Research Division
Federal Reserve Bank of St. Louis
Working Paper Series

Ethnic Networks and U.S. Exports

Subhayu Bandyopadhyay
Cletus C. Coughlin
and
Howard J. Wall

Working Paper 2005-069E
http://research.stlouisfed.org/wp/2005/2005-069.pdf

October 2005
Revised January 2007

FEDERAL RESERVE BANK OF ST. LOUIS
Research Division
P.O. Box 442
St. Louis, MO 63166

Ethnic Networks and U.S. Exports*

Subhayu Bandyopadhyay
West Virginia University and IZA, Bonn

Cletus C. Coughlin†
Federal Reserve Bank of St. Louis

Howard J. Wall
Federal Reserve Bank of St. Louis

January 2006

This paper provides new estimates of the effects of ethnic networks on U.S. exports. In line with recent research, our dataset is a panel of exports from U.S. states to 29 foreign countries. Our analysis departs from the literature in two ways, both of which show that previous estimates of the ethnic-network elasticity of trade are sensitive to the restrictions imposed on the estimated models. Our first departure is to control for unobserved heterogeneity with properly specified fixed effects, which we can do because our dataset contains a time dimension absent from previous studies. Our second departure is to remove the restriction that the network effect is the same for all ethnicities. We find that ethnic-network effects are much larger than has been estimated previously, although they are important only for a subset of countries.

JEL: F10, R10
Keywords: Ethnic networks, state exports

---

* We would like to acknowledge the comments and suggestions of an anonymous referee, Jim Dunlevy, Howard Shatz, and participants at the annual conference of the System Committee for Regional Analysis at the Federal Reserve Bank of San Francisco. We would also like to thank Lesli Ott for her research assistance. The views expressed are those of the authors and do not necessarily represent official positions of the Federal Reserve Bank of St. Louis or the Federal Reserve System.

† Corresponding author: Research Division, Federal Reserve Bank of St. Louis, P.O. Box 442, St. Louis, MO 63166-0442. E-mail: coughlin@stls.frb.org.

1. Introduction

Information is essential for identifying advantageous exchange possibilities. In addition to information, confidence or trust that the parties involved in an exchange will perform according to their commitments is crucial before transactions are agreed upon. A lack of information and a lack of trust are frequently identified as informal barriers to trade. These informal barriers to trade likely deter international trade to a larger extent than domestic trade and, therefore, contribute to explaining why, even after adjusting for economic size and distance, intra-national trade flows tend to swamp international trade flows.[1]

Prior research, theoretical as well as empirical, has identified immigrant networks as an important intermediary that can mitigate these informal barriers in home-country markets by providing information about demand, languages, business practices, and laws, as well as instilling confidence to facilitate international trade. By reducing the cost of searching across national borders and by serving as a means of enforcing contracts, immigrants increase the likelihood of a match between a buyer and a seller that results in a completed transaction. Our focus is on how immigrant networks have affected US exports at the level of individual states.

Our analysis departs from the existing literature in two ways. First, we allow for unobserved fixed effects when estimating our gravity model. As Cheng and Wall (2005) have demonstrated, gravity models that do not allow for fixed effects tend to provide biased estimates because such models fail to account for unobserved time-invariant factors that affect the level of trade and the independent variables used to explain the level of trade. Second, we allow for the immigrant network effects to vary across ethnic groups. For various reasons, the export-immigrant network relationship is likely to differ across countries. For example, as stressed by

[1] See McCallum (1995) for the seminal article exploring the impact of national borders. Obstfeld and Rogoff (2001) argue that even small differences in transactions costs can account for large border effects.

Dunlevy (2006) the trade-stimulating effects of immigrants should tend to be greater when the host and source countries differ more in terms of institutions, languages, and cultures. Here is when the special skills associated with ethnic networks can provide essential information and contract-enforcement services.

To set the stage for our analysis, we review the existing literature in the next section. Next, we lay out the most general specification of ethnic networks in a common gravity model. This general version allows us to show very easily the different types of models that have been estimated, as well as our departures. To highlight the importance of our departures, we show results following the existing literature as well. We use the common gravity model to generate pooled cross section estimates and fixed-effect estimates when the network effect is assumed to be the same for all ethnicities. We then remove this restriction on the network effect and allow for country-specific network effects. Finally, we provide our most general estimates: country-specific gravity models with country-specific network effects.

2. Literature

The traditional focus of research exploring the connection between immigration and international trade has been on how immigration affected factor supplies in the source and recipient countries. The change in factor supplies affects production and, ultimately, trade flows.[2] Recently, most notably due to the research of James Rauch and various co-authors, attention has been drawn to the network effects associated with immigrants.[3] Immigrant networks are thought to lower the transactions costs of international trade by providing

[2] In the Heckscher-Ohlin-Vanek framework, the movement of goods can be viewed as a movement of factor services. In a two-factor world, the exports of a capital-abundant country tend to contain larger amounts of capital services relative to labor services than its imports. Thus, the country is exporting capital services and importing labor services.

[3] See Rauch (2001) for a wide-ranging review of the literature.

information about trade possibilities and by aiding the enforcement of contracts.[4] Beginning with work by Gould (1994), a number of empirical papers have attempted to identify and quantify this complementary link.

Table 1 contains a summary of the key empirical papers that have examined the impact of immigrant networks on international trade. In this section, we focus on the results for a subset of these studies, leaving the discussion of econometric methods used in these studies to subsequent sections. Nearly all of the studies have focused on the trade flows of English-speaking countries. The major exception is a study by Rauch and Trindade (2002) that focuses on the impact of ethnic Chinese networks.

