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Networks and Selection in International Migration to Spain

by

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Abstract

This paper analyzes the role of ethnic communities in shaping the recent immigration boom to Spain. We find that ethnic communities exerted a strong positive effect on the scale and a strong negative effect on the skill structure of this immigration. Unlike previous studies, we explicitly acknowledge similarities among final migration destinations and thus partly relax the independence of irrelevant alternatives assumption. We strengthen our causal interpretation by controlling for observed and unobserved heterogeneity in bilateral migration costs, and by adopting an instrumental variables approach. Our results suggest that previous estimates of the scale effect are upward-biased by approximately 50%.

Keywords: international migration, ethnic networks, family and friends effect, skill structure of migration, Spain.

JEL classification: F22

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1 Introduction

Aggregate cross-border migration evolves gradually over time. This phenomenon has been partly attributed to the fact that settled migrants assist would-be migrants from the same country in, inter alia, their search for jobs and housing (Munshi, 2003). The on-site help provided by the co-ethnic peers has the potential to reduce the barriers to migration for prospective newcomers. This so-called family and friends (or network) effect entails that at the aggregate level migration begets further migration.[1] Although the relevance of this effect is widely acknowledged in the literature (Hatton, 1995; Clark et al., 2007), its exact empirical identification remains a challenging task.

Current discussions on immigration often center around the skills of new immigrants required to foster economic growth in the receiving economy, in addition to the optimal scale of immigration. Many OECD countries are primarily interested in high-skilled immigrants who are trained in specific fields, such as engineering or medical sciences. Chiswick (1999) argues that high-skilled individuals have lower effective costs of migration than low-skilled individuals, which opens up the possibility for migrants to be positively selected in terms of their skills.[2] At the same time, through its impact on migration costs, the family and friends effect could bias the skill structure of immigration towards the low-skilled individuals.

This paper provides new evidence on the importance of ethnic migrant communities in shaping the total size (scale) and skill structure of immigration, drawing on rich migration data from the recent immigration boom to Spain.[3] In addition to the fact that high quality data on aggregate migration are scarce, estimated migration functions often lack an explicit micro-foundation (Clark et al., 2007; Lewer & Van den Berg, 2008; Pedersen et al., 2008; Mayda, 2010).[4] To the extent that they do have a micro-foundation (Beine et al., 2011,2012; Beine & Salomone, forthcoming), they hinge on two strong assumptions. The first is the so-called independence of irrelevant alternatives (IIA) assumption.[5] It implies that the odds ratio between any two alternative migration destinations is independent of the number and characteristics of other migration destinations (Bertoli & Fernández-Huertas Moraga, 2011). The second assumption is that the unobserved heterogeneity

[1]The network externality generates a welfare loss in the laissez-faire transition path equilibrium (Carrington et al., 1996; Chau, 1997). This calls for policy intervention in the form of migration subsidies that accelerate the speed of migration.

[2]There is evidence that migrants are, in general, positively selected due to skill-dependent *absolute* income differences across countries (Grogger & Hanson, 2011). This casts doubt on the validity of the Roy model (Borjas, 1987), which highlights the importance of *relative* returns to skill; see also Belot & Hatton (forthcoming). The evidence on selection in the Mexican-U.S. migration corridor is mixed (Chiquiar & Hanson, 2005; Orrenius & Zavodny, 2005; McKenzie & Rapoport, 2007; Fernández-Huertas Moraga, 2011).

[3]The recent immigration experience in Spain has garnered a lot of attention among policymakers, business managers, and journalists. From 1997 to 2009, Spanish municipalities registered roughly six million new immigrants, of which Romanians account for 13.6%, followed by Moroccans (11.1%), Ecuadorians (8.2%), Colombians (6.1%), Britons (5.3%), and Bolivians (4.7%). These numbers are own calculations based on data from the Spanish Instituto Nacional de Estadística (INE).

[4]For the location choice of migrants within borders, see Zavodny (1997,1999), Chiswick & Miller (2004), Card & Lewis (2007), and Jayet et al. (2010), in addition to the pioneering work by Bartel (1989). Survey-based studies on migration decisions at the micro-level include Baghdadi (2005), Bauer et al. (2005,2009), and Dolfin & Genicot (2010).

[5]As an exception, the paper by Ortega & Peri (2009) does partly relax the IIA assumption. However, it does neither identify the family and friends effect nor does it address selection on skills.

in bilateral migration costs is uncorrelated with the size of the ethnic community abroad. Violations of either assumption can lead to a misspecified migration function and biased estimates.

We propose a novel identification strategy that is consistent with utility-maximizing behavior of individuals, and that relaxes both assumptions mentioned above. In the spirit of McFadden (1984, 1422-1428), we set up a nested multinomial logit (NMNL) migration model in which final migration destinations within the same country or region are considered to be similar in the sense that they share a common political, economic, and cultural background. It will be shown that acknowledging such similarities is incompatible with the IIA property. We estimate an aggregate migration function derived from the NMNL model in an extended fixed effects framework, controlling for unobserved heterogeneity in bilateral migration costs.[6] In addition to relaxing IIA, this approach goes a long way towards purging the estimates from endogeneity bias, relative to existing literature. Endogeneity has its roots in the two-way relationship between ethnic migrant communities and bilateral migration costs. On the one hand, through the family and friends effect, the size of ethnic migrant communities appears as an argument in the migration cost function determining future migration. On the other hand, the ethnic migrant community is the result of past immigration and thus itself influenced by bilateral migration costs. We furthermore control for bilateral trading and investment relationships and test for their potential to facilitate bilateral migration. The effects of ethnic communities on trade (Gould, 1994; Rauch & Trindade, 2002; Peri & Requena-Silvente, 2010) and foreign direct investment (FDI) (Javorcik et al., 2011) are relatively well understood, but the literature on the causal effects of trade and FDI on migration is scarce.

