Effects of Information Channels across Skill and Product Quality Groups: Evidence from Trade-Migration Nexus*

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Abstract

This paper examines the empirical linkage between immigrant driven ethnic networks on bilateral trade across different skill groups of immigrants and quality levels of commodities. Using a panel dataset of 19 high-income OECD countries and 99 low-income countries over the period of 1990-2005 and a newly available export quality index, we test for both direct and indirect effects of migrant networks on their host country trade. We establish a one-to-one casual linkage between migrants' skill level and export product quality controlling for potential endogeneity and unobserved heterogeneity.

Keywords: Immigration, International Trade, Structural Gravity Model, Skill Heterogeneity, Product Quality

JEL Codes: F10, F11, F12, F14, F22

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1 Introduction

Increasing size of international immigration has been at the forefront of policy debates for a large number of OECD countries over a considerable amount of time. Although most governments have been very willing to open the door to globalization through trade, this is not always the case for immigration. Academic debates in many cases have also focused on the potential negative effects the immigrants exert on host-country labor markets. Nonetheless, the total number of international migrants has increased immensely over the last couple of decades rising more than 50% between 1990 to 2015. During the same period world exports have also increased from 19.6% to 29.5% as a percentage of world GDP. This trend in international integration on both fronts has led researchers to look for new economic consequences that immigration may have. For example, do immigrant populations contribute to the host-country's international trade flows.

This discussion on the potential linkage between immigrant flows and trade flows actually dates back to the initial theories that have treated migration as an instance of factor arbitrage. In these theories the relationship between trade and immigration emerges from a general equilibrium model. These models do not differentiate between capital and labor as both generate income for households and can be used to produce outputs for given production technology. However, there are differences in opinion about how labor mobility across regions affects the pattern and volume of trade across those regions. The international trade literature has a long history of concentrating on commodity trade than on factor movements. The common wisdom among the trade theorists was that trade in commodities and factor movements are substitutes with the two being equivalent. Hence the gains from trade could be realized either through movements of goods or factors of production. In "International Trade and Factor Mobility", Mundell (1957) demonstrates the idea first in a two-good, two-factor, two-country treatment of the problem retaining the full set of Heckshер-Ohlin-Samuelson (HOS) assumptions. He shows that there is a substitutability of international trade in commodities and factor mobility, i.e., an increase in the volume of factor movement substitutes for trade through a reduction in the volume of goods traded. Policy debates have also frequently followed this logic as policymakers ague that a country engaging in free trade with another country can actually reduce the pressure for immigration. Early empirical work following Mundell (1957) such as by Horiba and Kirkpatrick (1983) also find results that follow the original idea of Mundell that there exists a substitutive relationship between trade and labor mobility.

However, subsequent theoretical work on this issue includes a number of models in which factor movements due to international factor price differences can actually lead to an increase in the volumes of trade, factor movements and trade in commodities are complements. All these models share a common idea that the basis for trade is something other than differences in factor proportions between countries and the concept that trade in goods and factors are substitute may be just a special result that only holds for Hecksher-Ohlin basis of trade. There are a variety of ways this subsequent theoretical work differs from Mundell's concept of trade in commodity and factor movements. Kemp (1966), Jones (1967), Svensson (1984), and Markusen and Svensson (1983) allowed for differences in technologies across countries. Markusen (1983) in his seminal paper introduces production taxes, monopoly market structure, external economies of scale or factor market distortions in the model to show the complementarity between trade and factor mobility.

Beginning with the work of Gould (1994), a number of empirical papers on this issue have attempted to identify the complementary linkages between migration and trade. Most of these studies used aggregate measures of bilateral trade flows for a single host country or a predetermined set of host-countries selected using an economic segmentation argument and address the relationship between trade and migration in the context of a gravity model (Head and Ries (1998); Dunlevy and Hutchinson (1999); and Girma and Yu (2002)). Head and Ries (1998) examined the Canadian immigration trade linkage while Girma and Yu (2002) examined similar relationships for United Kingdom. Blanes-Cristóbal (2003) had done the same empirical test on Spain and found a positive link between Spain's export and immigration flows. These studies were based on pooled cross-section gravity models. A second stream of studies are Co et al. (2004), Herander and Saavedra (2005), Dunlevy (2006) and Bandyopadhyay et al. (2008) who have exploited US state level export data to identify a positive linkage between interstate immigrants and commodity exports. Recent research has investigated bilateral trade and migration between many origin and destination countries. Egger et al. (2012) work with 27 OECD destination country and 103 origin country, Felbermayr and Jung (2009) use a panel data structure and covered North-South trade. One thing that is common to all these papers is that they all identify two channels by which immigrants can enhance bilateral trade between host and source country: the preference channel and information channel.

The 'preference channel' works through the preferences that immigrants have for home-country products. McCallum (1995) was the first to identify the preference channel, also known as the home-bias effect. This channel may increase host country's imports from the source countries substantially especially if there is a lack of home country products or reasonable substitute goods in the host's market. The second channel through which immigrants can potentially impact host-source country trade flows is the 'network effect'. This channel works mainly through the information network, as immigrants are thought to be one of the major sources of home country information towards the host countries (Rauch and Trindade, 2002). Information has long been deemed to be a crucial factor in identifying exchange possibilities. Lack of information has been identified as an informal barrier to trade and an important factor in discussions of the mystery of missing trade. Immigration from a particular country may increase information and enhance social/business ties between source and destination countries. This channel has the potential to reduce the search costs and increase the matching of potential trade partners. Because of increasing information flows as a result of immigration, the network effect has attracted much research. This paper also plans to investigate the importance of the network effect only on host countries' exports to avoid the potential identification issue of the two channels.

A relatively new migration dataset (Docquier and Marfouk, 2006) has made it possible for researchers to distinguish between skill levels of immigrants and explore the strong and significant correlation of immigrant stocks and trade volume (Felbermayr and Jung (2009); Giovannetti and Lanati (2017)). One important motivation in these papers lies in the trend and pattern of immigration worldwide. As shown in Table 1, while the overall increase in immigration is about 52% over 1990-2005, increase from the poor and middle income countries is much higher at about 75%. And most of this increase is actually triggered by increases in high skill immigrants. In this paper, we examine the effect of such changes in patterns on north-south trade channel and causal inference between international immigration networks of different skill levels and trade volume. We expect that ethnic network effect of high-skilled immigrants should be higher than both overall migrant network effect and low-skilled migrant network effects. Our hypothesis is that high-skilled migrants have better ability to receive and process information (Schultz, 1975) and have lesser liquidity constraint to start transactions with their native counterparts in their source country using this information. These give them comparative advantage over their counterparts while establishing trade linkages to their origin country.

Table 1: Change in Immigration over time in OECD Countries

Immigrants By Origin and Skill level Over 1995-2005					
No. of Country	Country Type	Total	High Skill	Med Skill	Low Skill
38	High Income	43.41%	45.53%	45.65%	40.13%
103	Non-High Income	56.59%	54.47%	54.35%	59.87%
% Change in Immigration by Origin & Skill level over 1990-2005					
No. of Country	Country Type	Total	High Skill	Med Skill	Low Skill
141	All	52.00%	79.20%	62.20%	25.30%
38	High Income	10.20%	40.30%	18.00%	-16.60%
103	Non-High Income	75.00%	99.80%	87.50%	48.50%

A very recent paper by Giovannetti and Lanati (2017) has further examined whether and to what extent a relationship exists between ethnic networks and trade by product quality. They conclude that pro-trade effect of high-skilled immigrants are higher across all product categories when compared to the effect of the overall migrant network. Our paper differs from this paper in three very important ways. First, we make use of new data on export-quality to measure product quality instead of unit value series. Unit value series can be volatile overtime due to changes in production cost or pricing strategy while quality upgradation is less volatile and a more strongly trended process. Second, instead of only focusing on the high-skilled immigrant networks (compared to the overall network), we try to establish a one-to-one linkage between migrants' skill level (high vs low) and product quality (high vs low). Third, we take advantage of the panel structure of our data to control for unobserved heterogeneity and test for strict exogeneity to establish a causal linkage from migration networks to international trade compared to the instrumental variable technique proposed by Giovannetti and Lanati (2017).