Because of our use of state exports, we restrict our discussion of existing studies to those that also use state exports. Many of the recent studies of US trade have used exports at the state level to examine the immigrant-export connection.[5] Such a focus is potentially important because the immigrant-export connection depends on networks of individuals and families in which proximity is likely to play a role. The use of state-level data allows for the use of proxies that are closer to what is suggested by economic theory. The underlying theory suggests that an increase in the number of immigrants from a specific country into a specific state increases the source country information in the state. The increased information effectively reduces transaction costs, which stimulates exports from the state to the country. As Dunlevy (2004) has argued, if the effect of immigrants cannot be found at the state level, then doubt is cast on the results based on national data.[6]

[4] On the import side, immigrants may affect trade by purchasing goods produced in their home countries.
[5] The reason that these studies examine only exports is that state-level import data do not exist.
[6] Dunlevy (2004) also points out that this use of disaggregated data entails some assumptions that might not hold. For example, immigrants located in a specific state are assumed to affect exports from that state only. It is possible, however that these immigrants might affect exports from other states (Herander and Saavedra, 2005).

Four recent studies — Co et al. (2004), Bardhan and Guhathakurta (2005), Herander and Saavedra (2005), and Dunlevy (2006) — have used state-level export data. The data in these studies cover the early to mid 1990s. Each examines the basic issue of the impact of immigrants on exports; however, they extend the basic literature in different ways. All are based on a gravity model, specifically a pooled cross-section model.

Co et al. (2004) examine state exports for 1993 using 48 states. They use 28 export destinations, 14 of which overlap with the destinations that we use. Export destinations are split into developed and developing countries. Separate network elasticities are estimated for the two sets of countries. These average elasticities are quite close, with an estimate of 0.29 for the ethnic-network elasticities of exports to developed countries and 0.27 for exports to developing countries.

Bardhan and Guhathakurta (2004) compare exports from the states on the east coast with those on the west coast using data for 1994-1996. The effects of two networks — one business network and one sociocultural — are explored. A statistically significant finding is that transnational business ties increase exports from both coasts. Meanwhile, a statistically significant relationship for immigrant networks is found only for west coast states. The ethnic-network elasticity of exports ranges from 0.24-0.26 for west coast states and 0.06-0.09 for east coast states.

Using state exports to 36 countries for 1993-1996, Herander and Saavedra (2005) examine the relationship between state exports and in-state and out-of-state immigrants. First, they examine the standard link between a state's immigrant population and its exports to the home country and find an ethnic-network elasticity of 0.18. Second, they argue that because a state's exporters have access to the ethnic networks of other states, the number of immigrants

from the destination market in the rest of the states should also matter. As they expected, they found that there was a positive link between a state's exports to a country and the number of immigrants from that country in the rest of the United States.

The final study relying on state exports to study the link between exports and immigrants is by Dunlevy (2006). Using average exports to 87 countries for 1990-1992, Dunlevy estimates various specifications and finds a range for the ethnic-network elasticity of exports from 0.24-0.47. Dunlevy also examines a number of corollaries associated with the basic proposition of a link between exports and immigrants. He finds immigrant networks are especially useful for exports to countries with more corruption and to those with a less similar language, while institutional differences were not found to affect exports.

3. A Common Gravity Model

We estimate the effect of ethnic networks on state-level exports using a gravity model, as does most of the existing literature. In gravity models, the volume of trade between two partners is a function of the sizes of the partners [gross domestic product (GDP) or its regional equivalent, such as gross state product (GSP), and population] and the distance between them. Additionally, gravity models control for cross-country differences in trade policy, usually by including dummy variables to indicate membership in preferential trading areas. For our first three sets of estimations, we use a gravity model that is common to all countries and states in the sense that the coefficients on the traditional gravity variables are assumed to be the same across all state/country pairs. The common gravity model (expressed in natural logs) with our most general specification of ethnic networks is:

$$\ln x_{ij}^t = \alpha_{ij} + \tau_j^t + \beta \ln Y_i^t Y_j^t + \gamma \ln N_i^t N_i^t + \delta \ln Dist_{ij} + \eta Contig_{ij} + \theta_j \ln F_{ij}^t + \varepsilon_{ij}^t . \tag{1}$$

In (1), *i* denotes a state, *j* denotes a country, and *t* denotes time. The dependent variable is x_{ij}^t, exports from state *i* to country *j* in year *t*. The gravity variables in (1) control for size and distance: Y_i^t is the GSP of state *i*, Y_j^t is the GDP of country *j*, N_i^t is the population of state *i*, N_j^t is the population of country *j*, $Dist_{ij}$ is the distance between *i* and *j*, and $Contig_{ij}$ is a dummy variable which takes the value of 1 if *i* and *j* are contiguous and zero otherwise.[7]

In addition to the gravity variables, equation (1) includes a time dummy τ_j^t that controls for changes in the trade policy of country *j*, including its levels of import tariffs and whether or not it has a preferential trading agreement with the United States. By allowing for time dummies to differ across countries, we are freed from having to quantify the trade stance of the countries, which is notoriously difficult.

Our first main departure from the literature is that we allow for properly specified fixed effects, which are denoted in (1) by α_{ij}.[8] As Cheng and Wall (2005) demonstrate, gravity models that do not allow for fixed effects tend to provide biased estimates because they fail to account for unobserved time-invariant factors that affect the level of trade as well as the independent variables that are used to explain the level of trade. Nonetheless, in common with the existing ethnic-network literature, we first estimate equation (1) without fixed effects.