We summarize our findings as follows. First, ethnic networks exert a strong positive effect on the scale and a strong negative effect on the skill structure of immigration. We estimate that a doubling of the size of the ethnic migrant community leads to a rise in future immigration from the same origin by almost 50%, and to a decline in the ratio of high-skilled to low-skilled individuals in this immigration by approximately 30%.[7] Second, unobserved heterogeneity in bilateral migration costs is indeed correlated with the size of the ethnic community abroad. Failing to account for this heterogeneity leads to an upward bias of about 50% in the estimation of the scale effect. Third, violations of the IIA property are pervasive in our data. These violations translate into cross-regional differences in estimated network elasticities which have gone unnoticed in the existing literature. Finally, bilateral trading and investment relations do not seem to have a relevant impact on the scale and skill structure of migration.

In terms of focus and econometric approach, our paper is most closely related to the two above-mentioned studies by Beine et al. (2011,2012), in spite of our novel identification strategy. Beine et al. (2011) investigate

[6]One might be tempted to advocate the use of panel methods in order to control for the time-invariant component of bilateral migration costs. Our approach is different, however, since a consistent framework for estimating a migration model with panel data is not yet available.

[7]We strengthen our causal interpretation by adopting an instrumental variables approach. Historical bilateral migration flows are shown to have significant explanatory power for the size of bilateral ethnic communities even after a relatively long period of time. The instrumental variables estimator is asymptotically consistent under the assumption that the historical migration flows are uncorrelated with the unobserved determinants of the scale and skill structure of the recent immigration boom.

the determinants of the size and skill content of migration flows between the years 1990 and 2000 into 30 OECD countries. The authors' estimates suggest an average elasticity of bilateral migration flows with respect to ethnic communities in the destination country of around 0.7. Furthermore, economies hosting large ethnic migrant communities from a given country can expect to receive a larger proportion of low-skilled migrants from that country.[8] The follow-up paper by Beine et al. (2012) employs a data structure similar to ours, focusing on U.S. immigration. It separately identifies what the authors call local and national network externalities, saying that local ethnic communities facilitate assimilation, while nation-wide ethnic communities reduce visa costs. Our definition of the family and friends effect corresponds to their local assimilation effect, while we treat the national network externality as a fixed effect in our estimation.

The remainder of this paper is organized as follows. Section 2 characterizes individual decision making in a random utility framework which partly relaxes the IIA assumption. We derive estimable equations from this model for the scale and skill structure of immigration. In section 3 we present our estimation strategy to deal with endogeneity issues and introduce in detail the data we employ in our econometric analysis. Section 4 presents our estimation results. Section 5 concludes.

2 The Model

Our main goal in this paper is to estimate the impact of migrant networks on the scale and skill structure of immigration flows to Spain. For this purpose, we set up a multi-country random utility framework with many origin and destination countries. Our framework takes the form of a nested multinomial logit (NMNL) model along the lines of McFadden (1984, 1422-1428).

2.1 Hierarchical Decision Making in Migration

We assume that the decision making process leading to migration follows a hierarchical structure in which similar alternative migration destinations are grouped into clusters. Individuals eliminate clusters until a single alternative migration destination remains. Decision making can be described in a hierarchical manner: first to which country to migrate (including the home country), second which region to move to within the chosen country, and third which destination to pick within the preferred region.[9] Let $i = \{1, \ldots, I\}$ index origins, $j = \{1, \ldots, J(i)\}$ index the final migration destinations, $z = \{1, \ldots, Z(i)\}$ index the primary clusters (countries), and $r = \{1, \ldots, R(i)\}$ index the secondary clusters (regions within countries), as perceived by

[8] McKenzie & Rapoport (2010) find that the probability of positive self-selection on education from Mexican migrants to the U.S. is the larger, the smaller the migrant network in the origin community. Bertoli (2010) uses rich individual-level data on Ecuadorian emigrants, confirming a positive interaction between the size of the ethnic community abroad and the extent of negative self-selection. Grogger & Hanson (2011) touch upon this interaction as well; see their robustness checks in table 7 on page 53.

[9] In Ortega & Peri (2009), the first decision of individuals is between going abroad and staying at home. Our model can incorporate this additional structure without affecting our econometric implementation.

individuals living in country i. Let country i be one element in each of the sets $\{1, \ldots, Z(i)\}$, $\{1, \ldots, R(i)\}$, and $\{1, \ldots, J(i)\}$, such that staying in the home country is always an option.[10] Define A_{izr} to be the set of final migration destinations belonging to region r in country z, and A_{iz} to be the set of regions belonging to country z, again from the viewpoint of individuals living in country i.

We write the utility of individual o who migrates from country i to destination j and lives in destination j as:

$$U_{ij}^{o} = \xi_{ij} + \pi_{iz} + e_{ij}^{o}, \tag{1}$$

where $o = \{1, \ldots, O(i)\}$ identifies individuals originating from country i, and ξ_{ij} and π_{iz} are sub-utility functions relevant for moving from country i to destination j and living in destination j, with $j \in A_{izr}$ and $r \in A_{iz}$. The value of the function ξ_{ij} varies across combinations of origin countries and final migration destinations. Among other things, it includes destination-specific economic conditions and bilateral migration costs. The value of the function π_{iz} varies across combinations of origin and destination countries, but not across migration destinations in a given country. It reflects the impact of country-specific immigration policies. Finally, e_{ij}^{o} is a stochastic (random) utility component, whose individual-specific realizations vary across final migration destinations.