This paper also explores the possibility of immigrants having an additional indirect network effect on trade due to an increasing diversification in terms of both origin and destination countries. This idea in essence is close to the 'super diversity' research introduced by Vertovec (2007). In large part owing to globalization, immigrant and ethnic minority populations are now bound to each other, to their 'hosts', and to distant counterparts by multiple strands of solidarity of varying thicknesses. Over the past few decades, patterns of international migration have shifted away from 'multiculturalism' based discrete 'cultural communities' meaning many migrants from a source go to a few places, towards a more complex pattern of social ties and tensions: patterns involving fewer migrants from and to more places. More and more new migration destinations have emerged in south-south migration direction and new channels of north-south immigration has also come in to place. It is therefore time that we acknowledge this growing complexity of global migration and incorporate this effect to the body of literature linking immigration and trade. Only a handful of paper such as Rauch and Trindade (2002), Felbermayr et al. (2010), Felbermayr and Toubal (2012) have allowed for the presence of strong third party effects in both trading countries as part of an information channel in the estimation of gravity models, and they show that such networks can foster trade in addition to the traditional bilateral migrant network. However, their treatment of the presence of third-party effects limits our ability to observe the diversity effect on country pairs that are not traditional migrant destination. In this paper we try to overcome this limitation and show that there are indirect ethnic network effects on the pairs of northern destination countries and southern origin countries.

Three main result stands out: (i) High-skilled ethnic networks have a stronger direct impact on aggregated bilateral trade; (ii) With disaggregated product quality, high-skilled ethnic networks trigger more high quality trade than low-skilled ethnic networks and low-skilled ethnic networks trigger more low quality trade than high-skilled ethnic networks; (iii) There is a positive indirect effect of secondary ethnic networks of third party nature on trade, and this effect is stronger for low quality products and more so through low-skilled migrants.

The rest of the paper is organized as follows. Section 2 provides an overview of the existing empirical models and our proposed model specification along with empirical strategy. Section 3 describes data. Section 4 presents the empirical findings and interpretation of the findings. Section 5 concludes.

2 Model Specification & Empirical Strategy

Most of the empirical literature that has attempted to infer the causal relationship running from immigrant networks to international trade thus far try to utilize the so called gravity framework: a log linear relationship that links bilateral international trade to a host of economic, geographic and political variables. Over the years, different variants of the gravity equation have been estimated. They have enjoyed a tremendous empirical success. Hence, the conceptual foundation of the gravity equation is worth reviewing before we present the version we use in this study.

2.1 Framework of the gravity equation

Tinbergen (1962) first applied the Gravity equation to explain trade flows. In our context, the simplest form of the gravity equation tells us that trade (export) of country j to country i, T_{ij}, is proportional to the countries' combined economic mass (Y_i and Y_j) and inverse to the distance between the two countries, $Dist_{ij}$:

$$T_{ij} = \Phi\left(\frac{Y_iY_j}{Dist_{ij}}\right) \tag{1}$$

We define country i as source or origin (importer) country and country j as host or destination (exporter) country here to keep consistency with the following sections of the paper. Higher source country GDP (Y_i) implies larger export markets for the host country products. On the other hand, higher host country GDP (Y_j)suggests a higher export capacity of the host country. The $Dist_{ij}$ variable is the proxy for transportation cost and Φ is the constant of proportionality. We expect trade flows to be positively correlated with both the GDPs while negatively correlated with the distance variable. Over the time, additional variables such as population (N_i and N_j) has often been included in the model to measure the size or degree of self-sufficiency of a country. Frankel et al. (1997), Rose (2000) and Masson and Pattillo (2004) have proposed a gravity specification that incorporates per capita GDP ($y_i = \frac{Y_i}{N_i}$ *and* $y_j = \frac{Y_j}{N_j}$) in the model as a measure of income along with GDP in the level term. The richer countries (in per capita terms) are expected to have higher trade while the poorer countries have lesser trade. Another common practice in gravity specifications is to include dummy variables to indicate whether the country pairs have geographical or cultural proximity.

However, the theoretical justification for the gravity equation explained above was not very clear. The equation was lacking microfoundation until Anderson and Van Wincoop (2003) developed a general equilibrium methodology under perfect competition to explain the importance of including a 'multilateral resistance' term in the structural gravity framework. In contrast to the notion of bilateral trade resistance (BTR) which is the size of the barriers to trade between countries i and j, multilateral trade resistance (MTR) refers to the barriers which each of i and j face in their trade with all their trading partners (including domestic or internal trade). The presence of multilateral trade resistance is what distinguishes this 'new' version of the gravity model from the 'empirical' or 'traditional' version used by earlier researchers such as Rose (2000). It introduces a substitutability between trade with a country's different partners that was previously lacking. Omission of this term results in biased estimates of gravity equations, and therefore one should never use the traditional estimating gravity equation to estimate trade costs (Baldwin and Taglioni, 2006). After Anderson and Van Wincoop (2003) more structural demand-sided model such as Melitz (2003) or symmetric Dixit-Stiglitz-Krugman monopolistic competition model have been proposed. A large part of the recent literature (Combes et al. (2005); Felbermayr and Toubal (2012)) focused on ethnic networks as one of the determinants of trade have actually mostly relied on the later mentioned type model. But for our purpose these models post estimation difficulties because the estimation requires elasticity of substitution parameter σ and there is no data when one allows for product quality differences. Fortunately, one can restrict the supply side to pin down the share of goods traded between two countries solely by the supply side in equilibrium. Drawing on the Ricardian model of international trade that incorporates technology and geographic barriers into a general equilibrium system of demand and supply, Eaton and Kortum (2002) derived the most famous supply-sided structural gravity model, commonly known as the EK model. For our purpose we derive an extension of EK model in the next section similar to the one proposed by Fieler (2011) characterizing the demand side and later incorporate ethnic network in the model.

2.2 Extension of the EK Model

Based on the Ricardian model, Eaton and Kortum (2002) propose the basic framework as follows: there are N countries with $j,\ n = 1, 2, \ldots\ldots, N$ each producing a continuum of goods $l \in [0,1]$ with goods specific productivity in country j: $z_j(l)$. Each country faces a unit input cost of $c_j$and therefore cost of producing good l in country j is $\left(\frac{c_j}{z_j(l)}\right)$. Countries face an iceberg trade cost: $d_{ij} > 1$ for $j \neq i$ *and* $d_{jj=1}$ with perfect competition. We depart from EK assumption of homothetic preference on the demand side, with constant elasticity of substitution and followed Fieler (2011) to propose that there can be different types of goods which may differ in demand and technology. For our purpose different types of goods corresponds to different quality segments of traded goods as they are by definition should have different factor intensities and different level of technology (Giovannetti and Lanati, 2017). The implication of having different quality of goods is that now each country with index j produce a continuum of goods $l_k \in [0,1]$ of quality k with goods specific productivity in country j:$z_j(l_k)$. Individuals of any country i have the following type of CES aggregation representing utility:

$$U_i = \sum_{k=1}^{K} [\int_0^1 Q_i(l_k)^{\frac{\sigma_k - 1}{\sigma_k}} dl_k]^{\frac{\sigma_k}{\sigma_{k-1}}} \tag{2}$$