The variable of most interest presently is F_{ij}^t, our proxy for the extent of ethnic networks, which is the number of residents of state *i* who were born in country *j*. Its coefficient, θ_j, is the ethnic-network elasticity of exports to country *j*. With the qualified exceptions of Rauch and

[7] As shown by Boisso and Ferrantino (1997), an equivalent specification replaces population with per capita gross domestic (state) product.

[8] There is somewhat of a semantic issue regarding what is and what isn't a model with fixed effects. According to the standard references (Greene, 2003; Hsiao, 1986), fixed-effects models allow for intercepts to differ across cross-sectional units, which, in the case of trade, are trading pairs. Wagner, Head, and Ries (2002) include country dummies, while Dunlevy (2006) includes country and state dummies. Although a model with such dummies allows for some variation in intercepts, it does so in a highly restricted fashion and is not a fixed-effects model as described by Hsiao and Greene.

Trindade (2002), Girma and Yu (2002), and Dunlevy (2006), every paper in the literature that has estimated the relationship has assumed that the ethnic-network elasticity is the same across countries.[9] In this sense, our second main departure from the literature is to allow for θ_j to differ across countries so as to identify differences in network effects across ethnic groups. It is reasonable to expect that the network effect associated with Irish immigrants to differ from that of Thai immigrants. Such a departure allows us to test whether the network effects, in fact, differ across ethnic groups. As we demonstrate later, the ethnic network effect found in existing studies is driven by a small number of countries.

Our dataset is limited by the availability of state-level data on the number of foreign-born residents, which is available from the decennial census and is sufficiently detailed only for 1990 and 2000. Nonetheless, this gives us two years of observations, which allows us to create a panel and to control for fixed effects. To smooth out our data, our trade, income, and population variables are two-year averages for 1989-1990 and 1999-2000. Distance is measured by the great-circle distance between largest cities. Our dataset begins with all nonzero exports from the 50 states plus the District of Columbia to 29 countries.[10] After applying the multivariate outlier test of Hadi (1994), which identifies 13 observations as outliers, we have 2,912 (out of a maximum of 2,958) observations of trade between 1,456 state/country trading pairs.[11]

[9] Rauch and Trindade (2002) assume that the effect is zero for all but ethnic Chinese residents; Girma and Yu (2002) assume that for U.K. trade the effect is zero for all but members of the British Commonwealth; and Dunlevy (2006) uses interaction terms to allow the ethnic-network elasticity to vary across countries because of language, corruption, and institutional differences.

[10] Our export data are from the Massachusetts Institute for Social and Economic Research (MISER). Our data are merchandise export shipments by state of origin of movement to various destinations throughout the world. Although this data is regarded as the best available for state exports, it has well-known weaknesses—the most important of which arise from the differences between the origin of movement and the origin of production. See Cronovich and Gazel (1999) and Coughlin and Mandelbaum (1991).

[11] For the outlier test we used the changes in the logs of: real exports, our income and population variables, and the number of foreign born residents. Because we use the changes over time, we can ignore the time-invariant variables in (1).

4. Pooled Cross Section vs. Fixed-Effect Estimates

As mentioned above, because of data limitations, existing estimates of the effect of ethnic networks on trade were limited to using the pooled cross section version of the gravity model. The most general of these allows for state and country effects (Dunlevy, 2006). This model can be obtained from equation (1) by assuming that each state/country fixed effect is the sum of a common intercept (α), a state dummy variable (λ_i), and a country dummy variable (ω_j). Although this allows for different intercepts across trading pairs, it does so by applying a complicated set of ad hoc restrictions on the trading-pair intercepts (Cheng and Wall, 2005).

For the time being, also assume that the network effect is the same for all ethnicities ($\theta_j = \theta$). Our pooled cross section regression equation is then

$$\ln x_{ij}^t = \alpha + \lambda_i + \omega_j + \tau_j^t + \beta \ln Y_i^t Y_j^t + \gamma \ln N_i^t N_j^t + \delta \ln Dist_{ij} + \eta Contig_{ij} + \theta \ln F_{ij}^t + \varepsilon_{ij}^t. \quad (2)$$

The results in Table 2 are from our estimation of equation (2) with and without the restriction that the effect of ethnic networks on trade is zero. The first set of results corresponds to a fairly typical gravity model that controls for changes in trade policy, the sizes of the trading partners, distance, and contiguity, but not for the effect of ethnic networks.[12] The results are quite standard: trade is positively related to both measures of size, negatively related to distance, and is higher for contiguous trading partners. The coefficients on all of our gravity variables are statistically significant.[13]

[12] All our equations are estimated by least squares. The existence of zero values for either the dependent variable or the independent variables raises problems for the estimation of a double log functional form. Recall, however, that our sample was chosen so that the level of exports was non-zero. To handle situations in which a state's immigrant population was zero, we simply added one to the level of the immigrant population. Because there are only four such observations, each with a different state and destination country, the alternative of eliminating the observations should have little effect on the results.

[13] Note that, throughout this paper, we use significance at the 10% level to indicate "statistical significance."