For the time being, let all individuals be of a single skill type. We then write:

$$\xi_{ij} = \alpha W_j + X_j - \gamma C_{ij}, \quad \alpha, \gamma > 0, \tag{2}$$

where W_j is the destination-specific wage per unit of human capital, X_j refers to other utility-relevant characteristics of destination j (for example the state of the housing market or the climate), and C_{ij} captures bilateral costs of moving and assimilation. The parameter α gives the units of human capital per individual such that all workers in j earn the same wage, αW_j. Similarly, the parameter γ represents the ease with which individuals are able to cope with migration costs, and γC_{ij} are effective costs of migration. The bilateral costs of moving and assimilation, C_{ij}, will be specified and discussed in more detail below. Suffice it to say here that we decompose them into three elements:

$$C_{ij} = \psi_{ir} + \vartheta_{wj} + c_{ij}, \tag{3}$$

where ψ_{ir} varies across combinations of origin countries and destination regions within countries, ϑ_{wj} varies across combinations of world regions and final migration destinations, and c_{ij} varies across combinations of origin countries and final migration destinations. For expositional convenience, we define $\tilde{\xi}_{ij} \equiv \xi_{ij} + \gamma\psi_{ir}$.

Each individual is assumed to choose from the set of final migration destinations (including the home country) the alternative from which she derives the highest utility:

$$j^{o} = \text{argmax}(U_{i1}^{o}, \ldots, U_{iJ(i)}^{o}), \qquad j^{o} \in \{1, \ldots, J(i)\}. \tag{4}$$

[10] The home country i is always a degenerate nest in the sense that it represents a single final migration destination.

The probability that individual o from country i migrates to destination j is equal to the probability that this individual associates the largest utility with moving to destination j:

$$\begin{aligned} P_i^o(j^o = j) &= \Pr(U_{ij}^o > U_{ik}^o \;\; \forall\, k \in \{1, \ldots, J(i)\} : k \neq j) \\ &= \Pr(e_{ik}^o - e_{ij}^o \leq \xi_{ij} - \xi_{ik} + \pi_{iz} - \pi_{iz'}; \\ &\quad \forall\, k \in \{1, \ldots, J(i)\} : k \neq j), \end{aligned} \tag{5}$$

where $j \in A_{izr}$, $r \in A_{iz}$, $k \in A_{iz'\ell}$, and $\ell \in A_{iz'}$.

By the laws of conditional probability, we can express this probability as a product of transition probabilities. For $j \in A_{izr}$, $r \in A_{iz}$, we have:

$$P_i^o(j^o = j) = P_i^o(j^o = j | j^o \in A_{izr}) P_i^o(j^o \in A_{izr} | j^o \in A_{iz}) P_i^o(j^o \in A_{iz}). \tag{6}$$

These probabilities depend on the distribution assumed for the random utility parameters, $e_{i1}^o, \ldots, e_{iJ(i)}^o$. The existing literature on network effects in migration assumes these parameters to be drawn independently from the same Extreme Value Type I distribution. This assumption implies the IIA property, according to which the ratio of two choice probabilities, $P_i^o(j^o = j)/P_i^o(j^o = k)$, is independent of the non-random utility components of migration destinations other than j and k.

We relax this assumption and assume a Generalized Extreme Value distribution (GEV) for the random utility parameters; see McFadden (1984, 1422-1428) for technical details. This generalization allows for the random utility parameters of final migrations destinations within the same country or region to be mutually correlated, whereas the parameters of destinations in different countries are independent. Define on the unit interval two functions, $\phi_z \equiv \phi(\mathbf{x}_z)$ and $\varphi_r \equiv \varphi(\mathbf{y}_r)$, measuring the similarity of final migration destinations in country z and region r, respectively. The vector $\mathbf{x}_z$ collects all attributes common to locations in z, and accordingly for the vector $\mathbf{y}_r$. Important elements of the vector $\mathbf{x}_z$ are the migration policy and the political system, while the vector $\mathbf{y}_r$ includes, among other things, the level of economic development and the cultural background. It will become evident below that this generalization has important implications for the specification of the migration function.

As shown by McFadden (1984, 1422-1428), each transition probability has a closed-form analytical solution:

$$P_i^o(j^o = j | j^o \in A_{izr}) = \frac{\exp[\tilde{\xi}_{ij}/(\lambda_z \kappa_r)]}{\sum_{k \in A_{izr}} \exp[\tilde{\xi}_{ik}/(\lambda_z \kappa_r)]}, \tag{7}$$

$$P_i^o(j^o \in A_{izr} | j^o \in A_{iz}) = \frac{\exp[\Phi_{ir}\kappa_r - \gamma\psi_{ir}/\lambda_z]}{\sum_{\ell \in A_{iz}} \exp[\Phi_{i\ell}\kappa_\ell - \gamma\psi_{i\ell}/\lambda_z]}, \tag{8}$$

$$P_i^o(j^o \in A_{iz}) = \frac{\exp[\pi_{iz} + \Omega_{iz}\lambda_z]}{\sum_{a=1}^{Z(i)} \exp[\pi_{ia} + \Omega_{ia}\lambda_a]}, \tag{9}$$

where $\lambda_z = 1 - \phi_z$ and $\kappa_r = 1 - \varphi_r$ measure the dissimilarity (increasing with higher values) of migration destinations in country z and region r, respectively, and Φ_{ir} and Ω_{iz} are "inclusive values" defined as:

$$\Phi_{ir} = \ln \sum_{k \in A_{izr}} \exp[\tilde{\xi}_{ik}/(\lambda_z \kappa_r)] \tag{10}$$

and

$$\Omega_{iz} = \ln \sum_{\ell \in A_{iz}} \exp[\Phi_{i\ell}\kappa_\ell - \gamma\psi_{i\ell}/\lambda_z]. \tag{11}$$