Where σ_k>1 for all k is the elasticity of substitution across goods of the same quality. Productivity in country j follows a Frechet (T_j, θ_k) distribution such that $z_j(l_k) < z$ is equal to the cumulative distribution function of a Frechet random variable :

$$F_{jk}(z) = P(z_j(l_k) < z) = e^{-T_j z^{-\theta_k}} \tag{3}$$

Where $T_j > 0$ governs the location of productivity distribution for country j (higher T_j higher productivity draw more likely for any good l) , $\theta k > 0$, governs variation in the productivity distribution within quality segment and assumed common across countries (higher θ less variability across goods, i.e; governs degree of comparative advantage). Our assumption of relating quality segments to θ_k is based on the empirical evidence presented by Giovannetti and Lanati (2017) who have similar country coverage as ours but use variation in export unit values (EUV) as a rough proxy for variation in labor efficiency. In this study though we use an export quality index as opposed to EUV as these two series are correlated Henn et al. (2013) and is a better and direct measure of quality. Unit values may reflect production costs, or pricing strategies (i.e., firms' choice of mark-up) and changes over time in unit values may reflect changes in quality-adjusted prices rather than changes in quality. The quality estimates presented in this section follow a modified version of Hallak (2006) and address these two shortcomings (Henn et al., 2013). Market segments k can thus be defined by percentile of quality index for each year. We have set k=3, namely 'high', 'medium' and 'low' quality good. Since the cost of producing good l of quality$k$in country j is $\left(\frac{c_j}{z_j(l_k)}\right)$, if we assume wage as the only input cost, that is $c_j = w_j$, and there is a iceberg trade costs: $d_{ij} > 1$ for $j \neq i\ and\ d_{jj=1}$, price charged by firms in country j to consumers in country i for good l of quality k:

$$P_{ij}\left(l_k\right) = \left(\frac{W_j}{z_j\left(l_k\right)}\right) d_{ij} \tag{4}$$

Total expenditures of country i on goods of quality k are X_i^k:

$$\int_0^1 p_i\left(l_k\right) Q_i\left(l_k\right) dl_k = X_i^k \tag{5}$$

The price of good $l_k$in country i is the minimum price across producers in all countries:

$$p_i(l_k) = \min\left\{p_{i1}(l_k),\ p_{i2}(l_k), \cdots, p_{iN}(l_k)\right\}$$

$$= \min\left\{\left(\frac{W_1}{z_1\left(l_k\right)}\right) d_{i1}, \left(\frac{W_2}{z_2\left(l_k\right)}\right) d_{i2}, \cdots, \left(\frac{W_N}{z_N\left(l_k\right)}\right) d_{iN}\right\}$$

Distribution of prices offered by firms in country j is governed by productivity distribution. Define $G_{ij}(p_k)$as the proportion of prices offered by country j to country i that are less than p_k and be derived by substituting equation (4) in equation (3):

$$
\begin{aligned}
G_{ij}\left(p_k\right) = Pr\left(P_{ij}\left(l_k\right) < p_k\right) = Pr\left(z_j\left(l_k\right) > \frac{w_j}{p_k} d_{ij}\right) \\
= 1 - F_{jk}\left(\frac{w_j d_{ij}}{p_k}\right) = 1 - e^{-T_j\left(w_j d_{ij}\right)^{-\theta_k} {p_k}^{\theta_k}}
\end{aligned}
\tag{6}
$$

Lowest price in country i will be $p_i\left(l_k\right)$ such that $P_{ij}\left(l_k\right) \geq p_i\left(l_k\right)\ \forall\ j$ (with equality for one j). Let $\mathrm{G}_i\left(p_k\right)$ be share of (minimal) prices offered in country i that are less than p_k:

$$
\begin{aligned}
G_i\left(p_k\right) &= Pr\left\{\min p_{ij}\left(l_k\right) \leq p_k\right\} = 1 - Pr\left\{\min p_{ij}\left(l_k\right) \geq p_k\right\} \\
&= 1 - Pr\left\{\bigcap_{j \in N} \left(\ p_{ij}\left(l_k\right) \geq p_k\right)\right\} = 1 - \prod_{j=1}^{N}\left(1 - G_{ij}\left(p_k\right)\right) \\
&= 1 - e_i^{-\Phi} {p_k}^{\theta_k}
\end{aligned}
\tag{7}
$$

Here, Φ_i is a country specific price parameter with $\Phi_i = \sum_{j=1}^{N} T_j (w_j d_{ij})^{\theta_k}$, T_j indexes how productive country j is (on average), w_j is how costly the labor are in country j, d_{ij} is how expensive (iceberg costs) it is to ship output from country j to country i. Φ_i differs across countries is due to differences in iceberg costs (d_{ij}). Note that model can handle autarky easily: $d_{ij} = \infty \forall j \neq i \rightarrow \Phi_i = T_i c_i^{-\theta\, k}$.So, the probability that country j is the lowest cost producer of good l_k to country i, π_{ij}, is:

$$
\begin{aligned}
\pi_{ij} &= \int_0^{\infty} \overbrace{\prod_{s=1, s \neq j}^{N} Pr(P_{is}(lk) > p_k)}^{\text{Prob. no other country offers a price} \leq \text{pk}} \underbrace{dPr(P_{ij}(lk) \leq p_k)}_{\text{Prob. country j offers a price} \leq \text{pk}} \\
&= \int_0^{\infty} \prod_{s=1, s \neq j}^{N} \left[1 - G_{is}(p_k)\right] dG_{ij}(p_k) \\
&= \frac{T_j (w_j d_{ij})^{-\theta\, k}}{\Phi_i} = \frac{T_j (w_j d_{ij})^{-\theta\, k}}{\sum_{s=1}^{N} T_s (w_s d_{is})^{-\theta\, k}}
\end{aligned}
\tag{8}
$$

This is the fraction of exported from j to i which just depends on $j's$ share in $i's$ Φ_i. As the distribution of prices are independent of origin of lowest cost producer, average expenditure per good doesn't depend on origin of good:

$$X_{ij}^k = \pi_{ij} X_i^k$$

$$\frac{X_{ij}^k}{X_i^k} = \pi_{ij} = \frac{T_j (w_j d_{ij})^{-\theta_k}}{\sum_{s=1}^{N} T_s (w_s d_{is})^{-\theta_k}} \tag{9}$$

Accordingly, the gravity expression can be expressed as the imports's of country i from country j relative to country i's domestic consumption:

$$\frac{X_{ij}^k}{X_{ii}^k} = \frac{\pi_{ij}}{\pi_{ii}} = \frac{T_j (w_j d_{ij})^{-\theta_k}}{T_i (w_i)^{-\theta_k}} \tag{10}$$

Taking log of equation (10) yields

$$lnX_{ij}^k = S_i + S_j - \ \theta_k ln d_{ij} \tag{11}$$

and generates a gravity equation that is isomorphic to the Armington framework. Here, S_i and S_j are country i and j fixed effect. Our baseline regression equation is similar to equation (11) and expresses export of any country j to i in product quality k. The equation includes two country-specific monadic term and a dyadic term for trade cost, d_{ij}. The two monadic terms not only depend on nominal economic size (for instance GDP), but also on non-linear functions of all pairwise dyadic terms, called the "Multilateral resistance Indices" (hereafter MRIs) (Anderson and Van Wincoop, 2003). One way to control for these monadic terms properly in gravity estimations is to adopt a fixed-effect approach (Anderson and Van Wincoop, 2003) by introducing two sets of dummies in the gravity equation: exporter dummy (S_j)and importer dummy (S_i). Since our data structure is panel in nature we allow the two dummies to vary over time and denote them as (S_{jt}) and (S_{it}) or exporter-year fixed effect and importer-year fixed effect. Following recent literature like Felbermayr and Jung (2009) the dyadic term, d_{ij} collects indicators of cultural and geographical proximity along with a bilateral trade policy indicator. As geographical proximity indicator we choose (i) the great circle distance between i and j, and (ii) a dummy indicating whether or not the countries are contiguous. Cultural proximity is represented by two dummy variables: (i) whether countries had a colonial relationship and (ii) whether partner countries have common language. We use a dummy variable to indicate whether country i and j has a trading agreement as our proxy of trade policy indicator. As in EK these indicators take the following multiplicative form:

$$d_{ij} = [distance_{ij} \quad exp^{(contiguity_{ij} \; colony_{ij} \; common\ language_{ij} \; RTA_{ijt})}]$$