The second set of results in Table 2 is analogous to those in the existing literature that have estimated the effects of ethnic networks: It does not impose the restriction that the ethnic-network effect is zero, although it does restrict the effect to be the same across ethnicities. From the table it is clear that inclusion of the number of foreign born affects the results in two ways. First, the estimated ethnic-network elasticity is positive, statistically significant, and within the typical range in the literature: A 10% increase in the number of residents born in a foreign country will increase state exports to that country by 2.7%. Second, inclusion of the foreign-born variable has a statistically significant effect on the rest of the model.[14] For example, the estimates of δ and η change a great deal when F_{ij} is included, suggesting that, because distance and contiguity are correlated with the number of foreign born. The general implication of this result is that gravity models that do not account for the effects of ethnic networks are providing biased estimates of the influence of other variables on trade volume. In other words, the point estimates in the second column are preferred statistically to those in the first column.

Despite the apparent reasonableness of the preceding results from the pooled cross-section estimation, there are serious doubts about their validity. These doubts are based on the fact that this version of the gravity model does not account properly for unobserved (or not included) heterogeneity between state/country trading pairs that might account simultaneously for the level of exports from state *i* to country *j* as well as the number of residents in *i* that were born in *j*. Gravity models that do not account properly for these fixed effects have been shown to generate seriously biased estimates (Cheng and Wall, 2005), even when exporter and importer effects are included, as in our estimation of equation (2).

[14] A likelihood-ratio test rejects the null hypothesis that the restriction that $\theta = 0$ does not have a statistically significant effect on the estimation. The value of the test statistic, 98.1 (twice the difference in the absolute values of the log-likelihood functions) exceeds its corresponding critical value, which is $\chi^2(1) = 3.84$ at the 5-percent level.

The presence of estimation bias is confirmed by Figure 1. In the figure, the residuals of the second estimation of equation (2) are plotted across the state/country pairs, with the pairs arranged in ascending order of their average residuals. Unbiased estimation would yield an average residual of zero for each state/country pair. Instead, there is a clear pattern of overestimating trade for some pairs and underestimating it for others. In fact, for about two-thirds of the trading pairs the residual has the same sign for both observations.

We address the problem of bias by allowing each state/country pair to have its own unrestricted intercept. Note that doing so means that it is not possible to estimate the effects of distance and contiguity separately from the intercept. Specifically, the new intercept, which encompasses all variables that are fixed over time but which differ across state/country pairs, becomes $\sigma_{ij} = \alpha_{ij} + \delta \ln Dist_{ij} + \eta Contig_{ij}$. Because the effects of distance and contiguity are not of interest presently, however, this does not pose a problem.[15] Our fixed-effects regression equation is

$$\ln x_{ij}^{t} = \sigma_{ij} + \tau_{j}^{t} + \beta \ln Y_{i}^{t} Y_{j}^{t} + \gamma \ln N_{i}^{t} N_{j}^{t} + \theta \ln F_{ij}^{t} + \varepsilon_{ij}^{t}. \tag{3}$$

We estimate (3) under the assumption that the ethnic-network effects are the same for all countries. The results of our estimations are summarized in Table 3. Note that the two earlier estimations of equation (2) summarized in Table 2 are restricted versions of those summarized in Table 3.

Our estimation of equation (3) is the fixed-effects version of the standard estimation in the ethnic-networks literature, which includes the ethnic-network variable and assumes that the

[15] By subsuming distance and contiguity in this way we are not eliminating them from our estimation. In fact, because we do not have to use any of the many flawed measures of distance, we would argue that we are controlling for them more accurately than when we estimated equation (2). A similar argument holds for contiguity in that we do not need to assume that all contiguity is the same regardless of the length of border, the terrain along the border, etc.

ethnic-network elasticity is the same across countries. Our estimated ethnic-network elasticity is 0.142, which is statistically significant. Note also that the inclusion of fixed effects reduces the estimated ethnic-network elasticity and, because the fixed-effects version of the model is preferred statistically to the corresponding pooled cross section version, the lower estimate is the preferred one.[16] This result suggests that previous studies provided biased estimates of the ethnic-network elasticity of US exports, tending to overstate the effect of such networks on trade.

5. Heterogeneous Ethnic-Network Effects

Having established that estimation of the ethnic-network elasticity of trade requires the proper controls for trading-pair fixed effects, we can move on to our second point that the effects of ethnic networks can differ dramatically across ethnicities. Although, previously, this has not received explicit attention empirically, the possibility that ethnic-network elasticities can differ across countries follows from the extant literature. Dunlevy (2006), for example, stressed how ethnic networks should be more important when the source and destination countries differ in their institutions, languages, and cultures.

In addition to the cultural and institutional attributes of the trading partners, Rauch (1999) has stressed how the importance of ethnic networks might depend on the degree of product differentiation. That is, trust and/or marketing might be more important for more-differentiated goods, and countries can differ in the extent to which they trade in highly differentiated products. Gould (1994), Dunlevy and Hutchinson (1999), and Rauch and Trindade (2002) find support for this, although Dunlevy (2004) does not.

[16] A likelihood-ratio test rejects the null hypothesis that the restriction the pair-specific intercepts are the same does not have a statistically significant effect on the estimation. The value of the test statistic, 3769.97, indicates this at better than the 5-percent level.

A final motivation for allowing for heterogeneous ethnic-network effects comes from Greaney (2005), who finds that foreign affiliates are much more likely to trade with their home countries than with other countries. Because this tendency was heterogeneous across countries, differences in the levels and types of foreign direct investment might lead to differences in ethnic-network effects if foreign affiliates are relatively more likely to export back to their home markets.