The inclusive values Φ_{ir} and Ω_{iz} summarize the characteristics of all migration destinations within region r and within country z, respectively. Using equations (6) to (11) and aggregating over all individuals from country i, we can write the rate of migration from country i to destination j as:

$$\frac{m_{ij}}{m_i} = \frac{\exp[\tilde{\xi}_{ij}/(\lambda_z \kappa_r) - \gamma\psi_{ir}/\lambda_z + \pi_{iz}]}{\sum_{a=1}^{Z(i)} \exp[\pi_{ia} + \Omega_{ia}\lambda_a] \exp[(1-\kappa_r)\Phi_{ir} + (1-\lambda_z)\Omega_{iz}]}, \tag{12}$$

where m_{ij} is the number of individuals migrating from i to j, and m_i is the initial population size of country i. This ij-specific bilateral migration rate will serve as the basis for our econometric implementation. It is not independent of the attractiveness of other migration destinations $k \neq j$, whether in the same region r (or country z) or not. For example, an increase in the wage rate of any destination k, $\mathrm{d}W_k > 0$, re-directs migration flows from all other destinations to destination k, $\partial(m_{ij}/m_i)/\partial W_k < 0$ and $\partial(m_{ik}/m_i)/\partial W_k > 0$. It is in this sense that we refer to the product below the fraction line in equation (12) as a "multilateral resistance" term.[11]

As opposed to the standard MNL model used by Beine et al. (2011,2012), our NMNL modelling framework allows for changes in economic conditions in migration destinations other than j to induce *non-uniform* effects on the ij-specific bilateral migration rate (12), depending on whether these destinations belong to the same country or region as j. In particular, as shown by McFadden (1984, 1422-1428), the migration rate, m_{ij}/m_i, is most sensitive to changes in other destinations in the same region. The phenomenon that such substitution effects are stronger within than across regions (and stronger within than across countries) is due to the similarity of migration destinations within the same region (and within the same country).

We now turn to a more precise definition of bilateral migration costs, C_{ij}. Following Beine et al. (2011), we assume that these costs are a decreasing and globally convex function of the size of the ethnic community in destination j, M_{ij}, such that $\partial C_{ij}/\partial M_{ij} < 0$ and $\partial^2 C_{ij}/\partial M_{ij}^2 > 0$. This assumption reflects the family and friends effect. Furthermore, we hypothesize that trading and investment relations, represented by t_{ij} and F_{ij}, respectively, exert a similar effect on migration costs, $\partial C_{ij}/\partial \delta_{ij} < 0$ and $\partial^2 C_{ij}/\partial \delta_{ij}^2 > 0$, $\delta \in \{t, F\}$. We may think of three reasons for a positive causal effect of trade on migration. First, intermediate input importers

[11] Mayda (2010) speaks of "multilateral pull" effects. The idea of "multilateral resistance" here is similar to that in the gravity equation for international trade flows; see Anderson & van Wincoop (2003). Anderson (2011) sketches a general equilibrium migration model with multilateral resistance.

and exporters alike host jobs which may be attractive for the trading partner's workers due to relationship-specific knowledge. Second, tight business links, reflected by high trade volumes, are often accompanied by a well-developed traveling and transportation infrastructure. This infrastructure can facilitate bilateral migration. Third, in case of relevant export volumes from country i to destination j, individuals from country i with home-biased preferences have lower barriers to migrate to destination j. Related arguments apply to the effects of bilateral capital flows to final migration destinations.[12] For example, corporate employees of foreign multinational enterprises (MNEs) investing in destination j may expect to find attractive employment opportunities in affiliated firms in destination j. Or, more generally speaking, it seems plausible to expect MNEs to exhibit a cultural bias when it comes to filling vacancies in their affiliates abroad. This bias may take the form of preferential treatments of job applicants from the country in which the MNEs' headquarters are located.

The variable t_{ij} is the sum of bilateral imports and exports in the period before migration takes place, and F_{ij} is the stock of bilateral investment in some final migration destination j, prior to migration. A convenient specification of migration costs that readily incorporates the idea of positive but diminishing returns to networks, trade, and FDI uses the logs of M, t, and F:

$$C_{ij} = \psi_{ir} + \vartheta_{wj} - \theta \ln(1 + M_{ij}) - \rho \ln(1 + t_{ij}) - \sigma \ln(1 + F_{ij}). \tag{13}$$

We add one to the variables M, t, and F before taking logs in order to abstract from infinitely large migration costs. The parameter $\theta > 0$ is a measure for the strength of the family and friends effect, and similarly for $\rho > 0$ and $\sigma > 0$ with respect to the trade and FDI effect, respectively.

An important determinant of the bilateral migration costs, C_{ij}, is the geographical and cultural distance between source and destination. We argue that all elements of this distance originate at the level of regions rather than provinces. In Spain, for example, this argument applies to linguistic differences across regions, as well as to other forces deriving from a political and historical context: The Basque Autonomous Community and Navarre both have strong cultural ties with the Northern Basque Country which is part of French national territory.[13] A similar argument applies to Catalonia as well. The region Galicia, in turn, has long been suffering from a chronic growth weakness, which has led to mass emigration in the 19th and 20th century, in particular to Latin American countries. In our specification of bilateral migration costs, we thus assume that the ir-specific term ψ_{ir} represents the full geographical and cultural distance between origin country i and all final migration destinations $j \in A_{izr}, r \in A_{iz}$.

Notice that we have so far defined ethnic communities in terms of origin countries. Our model could thus be prone to ignoring all potential network externalities that materialize at geographical, political, or cultural levels which go beyond this simple country-based definition. This issue seems to be an important shortcoming

[12]We only look at the effects of *inward* investments on *inward* migration; see Buch et al. (2006) for a study on the multi-faceted links between migration (inward and outward) and investment (inward and outward).

[13]The Basque Autonomous Community and Navarre form the Spanish part of the Basque Country (*País Vasco* in Spanish; *Euskal Herria* in Basque language).

in light of the cultural proximity among, for example, Latin American countries. It applies however to all existing studies we are aware of and may lead to biased estimates due to omitted variables. We therefore allow for network effects to occur at the bilateral level of world regions and final migration destinations, captured by the wj-specific term ϑ_{wj}. Our definition of world regions mostly follows that of the World Bank, distinguishing among Sub-Saharan Africa, Middle East & North Africa, East Asia & Pacific, South Asia, Latin America & Caribbean, Eastern Europe & Central Asia, Western Europe, and North America & Australia.