In order to capture the trade cost reducing effect of migration network, we follow Combes et al. (2005), Felbermayr and Jung (2009) and Giovannetti and Lanati (2017) and assume that trade costs do not only depend on cultural and geographical barrier but also correlated with the immigrant networks between country i and j. Immigrants are assumed to bring information about their home country and hence reduce trade cost through information channel. This lead us to redefine the trade cost term as follows:

$$d_{ij} = [\ I_{ij} \quad distance_{ij} \quad exp^{(contiguity_{ij} \; colony_{ij} \; common\ language_{ij} \; RTA_{ij})}]$$

Where I_{ij} denotes information cost. Literature relating migration and international trade has in most cases proxy this information channel with the stock of immigrants from country i to country j, M_{ij}. We follow the same notion and replaced I_{ij} with M_{ij}, at least in our benchmark model. We add an error term ε_{ijt} that controls for all unobservable time varying dyadic terms uncorrelated with the explanatory variables. The baseline specification we estimate is then the following two-way fixed-effect log-linearized equation:

$$
\begin{aligned}
lnX_{ijt}^{k} = S_{it} + S_{jt} + \theta_k lnM_{ijt} + \theta_k lndist_{ij} + \theta_k Contig_{ij} + \theta_k Comm\_lang_{ij} \\
+ \theta_k Colony_{ij} + \theta_k RTA_{ijt} + \varepsilon_{ijt}
\end{aligned}
\tag{12}
$$

However, there are few papers such as Rauch and Trindade (2002), Felbermayr et al. (2010), Felbermayr and Toubal (2012) that have incorporated strength of co-ethnic contact within the information channel of the gravity model. They assume the presence of strong third party in both trading partner countries and show that this can foster trade in addition to the traditional bilateral migrant network. The issue with defining centrality of partner countries with presence of third party effects is that it limits our country coverage to the countries that are all important migration destination. However, empirically one of the important international trade and migration channel is North-South trade and migration. A majority of the countries defined as 'South' are migrant origin not destination and hence will be excluded in such model specification. To solve this issue we define whether country pairs are more close to centrality in a different manner. Our hypothesis is that when an origin country i sends immigrants to some destination k other than country j, country i channels her home country information to a new hub k. Now, if country j reciprocates and in addition to welcoming immigrants of country i, expands its migration portfolio by accepting immigrants from country k; in addition to bring country k's home country information, they will also bring country i's information. This will make country k's agents in country j as a secondary immigration network for country i and hence should have additional positive effect on country i and j's bilateral trade. Now if the number of emigrants from country i in excess of country j is denoted by $D_{ik} = \sum_{k \neq j} M_{ik}$ and number of immigrants residing in country j in excess of country i is denoted by $D_{jk} = \sum_{k \neq i} M_{jk}$, then $D_{ik}D_{jk}$ denotes the possibility of forming this indirect migration network through a third country. We denote this indirect network variable as $IM_{ij}= D_{ik}D_{jk}$. Incorporating this new variable as part of information channel of trade cost, we can redefine I_{ij} as: $I_{ij} = [M_{ij} \;\; exp^{(IM_{ij})}]$ and change our regression specification as:

$$\begin{aligned} lnX^k_{ijt} = S_{it} + S_{jt} + \theta_k lnM_{ijt} + \theta_k IM_{ijt} + \theta_k lndist_{ij} + \theta_k Contig_{ij} \\ + \theta_k Com\_lang_{ij} + \theta_k Colony_{ij} + \theta_k RTA_{ijt} + \varepsilon_{ijt} \end{aligned} \tag{13}$$

In addition to the empirical interest in knowing the indirect effect of migration network, the inclusion of this new variable in equation (13) also creates an advantage over traditional structural gravity model: ability to measure the third country effect separately from the multilateral resistance term in a structural gravity equation.

2.3 Empirical Strategy

Most of the existing literature examining ethnic network effects on trade have exploited a pooled cross-section version of the gravity model, mainly due to the data limitations. Such papers include Dunlevy and Hutchinson (1999), Head and Ries (1998), Girma and Yu (2002) and Dunlevy (2006) to name a few. Dunlevy (2006) uses the most general form of the model by incorporating a country dummy into the model but did not control for the multilateral resistance (MTR). Following Anderson and Van Wincoop (2003) paper, it has become customary to control for the MTR. In our econometric model, we have done so by including exporter (destination) and importer (origin) specific dummy variables. Using our panel data structure, we have actually interacted time dummies with our exporter/importer fixed effects. Inclusion of these fixed effects help us control for the unobserved heterogeneity specific to a single exporter and importer that might also vary with time period. Given the presence of some zero observations in the migration database, and following Dunlevy (2006), we define $\ln M_{ijt} = \ln(Migration_{ijt} + 1)$ to avoid the loss of information. Additionally, in our sample we only work with non-zero trade flows and this helps us to avoid the issues with zero trade flows. We start our empirical estimation by running a pooled OLS of equation (12). For now, we assume a common θ across all product qualities and across all countries. However, we estimate equation (12) separately for overall migrant networks, high-skilled migrants and low-skilled migrants. We excluded the estimation of medium-skilled migrants for now as the distribution of migrants are usually bi-modular in nature. Our hypothesis in these set of estimations is that migrant networks have a positive and significant effect on bilateral trade across all skill levels. Additionally, we assume that high-skilled migrants have a better ability to receive and process information and have lesser liquidity constraint to start transaction with their native counterparts in their source country using this information. The ethnic elasticity of high-skilled workers should therefore be higher than both average elasticity and elasticity of the low-skilled migrants. Hence our first set of hypotheses are:

1. H_0 (i): $\beta_{avg} = 0$
2. H_0 (ii): $\beta_{High\ Skill} = 0$
3. H_0 (iii): $\beta_{Low\ Skill} = 0$
4. H_0 (iv): $\beta_{avg} \geq \beta_{High\ Skill}$
5. H_0 (v): $\beta_{Low\ skill} \geq \beta_{High\ Skill}$

The results of these estimation are presented in Table 3.

However, these estimates of network effects are prone to endogeneity bias. Endogeneity bias may arise from three sources: measurement errors, omitted variables or potential reverse causality between the exports and our variable of interest, migrant stock of country i in country j. In most cases migration is driven by differences in opportunities and living condition between countries and since trade influences these differences, most likely trade will also affect migratory flows (Markusen and Zahniser, 1997). In order to identify the true causal effect of migration on trade, we need to take care of potential endogeneity by finding good instruments for bilateral migration. This instrument should strongly influence bilateral migration but not bilateral trade, except through bilateral migration. Following Combes et al. (2005) we use a 15-year lagged migration stock as our instrument for the current migration stock. They argue that since trade variable is a yearly flow whereas network variables correspond to total stocks of migrants, use of this instrument should reduce both the simultaneity and the reverse causality issues. Since our proposed instrument is also stocks and computed 15 years earlier than the date at which commodity flows are observed, we think that the lagged stock variable provides good instruments for migrant networks. We thus take an instrumental variable approach and use a two stage least square dummy variable technique to estimate the instrumented version of equation (12). Then we can re-test the above mentioned null hypotheses. Table 4 shows the result of the estimations.

Another source of concern is that gravity models controlling for only importer and exporter fixed effects do not have the power to identify the unobserved heterogeneity among the country pairs. These heterogeneities can simultaneously affect both the level of bilateral exports and number of immigrants along with cultural and political determinants that could drive both migration and trade. Country-pair effects also related to initial conditions. In fact, a large literature has provided evidence that community networks, by reducing migration costs, positively influence the decision to migrate (Davis and Winters (2001); Munshi (2003); Beine et al. (2011)) and can provide biased estimates of the network effect. Cheng and Wall (2005) confirmed the hypothesis that the gravity models without properly specified fixed effects tend to generate biased estimates. Baier and Bergstrand (2007) also demonstrate evidence that heterogeneity can strongly distort estimates of gravity equation. To account for the unobserved heterogeneity properly we need to allow each country pair to have its own unrestricted intercept (fixed effect coefficient). Alternatively, we can adopt a first-difference estimation technique using our panel structure and thereby eliminate the dyadic effect of the error structure $\varepsilon_{ijt} = \xi_{ij} + u_{ijt}$. As Wooldridge (2010) (p.285) suggested after performing panel regression using these two methods one can also check for the assumption of strict exogeneity. With T>2, we opt to first difference equation (13) as suggested by Baier and

Bergstrand (2007) due to the error structure of gravity equation. We also performed fixed-effect estimation as part of robustness check and also because it allows us to test whether the fixed-effect version of the equation (13) satisfies the strict exogeneity assumption with T>2. This allows us to infer the causal effect of migration networks on trade.

