_dest	1.616***	1.427***	-	1.140***	-	1.486***	-
	(.010)	(.013)	-	(.014)	-	(.014)	-
contig	.284***	.163***	.079**	.126***	.144***	.139***	.017
	(.036)	(.035)	(.029)	(.035)	(.026)	(.036)	(.030)
comlang	.190***	.074***	.129***	.099***	.244***	.103***	.093***
	(.014)	(.015)	(.014)	(.016)	(.013)	(.016)	(.015)
colony	.608***	.451***	.455***	.332***	.313***	.390***	.443***
	(.033)	(.033)	(.029)	(.033)	(.026)	(.033)	(.030)
comcur	.373***	.293***	.298***	.357***	.270***	.256***	.300***
	(.048)	(.048)	(.043)	(.049)	(.039)	(.050)	(.045)
rta	.192***	.149***	.005	.286***	.009	.100**	0.041
	(.028)	(.027)	(.026)	(.028)	(.023)	(.028)	(.027)
migration	-	.150***	.128***	.189***	.140***	.114***	.113***
	-	(.006)	(.006)	(.006)	(.005)	(.006)	(.006)
R^2 adj	.640	.643	.752	.672	.820	.6043	.716
obs	29784	24105	27217	20908	23467	22256	24813

Instrum. (Altonji-Card)	total trade		diff. goods		homog. goods	
	ols	fe	ols	fe	ols	fe
intercept	-10.200***	6.323***	-11.181***	5.088***	-9.409***	6.087***
	(.118)	(.215)	(.124)	(.206)	(.123)	(.219)
distance	-.710***	-1.037***	-0.644***	-1.105***	-0.761***	-1.036***
	(.022)	(.021)	(.023)	(.020)	(.022)	(.022)
GDPpc_orig	0.901***	-	1.109***	-	.750***	-
	(.009)	-	(.009)	-	(.009)	-
GDPpc_dest	.788***	-	.655***	-	.784***	-
	(.009)	-	(.009)	-	(.009)	-
population_orig	1.685***	-	2.013***	-	1.451***	-
	(.014)	-	(.015)	-	(.014)	-
population_dest	1.509***	-	1.224***	-	1.564***	-
	(.013)	-	(.014)	-	(.014)	-
contig	.187***	.099***	.133***	.155***	.162***	.028
	(.036)	(.029)	(.036)	(.026)	(.036)	(.030)
comlang	.100***	.148***	.127***	.269***	.131***	.110***
	(.016)	(.015)	(.017)	(.014)	(.016)	(.016)
colony	.448***	.466***	.317***	.343***	.394***	.443***
	(.033)	(.030)	(.033)	(.027)	(.033)	(.031)
comcur	.302**	.310***	.363**	.284***	.279***	.320***
	(.048)	(.044)	(.049)	(.040)	(.050)	(.047)
rta	.150***	-.020	.299***	-.000	.096***	.013
	(.028)	(.027)	(0.028)	(.025)	(.029)	(.028)
migration	.131***	.111***	.189***	.120***	.092***	.103***
	(.007)	(.007)	(.007)	(.007)	(.007)	(.008)
R^2 adj	.653	.761	.680	.824	.614	.728
obs	20052	22492	17781	19782	18720	20715