2.2 Scale of Immigration Flows

Substituting $\tilde{\xi}_{ij}$ in equation (12) and using equation (13), taking logs, and rearranging terms yields the following migration function for $j \in A_{izr}, r \in A_{iz}$:

$$\begin{aligned} \ln(m_{ij}) \quad &= \quad \frac{\theta\gamma}{\lambda_z\kappa_r}\ln(1+M_{ij}) + \frac{\rho\gamma}{\lambda_z\kappa_r}\ln(1+t_{ij}) + \frac{\sigma\gamma}{\lambda_z\kappa_r}\ln(1+F_{ij}) \\ &\quad +\mu_i + \mu_{iz} + \mu_j + \mu_{wj} + \mu_{ir}, \end{aligned} \tag{14}$$

where

$$\begin{aligned} \mu_i &\equiv \ln(m_i) - \ln\sum_{a=1}^{Z(i)}\exp[\pi_{ia} + \Omega_{ia}\lambda_a], \\ \mu_{iz} &\equiv (\lambda_z - 1)\Omega_{iz} + \pi_{iz}, \\ \mu_j &\equiv (\alpha W_j + X_j)/(\lambda_z\kappa_r), \\ \mu_{wj} &\equiv -\gamma\vartheta_{wj}/(\lambda_z\kappa_r), \\ \mu_{ir} &\equiv (\kappa_r - 1)\Phi_{ir} - \gamma\psi_{ir}/\lambda_z. \end{aligned}$$

We summarize three characteristics of this migration function. First, even if we abstract from the effects operating through the multilateral resistance term, the elasticity of the migration inflow, m_{ij}, with respect to the size of the ethnic community, M_{ij}, is a function of the dissimilarities of final migration destinations in country z and region r, λ_z and κ_r. The same holds true for the elasticities of migration with respect to trade and FDI. Second, the multilateral resistance effects are jointly captured by the terms μ_i, μ_{iz}, and μ_{ir}. In the standard multinomial logit migration model ($\lambda_z = \kappa_r = 1 \; \forall z, r$), the multilateral resistance effects with dimension iz and ir, nested in μ_{iz} and μ_{ir}, collapse to zero. Third, bilateral migration costs impact on bilateral migration through the terms $\gamma\vartheta_{wj}/(\lambda_z\kappa_r)$ (nested in μ_{wj}) and $\gamma\psi_{ir}/\lambda_z$ (nested in μ_{ir}), in addition to the ij-specific effects of ethnic migrant communities, trade, and FDI.

Proposition 1. *Assume the effects operating through the multilateral resistance term remain constant.*

a) The number of new migrants arriving within a given period of time from some country i in some final migration destination $j \in A_{izr}, r \in A_{iz}$, is the larger, the larger the bilateral migrant community at the beginning of this period:
$\frac{\partial \ln(m_{ij})}{\partial \ln(1+M_{ij})} = \frac{\theta\gamma}{\lambda_z\kappa_r} > 0.$

b) This effect is the smaller, the larger the dissimilarity among final migration destinations in the same country and the same region:
$\frac{\partial^2 \ln(m_{ij})}{\partial \ln(1+M_{ij})\partial\lambda_z} = -\frac{\theta\gamma}{\lambda_z^2\kappa_r} < 0$ *and* $\frac{\partial^2 \ln(m_{ij})}{\partial \ln(1+M_{ij})\partial\kappa_r} = -\frac{\theta\gamma}{\lambda_z\kappa_r^2} < 0.$

Equivalent statements apply to the effects of bilateral trade and FDI on bilateral migration.

The intuition for the second part of proposition 1 is the following. If final migration destinations in the same country or region are very similar, it is relatively easy to substitute one destination $j \in A_{izr}$ by another destination $k \in A_{izr}, r \in A_{iz}$. Hence, small changes in the attractiveness of destination j will induce relatively large substitution effects among all final migration destinations in region r. The opposite holds true for final migration destination which are very dissimilar.

2.3 Skill Structure of Immigration Flows

We now relax the assumption of homogeneous skills across individuals. In particular, we distinguish between high-skilled and low-skilled individuals, denoted by h and l, respectively. Recall that in equation (2), the parameter α gives the units of human capital per individual and γ represents the ease with which individuals are able to cope with migration costs (decreasing with higher values). We assume that the parameters α and γ are skill-specific, and, more precisely, that α (γ) is larger (smaller) for high-skilled individuals than for low-skilled individuals, $\alpha^h > \alpha^l$ and $\gamma^h < \gamma^l$. This setup introduces two deterministic sources of utility differences across individuals, both of which originate in an individual's skill level: Individuals with higher skills (more human capital) earn higher wages and have lower effective costs of moving and assimilation. The latter assumption is in line with Chiswick (1999), who argues that the high-skilled can handle their migration process more efficiently than the low-skilled. We can thus formulate one migration function for each skill group by complete analogy to equation (14). Subtracting the equation for low-skilled immigrants from country i in destination j from the same equation for high-skilled immigrants, we obtain:

$$\begin{aligned} \ln\left(\frac{m_{ij}^h}{m_{ij}^l}\right) &= \frac{\theta\gamma^*}{\lambda_z\kappa_r}\ln(1+M_{ij}) + \frac{\rho\gamma^*}{\lambda_z\kappa_r}\ln(1+t_{ij}) + \frac{\sigma\gamma^*}{\lambda_z\kappa_r}\ln(1+F_{ij}) \\ &\quad +\mu_i^* + \mu_{iz}^* + \mu_j^* + \mu_{wj}^* + \mu_{ir}^*, \end{aligned} \tag{15}$$

where the variables with an asterisk (*) are differences between the corresponding parameters for high-skilled and low-skilled individuals, i.e., $\gamma^* \equiv \gamma^h - \gamma^l$, for instance. Given that $\gamma^l > \gamma^h$, we can state the following proposition.