Now, as we find ways to control for endogeneity and unobserved heterogeneity, we proceed to estimate equation (13) that accounts for both direct and indirect network effects. In this case we also relax the assumption on θ and allow it to vary by product quality k. Using technique similar to that of Rauch and Trindade (2002), we estimate equation (13) separately for different quality groups across immigrants' skill levels. Table 5 shows the first difference estimates along with the outcome of the test of strict exogeneity. Fixed-effect estimates which are similar to the first-difference estimates are available upon request.

3 Data

In this analysis, we use data from various sources. The final complete sample includes 19 OECD destination countries and 99 low-income non-OECD countries of origin. The destination countries are Australia, Austria, Canada, Chile, Denmark, Finland, France, Germany, Greece, Ireland, Luxembourg, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom and United States. List of origin countries are mentioned in the appendix.

We use data from the Center for International Data from Robert Feenstra on bilateral values and quantities of exports in thousand dollars disaggregated at 4 digit-SITC (Rev. 2) classification (1962 - 2000). For more recent data (2001 - 2014), we use data provided by UN Comtrade. The data covers a major portion of the north-south trade. In contrary to the existing literature that have measured export quality using unit values, we use a direct measure of quality developed by the IMF staff under an IMF-DFID research collaboration. IMF website provides export product quality series from 1962-2010 with higher values for the quality indices indicate higher quality levels. This measure of product quality is based on an updated version of the UN–NBER dataset, which harmonizes Comtrade bilateral trade flow data at the 4-digit SITC (Rev. 1) level. We have then used a correspondence table provided by UN statistics division to covert these qualities from Rev 1 to Rev 2 to be able to merge them with the existing trade data. The new product quality data are much less volatile and trend upward over time.

Skill level is measured by years of schooling completed. Data on bilateral migration by education level is collected from recent IAB brain-drain database developed by Abdeslam Marfouk (with Herbert Brücker and Stella Capuano) in 2013. The dataset provides information on the structure of immigration in 20 OECD countries by origin and education level for the years 1980-2010 (5 years' intervals). The migrants are defined as foreign-born individuals aged 25 years and older. Despite the small number of migrant destination country in the dataset, the sample covers seven out of ten top migrant destination countries along with an extensive coverage of origin countries and therefore approximately 30 percent of the world's stock of migrants for the year 2000. Due to the fact that migration data are only available from 1980 to 2005, our coverage for trade data also shrinks to the same time period with five-year interval. Data on weighted distance and all the geographic barriers used in this paper including a dummy variable for a common border, regional trade agreement (RTA), and cultural proximity (common language, colonial ties) are from CEPII gravity database. By getting rid of countries with no trade data and missing data on CEPII variables, our sample shrinks to 19 OECD destination country and 99 origin country. Given our interest in using the Instrumental Variable Estimator, our dataset further shrinks to 3 years of data: 1995, 2000 and 2005. The total number of observation is then 4327. Table 1 shows that exports increased by more than 100% over the sample period 1995 to 2005, although the sample has also increased during this time period due to less missing data. We can also see that high-skilled migration has increased by about 85% on an average while for low-skilled migrants the number is only 34%. This confirms our discussion in the first section about increasing flow of high-skilled workers migrating from south to north.

Table 2: Summary Statistics

	Year 1995		Year 2000		Year 2005	
Variables	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Export (in million)	93.21	1097.43	136.81	1715.00	206.32	2394.15
Total Migration Stock	11928.88	106200.60	14963.60	150232.80	19099.57	215168.60
High-Skilled	3349.16	22668.06	4245.02	28635.28	6197.53	42690.45
Med-Skilled	3018.23	28820.95	3780.30	38134.11	5431.71	64351.12
Low-Skilled	5561.49	62624.01	6938.28	92737.47	7470.33	120166.90
Distance (in km)	7825.54	3746.36	8010.81	3821.16	7755.26	3990.54
Common Boarder	0.01	0.07	0.01	0.07	0.01	0.08
Colony	0.07	0.25	0.06	0.24	0.05	0.22
Common Language(off)	0.18	0.39	0.18	0.39	0.16	0.37
RTA	0.03	0.16	0.06	0.24	0.09	0.28

Variation in the mean values of other variables are only due to differing sample sizes as these are time invariant variables. However, there are sufficient variance in dependent and independent variables to identify the effect of migration on international trade.

4 Results & Discussion

4.1 Pooled OLS Estimation

The estimation starts with the standard EK gravity model framework with common theta (θ) across all the countries and all product quality designations. However, in addition to estimating a pooled OLS on the overall migrant sample, we have also estimated equation (12) separately for high-skilled and low-skilled migrants. This allows us to test the hypothesis that high-skilled migrants have better ability to receive and process information and have less liquidity constraints to start transacting with their native counterparts in their source country using this information. So, we can expect a higher effect of high-skilled migrants on overall trade relative to that of both overall migrant stock or low-skilled migrants. The estimated coefficients are presented in Table 3.

Table 3: Pooled OLS Estimation

Variables	(1) OLS	(2) OLS	(3) OLS
All Migrants	0.045***		
	(0.013)		
High Skill Migrants		0.292***	
		(0.025)	
Low Skill Migrants			0.247***
			(0.024)
ln Distance	-0.730***	-0.515***	-0.511***
	(0.066)	(0.059)	(0.059)
Contiguity	0.927**	0.777**	0.661**
	(0.405)	(0.373)	(0.337)
Colony	0.586***	0.254*	0.224*
	(0.139)	(0.132)	(0.133)
Common Language	0.168**	0.009	0.094
	(0.077)	(0.072)	(0.071)
RTA	0.279**	0.433***	0.347***
	(0.134)	(0.131)	(0.131)
Constant	6.354***	4.036***	4.197***
	(0.706)	(0.633)	(0.634)
Observations	4,387	4,387	4,387
R-squared	0.815	0.830	0.828
Exp-Yr FE	YES	YES	YES
Imp-Yr FE	YES	YES	YES

Notes: Column 1,2 & 3 shows the results from regressions run for all migrant stock, high-skilled migrant stock and low-skilled migrant stock respectively.Robust standard errors in parentheses,***p < 0.01, **p < 0.05, *p < 0.1

We find a significant positive linkage between bilateral migrant stocks and exports when we consider the effect of aggregate bilateral migrant stocks. This result is in line with more recent but smaller set of papers that investigates bilateral trade and migration of many sources and destination countries (Hatzigeorgiou (2010); Egger et al. (2012); Felbermayr and Jung (2009); Giovannetti and Lanati (2017) instead of a country level single or regional study with single destination country. Our estimate of the ethnic network effect of 0.046 means that a 10% increase in the number of immigrants from a source country will increase the overall export of the host country to that specific source country by 0.46%. This estimate is very close to that of Giovannetti and Lanati (2017) who has used similar econometric specification with an exception of using product specific fixed effect and found the ethnic network coefficient to be 0.03. Our estimate of network effect rises significantly to 0.29 when we consider only the high-skilled migrants. This means a 10% increase in the number of high-skilled immigrants from a source country will increase the overall export of the host country to that specific source country by 2.9%. This confirms our hypothesis of a better information handling ability of the high-skilled immigrants. The network effect is smaller for low-skilled migrants at 0.24. However, this effect is higher than the overall effect. Presence of medium-skilled workers in the overall stock, who may work predominantly in the non-tradable sector, might explain this result. This result is also in line with previous studies such as Felbermayr and Jung (2009), Herander and Saavedra (2005), Felbermayr and Toubal (2012), Ehrhart et al. (2014) and Giovannetti and Lanati (2017) all of whom show higher pro-trade effects of high-skilled ethnic networks and Felbermayr and Jung (2009) who found that medium skilled migrants do not foster trade. However, these estimates of network effects seem prone to endogeneity bias as discussed before in section 2.3. This leads us to the instrumental variable estimation in the next section.