To account for the possibility of country-specific ethnic-network effects, we estimate the following gravity model, which differs from (3) only in that it relaxes the restriction that $\theta_j = \theta$:

$$\ln x_{ij}^t = \sigma_{ij} + \tau_j^t + \beta \ln Y_i^t Y_j^t + \gamma \ln N_i^t N_j^t + \theta_j \ln F_{ij}^t + \varepsilon_{ij}^t. \tag{4}$$

The results of this estimation are summarized in Table 4, in which the heterogeneity of the ethnic-network elasticities is apparent. Further, the use of a likelihood-ratio test leads to the rejection of the null hypothesis that the restriction that these elasticities are the same. These statistically most-preferred estimates suggest that ethnic networks are important for only five countries, and that the effects are much larger than has been estimated previously. The five countries whose estimated ethnic-network elasticity is statistically different from zero are Brazil, Colombia, Spain, Thailand, and Turkey. In terms of institutions, language, and culture, these countries appear to have very little in common with each other, so it is not immediately apparent how our results can be explained by these differences. Perhaps, therefore, the degree of product differentiation is relatively more important, although this question is beyond our present scope.

Note also that the ethnic-network elasticities for these five countries are much larger than has been found in any previous estimation. For all five, the absolute value of their ethnic-network elasticities are more than four times the common ethnic-network elasticity we reported in Table 3. Oddly, though, these results also suggest that for Colombia the ethnic-network

elasticity is negative and very large: A 10-percent increase in the number of residents born in Colombia should decrease exports to Colombia by 5.8%.[17] Nevertheless, this version of the model and the results it provides are preferred statistically to all other versions up to this point.

We should caution that our results do not rule out the possibility that ethnic networks are important for countries other than these five. In fact, there are a number of countries with large point estimates for their ethnic-network elasticities, such as Ireland and the United Kingdom, that are not statistically significant. With more years of data there might be a longer list of countries whose ethnic-network elasticity is statistically significant. Nevertheless, our point is that when you allow for the effects of ethnic network effects to differ, you find that the effects are not present for all countries and are much larger than when you restrict them to be the same across countries.

Our fairly large data set, which has nearly fifteen hundred observations for each of two years, has allowed us to remove two sets of restrictions from the standard gravity model, both of which are not supported statistically or by theory. It also allows us to remove even more restrictions that might be biasing our above results. In particular, because we have at least 94 observations for each country, we can estimate separate country-specific gravity models, thereby allowing the coefficients on the gravity variables to differ across countries. After all, in the theoretical gravity model of Bergstrand (1989), it is perfectly reasonable to expect not only different magnitudes on the coefficient on the population variable but also different signs. If larger states (countries) are more self-sufficient, then population is related negatively to exports. On the other hand, larger populations might promote a division of labor that increases trade opportunities for a variety of goods. As a result, a model requiring identical coefficients for state exports to various countries might not be appropriate for some countries. In other words, our

[17] Additional discussion of the results for Columbia is provided later in the paper.

estimates might be biased by the restrictions that the signs on the gravity variables are the same across countries.

We estimate separately for each country the following fixed-effects gravity model:

$$\ln x_{ij}^{t} = \sigma_{ij} + \tau_{j}^{t} + \beta_{j} \ln Y_{i}^{t} Y_{j}^{t} + \gamma_{j} \ln N_{i}^{t} N_{j}^{t} + \theta_{j} \ln F_{ij}^{t} + \varepsilon_{ij}^{t}. \qquad (5)$$

The results of our estimations are summarized in Table 5. The first thing to notice is the significant difference in the performance of the gravity model in explaining state exports, as evidenced by the large differences in the magnitudes of the coefficients on the gravity variables, the differences in R^2s, and in the results of *F*-tests. In fact, for South Africa and Sweden an *F*-test fails to reject the null hypothesis that the model has no explanatory power.

For our purposes, the importance of allowing for country-specific gravity models is to see how it affects the estimates of the countries' ethnic-network elasticities. For these results, there are five countries whose estimated ethnic-network elasticities are statistically different from zero: Brazil, Canada, Italy, Spain, and Turkey. The elasticities for Spain and Turkey are the largest: A 10% increase in the number of foreign residents from Spain or Turkey should increase exports to the respective country by about 11%. For the other three countries, the elasticities are much larger than has been reported in the literature and range from 0.4 to 0.8

Note that the set of countries is different compared to our previous results: While both models indicate that ethnic networks are important for exports to Brazil, Spain, and Turkey; Colombia and Thailand have been replaced by Canada and Italy. In obtaining the first set of country-specific results, we were injecting bias for Colombia, Thailand, Canada, and Italy because of our assumption that the coefficients on the gravity variables were the same across countries. This is readily seen by comparing the results in Table 4, for which gravity model was

assumed to be the same across countries, to those in Table 5, for which each country is allowed to have its own gravity equation.

For example, Colombia's earlier, peculiar result that its ethnic-network effect is negative arose because the gravity model for Colombia is extremely idiosyncratic: alone among the 29 countries, and counter to all theory regarding gravity models, the coefficient on its income variable is very negative and is statistically significant. In addition, the coefficient on Colombia's population variable is more than 17 times the common coefficient from Table 4. As a consequence of Colombia's idiosyncratic gravity model, the earlier estimate of its negative ethnic-network effect disappears when the restriction on Colombia's gravity equation is relaxed. Similarly, for Thailand, Canada, and Italy, the differences between their country-specific gravity equation and the common gravity equation account for the different estimates in their ethnic-network elasticities between Tables 4 and 5.