Proposition 2. *Assume the effects operating through the multilateral resistance term remain constant.*

a) The ratio of new high-skilled to new low-skilled migrants arriving within a given period of time from some country i in some final migration destination $j \in A_{izr}, r \in A_{iz}$, is the smaller, the larger the *bilateral migrant community at the beginning of this period:* $\frac{\partial \ln(m^h_{ij}/m^l_{ij})}{\partial \ln(1+M_{ij})} = \frac{\theta\gamma^*}{\lambda_z\kappa_r} < 0.$

b) *This effect is the smaller, the larger the dissimilarity among final migration destinations in the same country and the same region:* $\frac{\partial^2 \ln(m^h_{ij}/m^l_{ij})}{\partial \ln(1+M_{ij})\partial\lambda_z} = -\frac{\theta\gamma^*}{\lambda_z^2\kappa_r} > 0$ *and* $\frac{\partial^2 \ln(m^h_{ij}/m^l_{ij})}{\partial \ln(1+M_{ij})\partial\kappa_r} = -\frac{\theta\gamma^*}{\lambda_z\kappa_r^2} > 0.$

Equivalent statements apply to the effects of bilateral trade and FDI on bilateral migration.

The specification of migration costs in equation (13) is independent of an individual's skill level, which means that the cost-reducing effect of the ethnic community abroad is equally strong for high-skilled and low-skilled individuals. The same holds true for the effects of bilateral trade and investment relations. However, individuals differ in their abilities to cope with the costs of moving and assimilation, and therefore in their *effective* costs of migration. Intuitively, the first part of proposition 2 tells us that this difference is less important for low levels of migration costs. Hence, it is the low-skilled individuals who benefit the most from a reduction in migration costs. This result can also be seen against the backdrop of recent work by Mrázowá & Neary (2011) on selection effects with heterogeneous firms. The authors show that more efficient firms will select into the activity with lower market-access costs if and only if firms' maximum profits are supermodular in production and market-access costs.[14]

To show the similarity to our setup of selection into migration, we define the *migration gain* as the difference in utility from migrating from country i to destination j and staying in country i:

$$\overline{U}_{ij}(W, C, \pi, \alpha, \gamma, \cdot) := U_{ij} - U_{ii} = \alpha\overline{W}_{ij} + \overline{X}_{ij} - \gamma\overline{C}_{ij} + \overline{\pi}_{iz} + e_{ij} - e_{ii}, \tag{16}$$

where a variable with a bar represents the difference in that variable for individuals from country i who migrate to destination j and individuals from country i who stay in their home country. Let Δ_s be the finite difference between the values of a function evaluated at parameter values for high-skilled individuals and those for low-skilled individuals. We then have:

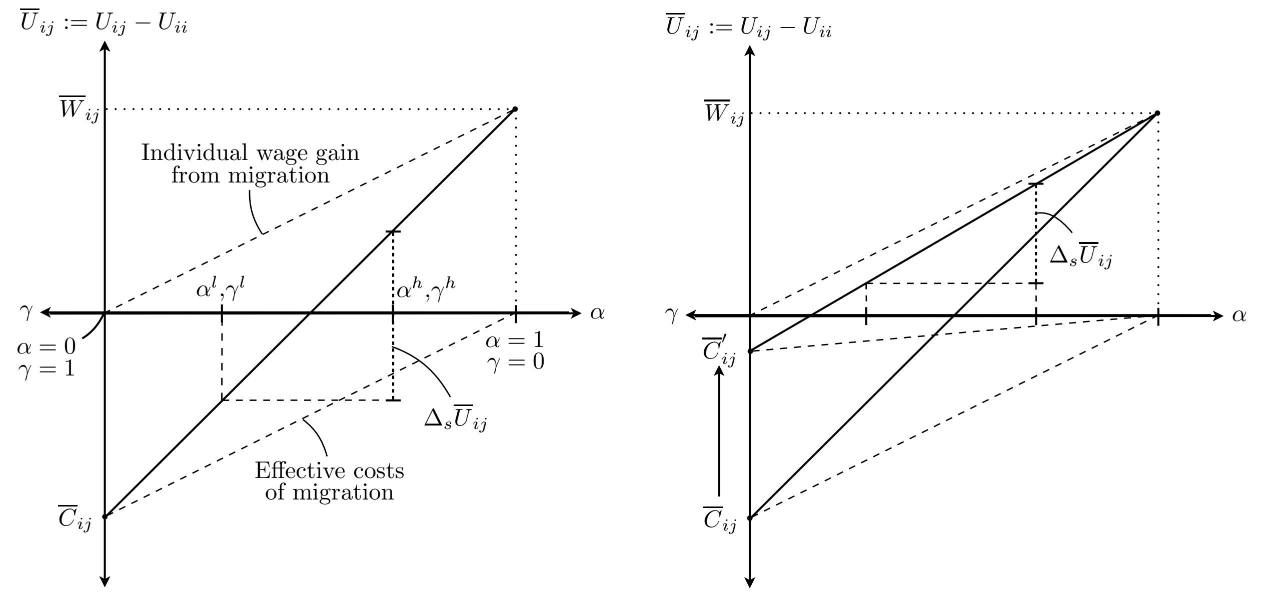
$$\begin{aligned} \Delta_s\overline{U}_{ij}(W, C, \pi, \alpha, \gamma, \cdot) &= \Delta_s U_{ij} - \Delta_s U_{ii} \\ &= \underbrace{(\alpha^h - \alpha^l)\overline{W}_{ij}}_{\text{Wage effect}} + \underbrace{(\gamma^l - \gamma^h)\overline{C}_{ij}}_{\text{Cost effect}} + \underbrace{\overline{\pi}^h_{iz} - \overline{\pi}^l_{iz}}_{\text{Policy effect}}, \end{aligned} \tag{17}$$

which is the difference in migration gains across skill types. The first term on the right-hand side of equation (17) is positive, provided the wage rate is larger abroad than at home. The incentive to migrate for any positive wage differential becomes magnified through the individual amount of human capital. Accordingly, the migration gain from international wage differences is larger for high-skilled than for low-skilled individuals (*wage*