Table 4 presents TSLSDV (Two Stage Least Square Dummy Variable Model) controlling for exporter and importer level heterogeneity over time and endogeneity in migration numbers. The table provide us with only the second-stage results. In the first stage, the absolute value of bilateral immigrant stock is regressed on their 15-year lagged values. The results (See Appendix: Table A2) show a strong correlation between the instruments and the endogenous regressors. The first stage test statistics (See Appendix: Table A3) show the underidentification and weak test instrument. Comparing the F statistics with the Stock and Yogo thresholds, we can observe that our instruments are not weak. Since we have exactly one relevant instrument for our endogenous variable, our equation is exactly identified. However, this comes with a caveat that we will not be able to check for the exogeneity restriction exclusively. Nonetheless, available data limit us to a 15-year maximum lag in migration stocks, and we proceed as in influential papers such as Combes et al. (2005). We go ahead and treat the 15-year lagged value of migrants as a reasonable instrument for migrant networks. Moreover, comparing results with the non-instrumented regression (Table 3), instrumented regression does provide point estimates that are not different in ranking or direction.

Table 4: Two-Stage Least Square Dummy Variable Estimation (2nd Stage Results)

Variables	(1) TSLSDV	(2) TSLSDV	(3) TSLSDV
All Migrants	0.095***		
	(0.025)		
High-Skilled Migrants		0.333***	
		(0.030)	
Low-Skilled Migranst			0.282***
			(0.029)
ln Distance	-0.626***	-0.472***	-0.467***
	(0.078)	(0.061)	(0.060)
Contiguity	0.919**	0.755**	0.622*
	(0.393)	(0.358)	(0.323)
Colony	0.469***	0.193	0.157
	(0.142)	(0.128)	(0.130)
Common Language	0.114	-0.021	0.077
	(0.076)	(0.070)	(0.069)
RTA	0.321**	0.460***	0.363***
	(0.131)	(0.128)	(0.127)
Constant	5.069***	3.545***	3.725***
	(0.877)	(0.655)	(0.650)
Observations	4,387	4,387	4,387
R-squared	0.814	0.829	0.828
Exp-Yr FE	YES	YES	YES
Imp-Yr FE	YES	YES	YES

Notes: Column 1,2 & 3 shows the results from regressions run for all migrant stock, high-skilled migrant stock and low-skilled migrant stock respectively.Robust standard errors in parentheses,***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

It appears that endogeneity introduce a downward bias only, if anything. Coefficients for migrant network variables are larger across all specification, when instrumented. This strengthen the believe that our results are not caused by endogeneity issues, or driven by a reverse causality or an omitted variable bias.

4.2 Panel data First Differenced Estimation

Although instrumental variable estimation helps to control for the potential endogeneity bias, it does not guarantee the validity of the least square estimator. In fact, in the presence of unobserved country-pair specific cofounding factors explanatory variables will be correlated with the error term ε_{ijt} making least square estimation invalid. The residual plot in Figure 2 (Cheng and Wall, 2005) also shows evidence of a non-random pattern in the residuals, which may lead us to biased estimates.

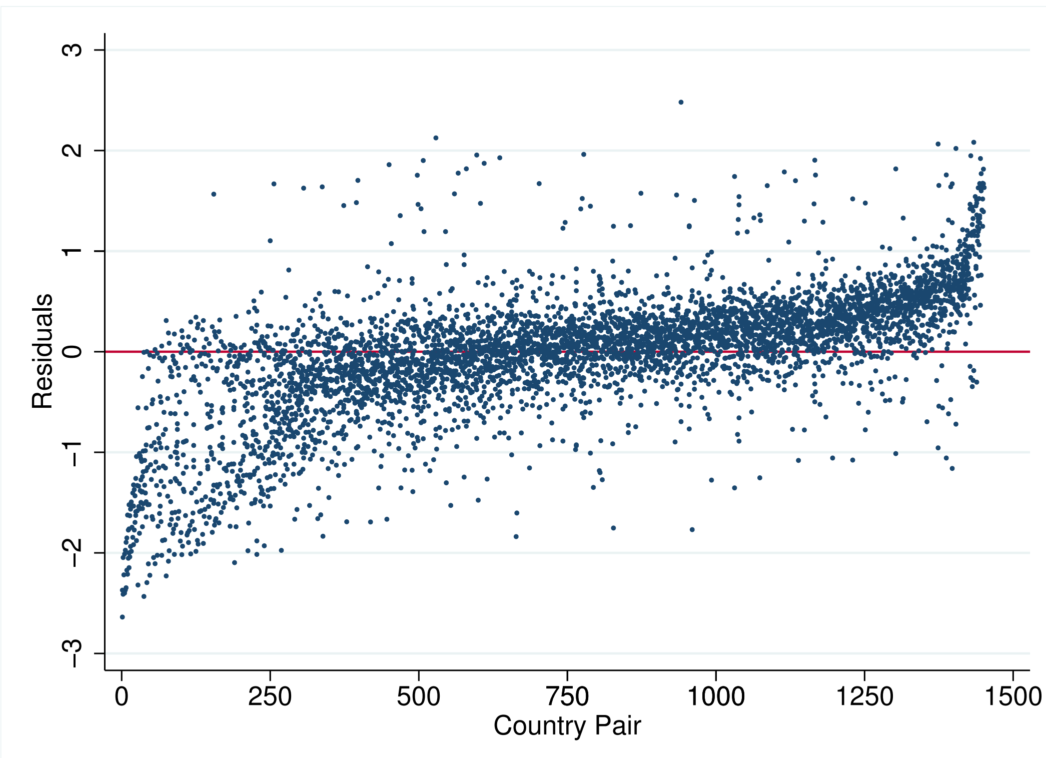

Figure 1: Residuals from Pooled Cross-section

One way to correct this issue is to use a within-estimator or first-differencing the data.

Both estimates should provide close results for smaller T (time period). Table 5 provides the first-difference estimators along with the outcome of a strict exogeneity test. Since this is our preferred specification where cofounding factors are differenced out, we relax our assumption about θ so that it varies by product quality k and finally include the variable that to account for the indirect migrant network in equation (13).

Table 5: First Differenced Model

Panel A: All Products

Variables	(1) FD	(2) FD	(3) FD
All Migrants	0. 034* (0.020)		
High-Skilled Migrants		0.132*** (0.037)	
Low-Skilled Migrants			0.075* (0.044)
Indr Effect(All)	0. 043** (0.019)		
Indr Effect (High)		0.006 (0.018)	
Indr Effect (Low)			0.026* (0.017)
RTA	0. 207** (0.096)	0.210*** (0.0945)	0.207** (0.096)
Regression Based F-test for exogeneity (p Value)	0.444	0.400	0.840
Observations	2,694	2,694	2,694
R-squared	0.242	0.243	0.242
Exp-Yr FE	YES	YES	YES
Imp-Yr FE	YES	YES	YES
Country Pair	YES	YES	YES

Notes: Column 1,2 & 3 shows the results from regressions run for all migrant stock, high-skilled migrant stock and low-skilled migrant stock respectively.Robust standard errors in parentheses,***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1

Comparing the results from first differencing the data with that of TSLSDV results (See