6. Conclusion

Our estimation of various gravity models shows very clearly that the estimates of ethnic-network elasticities are sensitive to the restrictions imposed on the models. When we removed the restriction that the intercepts are the same for all country pairs, we found a smaller network effect than we did with the restricted model. When we allowed network effects do differ across countries, we found statistically significant network effects for only five of the 29 countries in our sample. Finally, when we allowed for country-specific gravity models, we found statistically significant and network effects for a different set of five countries.

Prior research examining the relationship between immigrants and international trade has tended to estimate a single ethnic-network elasticity for trade flowing from one country to a

group of countries. Our main finding is that, in doing so, prior research has masked a great deal of heterogeneity in the effects of network effects on trade. In unmasking this heterogeneity, our bottom line is that ethnic-network elasticities are actually much more important than has been reported previously, but that they are most important for a subset of countries. Of course, unmasking the heterogeneity at the country level leaves for future research the identification of the reasons for the differences across countries. At this point we have pointed to some research that provides potential reasons for our results.

We must stress, however, that we are not arguing that immigrant networks are unimportant for exports to countries in which we do not find statistical significance. Our analysis relies on the standard proxy for immigrant networks that is based on the number of immigrants in a state. This proxy is undoubtedly less than ideal and may be seriously flawed as a measure of networks for some countries. Networks are not necessarily larger for each new immigrant, but rather depend on the skills of the immigrants, which might not be accurately gauged by the quantity of immigrants.[18]

[18] In their study of Canadian exports, Head and Ries (1998) found that immigrants classified as independents (mostly professionals) affected trade relatively more than entrepreneurs and refugees.

References

Bardhan, Ashok Deo and Guhathakurta, Subhrajit, "Global Links of Subnational Regions: Coastal Exports and International Networks," *Contemporary Economic Policy* 22 (2004):225-36.

Bergstrand, Jeffrey H., "The Generalized Gravity Equation, Monopolistic Competition, and the Factor-Proportions Theory in International Trade," *Review of Economics and Statistics* 71 (1989):143-53.

Boisso, Dale and Ferrantino, Michael, "Economic Distance, Cultural Distance, and Openness in International Trade: Empirical Puzzles," *Journal of Economic Integration* 12 (1997):456-84.

Bryant, John; Genç, Murat and Law, David, "Trade and Migration to New Zealand," New Zealand Treasury Working Paper 04, 2004.

Cheng, I-Hui and Wall, Howard J., "Controlling for Heterogeneity in Gravity Models of Trade and Integration," Federal Reserve Bank of St. Louis *Review* 87 (2005):49-63.

Co, Catherine Y.; Euzent, Patricia; and Martin, Thomas, "The Export Effect of Immigration into the USA," *Applied Economics* 36 (2004):573-83.

Coughlin, Cletus C. and Mandelbaum, Thomas B., "Measuring State Exports: Is There a Better Way?" Federal Reserve Bank of St. Louis *Review* 73 (1991):65-79.

Cronovich, Ron and Gazel, Ricardo C., "How Reliable Are the MISER Foreign Trade Data?" unpublished manuscript, 1999.

Dunlevy, James A. and Hutchinson, William K., "The Impact of Immigration on American Import Trade in the Late Nineteenth and Early Twentieth Centuries," *Journal of Economic History* 59 (1999):1043-62.

Dunlevy, James A., "Interpersonal Networks in International Trade: Evidence on the Role of Immigrants in Promoting Exports from the American States," Working Paper, Miami University, 2004.

——————, "The Influence of Corruption and Language on the Protrade Effect of Immigrants: Evidence from the American States," *Review of Economics and Statistics* 88 (2006):182-86.

Girma, Sourafel and Yu, Zhihao, "The Link between Immigration and Trade: Evidence from the United Kingdom," *Weltwirtshcaftliches Archiv/Review of World Economic*s 138 (2002):115-30.

Gould, David M., "Immigrant Links to the Home Country: Empirical Implications for US Bilateral Trade Flows," *Review of Economics and Statistics* 76 (1994):302-16.

Greaney, Theresa M., "Measuring Network Effects on Trade: Are Japanese Affiliates Distinctive?" *Journal of the Japanese and International Economies* 19 (2005):194-214.

Greene, William, *Econometric Analysis*, New York: Prentice Hall, 5th Edition, 2003.

Hadi, Ali S., "A Modification of a Method for the Detection of Outliers in Multivariate Samples," *Journal of the Royal Statistical Society, B* 56 (1994):393-96.

Head, Keith and Ries, John, "Immigration and Trade Creation: Econometric Evidence from Canada," *Canadian Journal of Economics* 31 (1998):47-62.

Herander, Mark G. and Saavedra, Luz A., "Exports and the Structure of Immigrant-Based Networks: The Role of Geographic Proximity," *Review of Economics and Statistics* 87 (2005):323-35.

Hsiao, Cheng, *Analysis of Panel Data*. Cambridge: Cambridge University Press, 1986.

McCallum, John, "National Borders Matter: Canada-US Regional Trade Patterns," *American Economic Review* 85 (1995):615-23.

Mundra, Kusum, "Immigration and International Trade: A Semiparametric Empirical Investigation," *Journal of International Trade and Economic Development* 14 (2005):65-91.

Obstfeld, Maurice and Rogoff, Kenneth, "The Six Major Puzzles in International Macroeconomics: Is There a Common Cause?" *NBER Macroeconomics Annual 2000*, Cambridge and London: MIT Press, 2001.