[14]In the context of Mrázowá & Neary (2011), supermodularity means that higher variable trade costs reduce the absolute cost disadvantage of low-productivity firms relative to high-productivity firms.

effect). The second term is also positive, given that migration entails some costs of moving and assimilation. The effective costs are lower for high-skilled than for low-skilled individuals, so that there is also a *cost effect* on selection. It is precisely this cost channel through which the family and friends effect impacts on the extent of positive selection in migration. The last two terms together (*policy effect*) are positive if policies facilitating high-skilled immigration apply, and zero if immigration policies are skill-neutral.

Figure 1: Skill-specific Individual Migration Gains†



(a) Zero Ethnic Community Abroad

(b) Large Ethnic Community Abroad

† The figure shows the differential migration gain for high-skilled individuals over low-skilled individuals, (a) for a zero ethnic community abroad, and (b) for a large ethnic community abroad. For the sake of exposition, both subfigures assume $\pi_{iz} = \pi_{ii}$, $X_j = X_i$, $e_{ij} = e_{ii}$, and $\alpha^s = 1 - \gamma^s$, $s \in \{h, l\}$. The migration gain $\overline{U}_{ij}$ is a function of α and γ, and given by the upward sloping solid black line. It is the difference between the individual wage gain from migration, $\alpha^s\overline{W}_{ij}$, and the effective costs of migration, $\gamma^s\overline{C}_{ij}$, $s \in \{h, l\}$. In panel (a), low-skilled individuals exhibit a negative migration gain and high-skilled individuals a positive migration gain. The difference between the two is the differential migration gain $\Delta_s\overline{U}_{ij}$. In panel (b), the low level of migration costs, given by $\overline{C}'_{ij}$, renders the migration gain positive for both types of skill. Importantly, the differential migration gain is strictly smaller in panel (b) than in panel (a) because low-skilled individuals benefit more from the cost reduction than high-skilled individuals.

In sum, there is a differential migration gain for high-skilled individuals over low-skilled individuals; see figure 1 for a graphical exposition. Leaving the policy effect aside, we see that high-skilled individuals are more likely to self-select into migration out of both wage and cost considerations.[15] Importantly, however, the bilateral moving costs are reduced through the family and friends effect, which brings down the differential migration gain and thus attracts a larger proportion of low-skilled individuals; see figure 1(b).[16] The marginal

[15]In the terminology of Mrázowá & Neary (2011), our utility function is supermodular in *(i)* wages and individual skills and *(ii)* migration costs and individual skills.

[16]There is a second obvious reason why the differential migration gain could be endogenous to the level of migration. If equilibrium

reduction of the differential migration gain is the larger, the larger the difference between γ^l and γ^h.

3 Estimation Strategy and Data

This section describes our estimation strategy and presents the different variables we employ in our econometric analysis. We use Spanish data to estimate different variants of the models given by equations (14) and (15), each coupled with a stochastic error term. All migration data come from the Spanish Instituto Nacional de Estadística (INE).[17] A major advantage of these data is that they include both documented and undocumented immigrants. This holds true for data on both the scale and the skill structure of immigration flows, although the variables are derived from two different data sources provided by INE. The full internet sources of our data are listed in table A.1 in the appendix.

We consider two different aggregation levels for final migration destinations in Spain. The first model for the scale of immigration flows, given by equation (14), is estimated at the level of Spanish provinces (*provincias*). Due to reasons of data availability, the second model for the skill structure of immigration flows, given by equation (15), is estimated at the level of Spanish regions (*comunidades autónomas*).[18] For both models, our sample comprises the 55 most important migrant-sending countries, which are listed in table A.2 in the appendix.[19]

3.1 Scale of Immigration Flows

A simple fixed effects specification computes all variables of equation (14) as deviations from their country means (within-transformation), which wipes out all country-specific fixed effects.[20] These are all effects nested

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wages are a function of a country's labor supply, the first summand on the right-hand side of equation (17) is the smaller, the larger the stock of immigrants, ceteris paribus. Hence, any immigration shock depresses the differential migration gain, $\Delta_s \overline{U}_{ij}$, and thus induces the ratio of new high-skilled to new low-skilled migrants to decline. This relationship can also be seen by differentiating equation (15) with respect to the wage rate at destination and holding the multilateral resistance term constant, $\partial \ln(m_{ij}^h/m_{ij}^l)/\partial W_j = \alpha^*/(\lambda_z \kappa_r) > 0$.

[17] The website is `http://www.ine.es`.

[18] Officially, Spain is divided into 52 provinces which are nested in 19 regions. We exclude the enclaves Ceuta and Melilla due to their specific geographical location. This yields a total of 50 provinces and 17 regions for the estimations of the first and the second model, respectively. See `http://www.ine.es/daco/daco42/codmun/cod_provincia.htm` and `http://www.ine.es/daco/daco42/codmun/cod_ccaa.htm` (both accessed on 04/17/2012) for a list of provinces and regions, respectively.

[19] The 55 most important migrant-sending countries are those with an ethnic community in Spain of at least 630 migrants in the year 1996.