Panel B: High Quality Products

VARIABLES	(1) FD	(2) FD	(3) FD
All Migrants	0. .032		
	(0.025)		
High-Skilled Migrants		0.128**	
		(0.055)	
Low-Skilled Migrants			-0.039
			(0.071)
Indr Effect(All)	0. 070**		
	(0.033)		
Indr Effect (High)		0.043*	
		(0.024)	
Indr Effect (Low)			0.048*
			(0.026)
RTA	0. 331**	0.327**	0.330**
	(0.014)	(0.14)	(0.144)
Regression Based F-test for exogeneity (P Value)	0.780	0.450	0.900
Observations	2,028	2,028	2,028
R-squared	0.269	0.270	0.268
Exp-Yr FE	YES	YES	YES
Imp-Yr FE	YES	YES	YES
Country Pair	YES	YES	YES

Notes: Column 1,2 & 3 shows the results from regressions run for all migrant stock, high-skilled migrant stock and low-skilled migrant stock respectively.Robust standard errors in parentheses,***p < 0.01, **p < 0.05, *p < 0.1

Panel C: Low Quality Products

VARIABLES	(1) FD	(2) FD	(3) FD
All Migrants	0. .059*		
	(0.030)		
High-Skilled Migrants		0.099**	
		(0.045)	
Low-Skilled Migrants			0.1095*
			(0.057)
Indr Effect(All)	0. 101***		
	(0.024)		
Indr Effect (High)		0.047**	
		(0.022)	
Indr Effect (Low)			0.102***
			(0.022)
RTA	0. 142	0.150	0.123
	(0.110)	(0.11)	(0.109)
Regression Based F-test for exogeneity (P Value)	0.470	0.167	0.505
Observations	2,236	2,236	2,236
R-squared	0.210	0.206	0.213
Exp-Yr FE	YES	YES	YES
Imp-Yr FE	YES	YES	YES
Country Pair	YES	YES	YES

Notes: Column 1,2 & 3 shows the results from regressions run for all migrant stock, high-skilled migrant stock and low-skilled migrant stock respectively.Robust standard errors in parentheses,***p < 0.01, **p < 0.05, *p < 0.1

Appendix: Table A4), we find that OLS estimates always overestimate the effect of migration on trade. But, as we plot the residuals from our first-difference regression against the country pairs, we find that the systematic pattern is now gone.

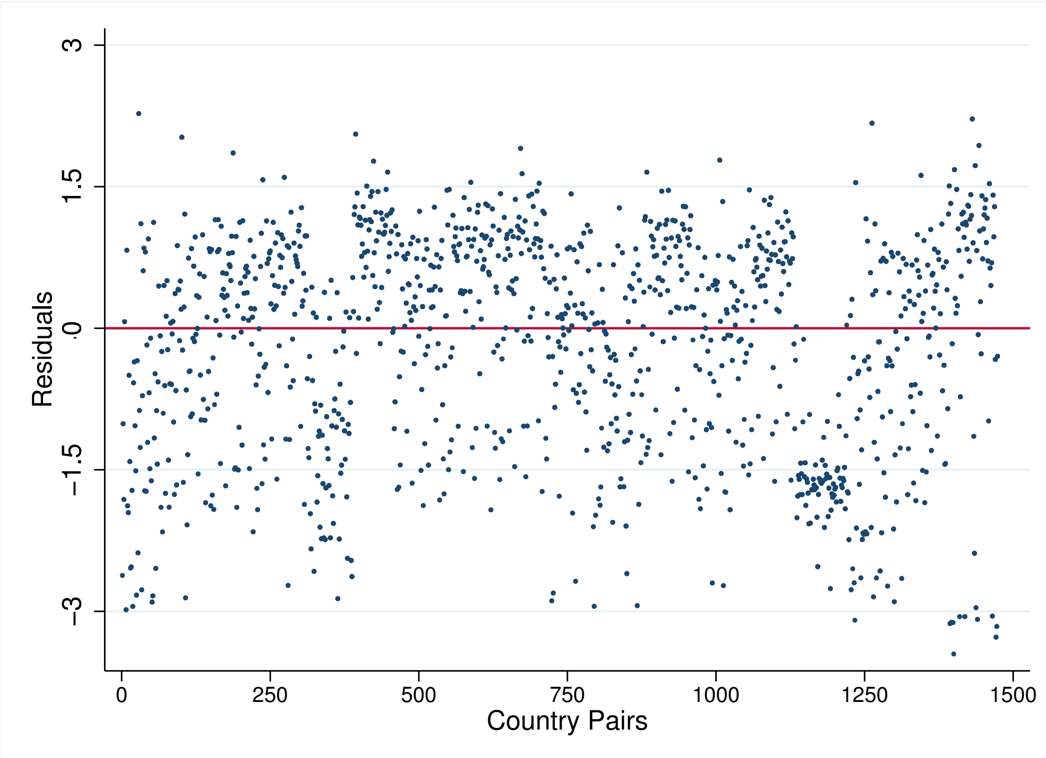

Figure 2: Residuals from First Differenced estimation

This random pattern is an encouraging result because it suggests we have successfully controlled for unobserved heterogeneity. However, the direction and ranking of our previous results are robust to the first-difference estimation. Given the new results, we can still reject all of our first five null hypotheses. A 10% increase in the overall bilateral migrant stock increases trade between country pairs by 0.3%. The estimate is similar to the magnitude reported by Felbermayr et al. (2012) based on the Özden et al. (2011) data merged with the DoT data while using first-differencing technique. The increase in trade rises to 13.2% in case of high-skilled migrants and 0.75% in case of low-skilled migrants (similar to Felbermayr and Jung 2009) using same technique and similar country coverage). Additionally, we can see that high-skilled migrants trigger more of high quality trade than of low quality trade:

1.28% vs 0.9% for a 10% increase in bilateral high-skilled migrant stocks. On the other hand, low-skilled immigrant networks do not seem to have any significant impact on the export of high quality products to their origin country. In fact, the coefficient is negative. However, their impact on low quality product trade is positive and substantial (0.11) and higher than that of both high-skilled migrant network (0.09) and overall migrant network (0.06). These results show a clear pattern between migrants' skill level and product quality with respect to direct network effect on trade. Due to better communication skills, ability to handle complex tasks and knowledge about higher quality products, higher-skilled migrants have a comparative advantage in working in the export-oriented sector in general and that advantage is higher in case of industry affiliated with high quality product exports. This is evident in our result. The result concerning low-skilled migrants is actually very interesting and enlightening. In general, this is the group of people who are believed to have higher language barriers and lower education and hence are not in sync with the labor market of developed hosting countries and are not expected to foster host country trade. But contrary to the common believe it seems that low-skilled migrants can actually penetrate via their home country knowledge into the export-oriented sector of lower product quality in the host country. Given that in 2005 our sample mean for overall export volume is 206 million, lower quality export is 55 million and average number of low-skilled migrant stock is 7470 persons, our results indicate that one additional low-skilled immigrant can create $2068 (=0.075 X 1/7470 X 206 million) of additional trade with $806 of the trade being in low quality products.

Another set of important results that emerges from Table 5 is the indirect effect of migrant networks through third-country migrants who have the potential to become a secondary co-ethnic network. Out of the nine sets of regression results, the estimate of the indirect effect comes out positive and significant in eight cases. However, the effect is stronger for lower quality products and low-skilled migrants. The result may be due to the fact that south – south diversification in migration has happened mainly in the low-skilled category and they have conveyed information about their home country demand for low quality products to their low-skilled counterpart in these new destination countries. This creates the possibility of a secondary trade fostering channel of low-skilled migrant network to affect trade in low quality products.

5 Conclusion

In this paper we explore both the direct and indirect effects of immigrants in generating exports with their origin country utilizing their ethnic networks in the host country and other ethnic groups common to both origin and destination country in question. We examine these effects for migrants of different skill and product quality levels. To our knowledge this seems to be the first paper of its kind that has accounted for indirect ethnic network effects across various skill group and product quality.