Rauch, James E., "Networks versus Markets in International Trade," *Journal of International Economics* 48 (1999):7-35.

——————, "Business and Social Networks in International Trade," *Journal of Economic Literature* 39 (2001):1177-203.

Rauch, James E. and Trindade, Vitor, "Ethnic Chinese Networks in International Trade," *Review of Economic Studies* 84 (2002):116-30.

Wagner, Don; Head, Keith; and Ries, John, "Immigration and the Trade of the Provinces," *Scottish Journal of Political Economy* 49 (2002):507-25.

Table 1. Summary of Empirical Papers

	Data	Econometrics	Ethnic-network elasticity of exports	Ethnic-network elasticity of imports
Gould (1994)	US aggregate trade, 1970-86, 47 countries	Not a gravity model	0.02	0.01
Head and Ries (1998)	Canadian aggregate trade, 1980-92, 136 countries	Simple PCS	0.10	0.31
Dunlevy and Hutchinson (1999)	US aggregate and disaggregated trade 1870-1910, 17 countries	Simple PCS	0.08	0.29
Rauch and Trindade (2002)	aggregate and disaggretated, 63 and 160 countries, respectively	Simple PCS	0.47 (differentiated)	0.47 (differentiated)
Girma and Yu (2002)	UK aggregated trade, 1981-93, 48 countries	Simple PCS, effect of foreign born from Commonwealth	0.16 (non-Commonwealth)	0.10 (non-Commonwealth)
Wagner, Head, and Ries (2002)	Canadian provinces, 1992-95, 160 countries	PCS with country dummies	0.013	0.092
Co, Euzent, and Martin (2004)	US state exports, 1993, 28 countries	Simple PCS	0.27 – 0.30 0.27 low income 0.29 high income	
Bardhan and Guhathakurta (2004)	US state exports, 1994-96, 51 countries	Simple PCS, east coast vs. west coast.	0.24 - 0.26 W 0.06 - 0.09 E	
Herander and Saavedra (2005)	US state exports, 1993-96, 36 countries	PCS with state and country dummies, includes out-of-state network effect.	0.18	
Dunlevy (2006)	US state exports, 1990-92 average, 87 countries	PCS with state and country dummies.	0.24 – 0.47	
Bryant, Genç, and Law (2004)	New Zealand aggregate trade, 1981-2001, 170+ countries	Random effects	0.05 (all goods) 0.10 (exc. ag)	0.19 (all goods) 0.23 (exc. oil)
Mundra (2005)	US aggregate trade, intermediate and finished goods, 1973-80, 47 countries	Semiparametric fixed effect instrumental variable in a panel	Not estimated, network effect for finished goods, but not necessarily for intermediate goods	Not estimated, network effect always positive

Notes: PCS = pooled cross section. Unless otherwise noted, all papers use a gravity model. Some of the elasticity calculations are from Wagner, Head, and Ries (2002).

Table 2. Pooled Cross-Section with Common Network Effect

	No Network Effect ($\alpha_{ij} = \alpha$ and $\theta_j = 0$)			Common Network Effect ($\alpha_{ij} = \alpha$ and $\theta_j = \theta$)		
	Coeff.	S.E.	t-stat.	Coeff.	S.E.	t-stat.
Intercept (α)	-15.315*	5.690	-2.69	-13.969	5.597	-2.50
State and country dummies	yes			yes		
Time/policy dummies (τ_j)	yes			yes		
ln Y_iY_j (β)	0.700*	0.346	2.02	0.638†	0.341	1.87
ln N_iN_j (γ)	0.863†	0.523	1.65	0.606	0.515	1.18
ln $Dist_{ij}$ (δ)	-1.310*	0.093	-14.10	-1.076*	0.094	-11.40
$Contig_{ij}$ (η)	0.640*	0.183	3.49	0.243	0.185	1.31
ln F_{ij} (θ)	-			0.266*	0.027	9.79
Log-likelihood	-3719.90			-3670.85		
F-statistic	F(61, 2800) = 103.95			F(62, 2799) = 107.29		
$\bar{R}^2$	0.787			0.781		

Statistical significance at the 10 and 5% levels are indicated by "†" and "*", respectively. Each regression uses 2912 observations.

Table 3. Fixed-Effects Model with Common Network Effect

	Common Network Effect ($\theta_j = \theta$)		
	Coeff.	S.E.	t-stat.
Pair-specific intercept (α_{ij})	yes		
Time/policy dummies (τ_j)	yes		
ln Y_iY_j (β)	1.001*	0.151	6.62
ln N_iN_j (γ)	0.461	0.348	1.33
ln F_{ij} (θ)	0.142*	0.063	2.26
Log-likelihood	-1785.87		
F-statistic	F(31,1425) = 26.91		
$\bar{R}^2$ (within)	0.369		

Statistical significance at the 10 and 5% levels are indicated by "†" and "*", respectively. The regression uses 2912 observations and has 1456 state/country pairs.