In line with existing literature, we find that immigrants exert a positive influence on host country exports to their respective source countries. We adopted an instrumental variable estimator to counter the endogeneity issue and still finds that our results are robust. However, our first-differenced estimates clearly show that the magnitudes of these positive impacts are sensitive to the restrictions imposed on the model. We find a much smaller network effect when we remove the restriction that the intercepts are the same for all country pairs by first differencing the model. This estimation also allows us to ensure exogeneity of the migrant stocks. When we disaggregate the overall migrant network by skill level, we find that high-skilled ethnic networks have a stronger direct impact on aggregated bilateral trade, owing to their higher human capital, lesser liquidity constraint and better information handling skill. One strong result that emerges from our estimation is that when we disaggregate product quality, high-skilled ethnic networks trigger more high quality trade than low-skilled ethnic network while low-skilled ethnic networks triggers more low quality trade than high-skilled ethnic networks. Better ability to handle complex job provides high-skilled migrants with opportunities to work in high quality export oriented industries and forge trade linkages with their home country. Although low-skilled migrants are constrained by their low level of human capital and higher liquidity constraint, they also use their home country knowledge to their advantage and penetrate the low quality export-oriented industry for which their home country has higher demand. On average one additional low-skilled immigrant can create $2068 of additional trade with $806 trade in lower quality products for their host country. This result has very important policy implications for welfare analysts as this potential gain in export earning might help to offset much talked about welfare losses from low-skilled immigration. Finally, we find that there is a positive indirect effect of a third party acting as a secondary ethnic network on bilateral trade, and this effect is stronger for low quality products and more so through low-skilled migrants. This result is important to policy makers suggesting advantages of a diversified immigrant portfolio as with increasing integration of international migration networks. One ethnic group can act as complement to another ethnic group via their own bilateral immigration channel.

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Appendix

Table A1: List of Countries

Destination Countries (Exporter)
"Australia" "Austria" "Canada" "Chile" "Denmark" "Finland" "France" "Germany" "Greece" "Ireland" "Luxembourg" "New Zealand" "Norway" "Portugal" "Spain" "Sweden" "Switzerland" "UK" "USA"
Origin Countries (Importer)
"Albania" "Algeria" "Angola" "Argentina" "Armenia" "Azerbaijan" "Bangladesh" "Belarus" "Belize" "Benin" "Bolivia" "Brazil" "Bulgaria" "Burkina Faso" "Burundi" "Cameroon" "Cape Verde" "Chad" "China" "Central African Republic" "Colombia" "Comoros" "Congo, Rep. of the" "Costa Rica" "Cote d'Ivoire" "Djibouti" "Dominica" "Dominican Republic" "Ecuador" "Egypt" "El Salvador" "Equatorial Guinea" "Ethiopia" "Fiji" "Gabon" "Gambia, "Georgia" "Ghana" "Grenada" "Guatemala" "Guinea" "Guyana" "Guinea-Bissau" "Haiti" "Honduras" "Lebanon" "Liberia" '"Libya" "Macedonia" "Madagascar" "Malawi" "Malaysia" "Maldives" "Mali" "Mexico" "Mauritania" "Mauritius" "Moldova" "Morocco" "Mozambique" "Nepal" "Nicaragua" "Niger" "Nigeria" '"Pakistan" "Panama" "Papua New Guinea" "Paraguay" "Peru" '"Philippines" "Russia" "Rwanda" "Saint Lucia" "Saint Vincent and the Grenadines" "Samoa" "Senegal" "Sierra Leone" "Solomon Islands" "South Africa" "Sri Lanka" "Sudan" "Suriname" "Syria" "Tajikistan" "Tanzania" "Thailand" "Togo" "Tonga" "Tunisia" "Turkey" "Turkmenistan" "Uganda" "Ukraine" "Uzbekistan" "Vanuatu" "Venezuela" "Vietnam" "Zambia" "Zimbabwe"

Table A2: 1st Stage Regression Result

VARIABLES	(1) TSLSDV	(2) TSLSDV	(3) TSLSDV
All Migrants	.453***		
	(.022)		
High-Skilled Migrants		.880***	
		(.020)	
Low-Skilled Migrants			.804***
			(.020)
Observations	4,387	4,387	4,387
R-squared	0.815	0.830	0.828
Control	YES	YES	YES
Exp-Yr FE	YES	YES	YES
Imp-Yr FE	YES	YES	YES

Notes: Column 1,2 & 3 shows the results from regressions run for all migrant stock, high-skilled migrant stock and low-skilled migrant stock respectively.Robust standard errors in parentheses,***p < 0.01, **p < 0.05, *p < 0.1

Table A3: Relevance of IV (From 1st Stage Regression)

Panel A: All Migrants

			Under Identification		Weak Identification
Variable	F (1, 1681)	P-val	SW Chi-sq(1)	P-val	SW F (1,1681)[a]
Lagged_Migration	414.78	0.00	448.91	0.00	414.78

Weak identification test	
H_0:Equation is weakly identified	
Cragg-Donald Wald F statistics	1615.80
Kleibergen-Paap Wald rk F statistic	414.78
Stock-Yogo[a] (2005) Weak ID F test critical values	
for single endogeneous regressor	
5% maximal IV size	16.38
10% maximal IV size	8.96
20% maximal IV size 6.66	6.66
25% maximal IV size 5.53	5.53

Panel B: High-skilled Migrants

			Under Identification		Weak Identification
Variable	F (1, 1681)	P-val	SW Chi-sq(1)	P-val	SW F (1,1681)[b]
Lagged_Migration	1831.17	0.00	1981.82	0.00	1831.17

Weak identification test	
H_0:Equation is weakly identified	
Cragg-Donald Wald F statistics	6735.82
Kleibergen-Paap Wald rk F statistic	1831.17
Stock-Yogo[b] (2005) Weak ID F test critical values	
for single endogeneous regressor	
5% maximal IV size	16.38
10% maximal IV size	8.96
20% maximal IV size 6.66	6.66
25% maximal IV size 5.53	5.53

Panel C: Low-skilled Migrants

			Under Identification		Weak Identification
Variable	F (1, 1681)	P-val	SW Chi-sq(1)	P-val	SW F (1,1681)[b]
Lagged_Migration	1568.47	0.00	1697.51	0.00	1568.47

Weak identification test	
H_0:Equation is weakly identified	
Cragg-Donald Wald F statistics	5889.77
Kleibergen-Paap Wald rk F statistic	1568.47
Stock-Yogo[b] (2005) Weak ID F test critical values	
for single endogeneous regressor	
5% maximal IV size	16.38
10% maximal IV size	8.96
20% maximal IV size 6.66	6.66
25% maximal IV size 5.53	5.53

Table A4: TSLSDV with Direct and Indirect Effects

VARIABLES	(1) TSLSDV	(2) TSLSDV	(3) TSLSDV
All Migrant	0.071***		
	(0.023)		
High Skill Migrant		0.188***	
		(0.038)	
Low Skill Migrant			0.198***
			(0.029)
Indr Effect(All)	0.096***		
	(0.007)		
Indr Effect (High)		0.068***	
		(0.009)	
Indr Effect (Low)			0.078***
			(0.008)
Ln Distance	-0.626***	-0.577***	-0.547***
	(0.071)	(0.061)	(0.060)
Contiguity	1.072***	0.905***	0.920***
	(0.284)	(0.281)	(0.287)
Colony	0.595***	0.435***	0.387***
	(0.132)	(0.130)	(0.130)
Common Language	0.147**	0.0780	0.135**
	(0.070)	(0.069)	(0.066)
RTA	0.487***	0.512***	0.440***
	(0.120)	(0.117)	(0.122)
Constant	-19.01***	-9.644***	-13.01***
	(2.017)	(1.798)	(1.795)
Observations	4,381	4,372	4,381
R-squared	0.836	0.840	0.838
Exp-Yr FE	YES	YES	YES
Imp-Yr FE	YES	YES	YES

Notes: Column 1,2 & 3 shows the results from regressions run for all migrant stock, high-skilled migrant stock and low-skilled migrant stock respectively.Robust standard errors in parentheses,***$p < 0.01$, **$p < 0.05$, *$p < 0.1$