Table 4. Country-Specific Networks

	Country Network Effects (θ_j unrestricted)		
	Coeff.	S.E.	t-stat.
Pair-specific intercept (α_{ij})	yes		
Time/policy dummies (τ_j)	yes		
ln Y_iY_j (β)	0.768*	0.256	3.00
ln N_iN_j (γ)	0.601	0.390	1.54
ln F_{ij} (θ_j)			
Argentina	0.366	0.282	1.30
Australia	-0.212	0.426	-0.50
Brazil	0.603*	0.291	2.07
Canada	0.231	0.536	0.43
Chile	0.016	0.226	0.07
China	0.208	0.448	0.46
Colombia	-0.581†	0.315	-1.84
Egypt	-0.302	0.314	-0.96
France	0.121	0.504	0.24
Germany	0.184	0.734	0.25
Hong Kong	0.134	0.334	0.40
India	0.068	0.382	0.18
Indonesia	0.258	0.260	0.99
Ireland	0.650	0.449	1.45
Israel	0.118	0.223	0.53
Italy	0.367	0.492	0.75
Japan	0.140	0.604	0.23
Malaysia	0.204	0.196	1.04
Mexico	-0.081	0.204	-0.39
Netherlands	0.293	0.467	0.63
Philippines	-0.399	0.514	-0.78
South Africa	-0.221	0.310	-0.71
South Korea	-0.186	0.510	-0.36
Spain	0.913*	0.373	2.44
Sweden	0.024	0.259	0.09
Thailand	0.665†	0.378	1.76
Turkey	1.090*	0.305	3.58
United Kingdom	0.622	0.711	0.88
Venezuela	-0.179	0.246	-0.73
Log-likelihood	-1746.21		
F-statistic	$F(60,1396) = 14.64$		
$\bar{R}^2$ (within)	0.386		

Statistical significance at the 10 and 5% levels are indicated by "†" and "*", respectively. The regression uses 2912 observations and has 1456 state/country pairs.

Table 5. Country-Specific Gravity Models

	Time dummy		ln Y_iY_j		Ln N_iN_j		ln F_{ij}		$F\left(4, \frac{n}{2}-4\right)$	$\overline{R}^2$	
	τ	s.e.	β	s.e.	γ	s.e.	θ	s.e.		(within)	n
Argentina	0.266	1.059	0.151	1.325	3.297	2.039	0.199	0.292	32.42	0.738	100
Australia	0.303	0.268	1.599	0.987	-2.057	1.520	-0.071	0.342	2.99	0.203	102
Brazil	0.411	0.480	1.936	1.497	-2.031	2.182	0.600†	0.334	12.66	0.524	100
Canada	0.311*	0.112	0.169	0.447	0.585	0.700	0.404†	0.212	48.06	0.804	102
Chile	0.692	0.918	-0.897	1.264	2.659	1.847	0.045	0.218	6.98	0.378	100
China	-2.736†	1.605	3.893*	1.656	-3.655	2.407	-0.096	0.584	17.31	0.596	102
Colombia	2.425*	0.848	-5.628*	1.549	10.238*	2.238	-0.258	0.394	12.88	0.523	102
Egypt	-1.226	1.648	3.578	2.710	-4.061	3.346	-0.344	0.388	4.56	0.293	96
France	0.170	0.157	1.111	0.710	-1.852†	1.109	0.363	0.292	5.34	0.313	102
Germany	0.054	0.154	0.454	0.606	-0.061	1.040	0.465	0.405	5.27	0.310	102
Hong Kong	-1.475*	0.735	2.302*	1.113	0.290	1.827	-0.086	0.346	10.76	0.483	100
India	-0.146	0.560	2.578	1.960	-2.003	2.416	-0.099	0.636	2.20	0.161	100
Indonesia	-0.219	0.563	-0.643	2.327	3.326	3.134	0.178	0.335	3.34	0.229	98
Ireland	-2.124†	1.087	3.240*	1.586	0.931	2.531	0.390	0.582	12.17	0.514	100
Israel	-0.623	0.863	-0.698	1.448	4.744*	2.351	-0.064	0.275	8.91	0.431	102
Italy	-0.036	0.213	4.153*	1.082	-5.257*	1.780	0.796†	0.458	4.23	0.265	102
Japan	-0.481†	0.275	1.367†	0.772	-0.772	1.121	0.180	0.389	2.12	0.153	102
Malaysia	-0.262	0.877	-0.906	1.780	5.682†	2.921	-0.065	0.292	14.65	0.560	100
Mexico	1.728*	0.632	-2.252*	1.142	3.827*	1.627	0.125	0.180	29.55	0.729	96
Netherlands	-0.141	0.289	0.479	0.925	1.109	1.476	0.265	0.358	3.89	0.249	102
Philippines	-0.216	0.640	0.457	1.416	3.902	2.677	-1.240	0.859	8.32	0.420	100
South Africa	0.041	0.537	-0.009	1.242	1.110	1.974	-0.177	0.321	1.56	0.122	98
South Korea	0.579	0.727	-0.152	1.354	0.242	2.036	-0.021	0.543	3.88	0.248	102
Spain	-0.025	0.331	-0.620	1.441	0.300	2.137	1.107*	0.423	2.09	0.151	102
Sweden	-0.146	0.258	1.253	1.337	0.081	2.151	0.059	0.282	0.71	0.057	102
Thailand	0.302	0.564	-0.325	1.546	0.862	2.415	0.706	0.467	5.48	0.318	102
Turkey	-0.599	0.776	1.369	2.324	0.647	3.529	1.067*	0.512	4.86	0.311	94
United Kingdom	-0.507	0.376	1.606†	0.917	-0.782	1.482	0.691	0.653	5.34	0.312	102
Venezuela	-1.375†	0.760	2.653*	1.207	-1.495	1.771	-0.314	0.231	4.33	0.273	100

Statistical significance at the 10 and 5% levels are indicated by "†" and "*", respectively.

Figure 1. Residuals from Pooled Cross Section