[20] An alternative approach would be to estimate the fixed effects by including a dummy variable for each origin country i. Such a specification would not be without problems. To see this, note the following: Although we employ cross-sectional data, their structure is similar to that of panel data. Since we distinguish origin countries (dimension i) and destination provinces in Spain (dimension j), we have a cluster sample in the sense that each observation (dimension ij) belongs to a single country i (the primary cluster). One can think of the total number of destinations in Spain as being fixed. However, if this number is fixed and the total number of origin countries goes to infinity, $I \to \infty$, the country-specific parameters, μ_i, would be inconsistently estimated. The reason is that the number of fixed effects to be estimated increases with sample size; see the incidental parameters problem described in Neyman & Scott (1984). The problem would be particularly relevant at later stages of our analysis when consistently estimated fixed effects are

in the term μ_i, but also those nested in the term μ_{iz}, given that our migration data refer to a single country z (Spain). Notice that this simple fixed effects model thus controls for the multilateral resistance effects in the terms μ_i and μ_{iz} and allows for violations of the IIA property for final migration destinations located in different countries.

The dependent variable is the log of the bilateral migration flow into Spanish provinces, obtained from the Spanish Residential Variation Statistics and aggregated from the beginning of 1997 until the end of 2006.[21] This period covers Spain's unprecedented immigration boom, which was eventually attenuated by the global financial and economic crisis starting in the year 2007. As to the explanatory variables, we use data for earlier years where possible, in order to exclude the possibility of reverse causality. The size of the ethnic community, M_{ij}, is measured by the number of settled bilateral migrants in the year 1996, as reported by the Spanish Municipal Register. We rely on population figures disaggregated by nationalities and Spanish provinces as of 1 May 1996. The reason why these migration data include documented and undocumented migrants is that all immigrants are strongly incentivized to register in the local Municipal Register, irrespective of their legal status. This incentive derives from the *Law on the Rights and Freedoms of Aliens in Spain and their Social Integration* in 2000 (*Ley Orgánica 4/2000, artículo 12*), which entitles all registered foreigners (with or without legal residence permits) to free medical care under the same conditions as Spanish nationals. Each registrant must provide his or her name, surname, sex, usual domicile, nationality, passport number, as well as the place and date of birth.[22] Importantly, this information must be treated confidentially by the Municipal Register. In particular, it must not be communicated to other administrative units, such that the probability of forced repatriation is independent of registration.

Data on both trade and FDI are provided by the Spanish Ministry of Industry, Tourism and Trade. We measure bilateral trade flows, t_{ij}, by the sum of exports and imports (in Euros) between country i and Spanish province j in the year 1996. These information are taken from DataComex Statistics on Spanish Foreign Trade. Ideally, we would like to use bilateral FDI stocks to measure inward investment, F_{ij}, but we only have information on bilateral gross FDI inflows (in Euros) observed at the level of Spanish regions. These are detailed by the country of the last owner and are available from DataInvex Statistics on Foreign Investments in

essential (as in the first stage of two stage least squares analysis) or non-linear models are employed (as in the first stage of Heckman's two step selection model). An important circumstance in which our fixed effects estimator delivers inconsistent estimates is when zero values inflate the dependent variable; see Santos Silva & Tenreyro (2006) for arguments in favor of the Poisson estimator in the gravity context of international trade. In our sample we observe only a modest number of zero migration flows (5.75% of all country-province pairs) and therefore apply the fixed effects estimator.

[21] We aggregate all migrants who registered at Spanish municipalities between 1 January 1997 and 31 December 2006 by their country of origin. Migrants are defined as individuals for whom the last country of residence (other than Spain) corresponds to their country of birth and nationality. In their raw form, the migration flow data are observed for periods of less than a year. Aggregating the data over time precludes the possibility of applying panel estimation techniques. We do so on purpose, however, because the model cannot deal with a time dimension in any convenient way, unless we make the very strong assumption that each individual left in the home country draws new realizations of the random term for all destinations (including the home country) in every period. Alternatively, one would have to assume that the pool of potential migrants from a given source country does not change over time.

[22] For further information, see INE at `http://www.ine.es/en/metodologia/t20/t203024566_en.htm`, accessed on 08/19/2011.

Spain. Due to limited data availability, we have to use FDI flows for the year 1997. We argue, however, that endogeneity is unlikely, given that firms base their investment decisions on long-term considerations instead of short- or medium-term forecasts. All effects specific to destination provinces, nested in μ_j, are to a large extent unobservable. We therefore include a comprehensive set of dummy variables to mitigate endogeneity concerns due to omitted variables bias.

More demanding specifications of our fixed effects model control for country-and-region fixed effects. These are eliminated by computing all variables as deviations from their country-and-region means instead of country means. This approach greatly reduces the probability of omitted variables bias, because it eliminates the term μ_{ir} in the model of equation (14). As we have argued above, this term captures both the multilateral resistance effects with dimension ir and the full geographical and cultural distance between source and destination.[23] The complete specification of our fixed effects model furthermore controls for the term μ_{wj} through a comprehensive set of dummy variables.

In a first set of regressions, we estimate *average* values for the elasticity of the migration inflow variable with respect to the migrant stock variable for Spain (network elasticity).[24] This approach allows us to compare our estimates to those reported in the existing literature. The second part of proposition 1, however, tells us that the estimated network elasticity should be large for regions with similar provinces (small κ_r) and small for regions with dissimilar provinces (large κ_r). Hence, we also estimate region-specific network elasticities, interacting the migrant stock variable with dummy variables for the different Spanish regions. This estimation can be seen as a test of whether or not the IIA assumption is violated for final migration destinations located in different Spanish regions, as is possible in our model. In case we do find cross-regional differences in the estimated network elasticity, this is strong evidence for a violation of the IIA property.

Finally, if variables specific to country-province combinations and correlated with both m_{ij} and M_{ij} are omitted from the model, the size of the ethnic community is endogenous to the subsequent migrant flow. In this case, the fixed effects model produces biased and inconsistent estimates. Consistent estimation is still possible, however, provided an instrument which is uncorrelated with the structural error term but correlated with the endogenous regressor is available. We adopt an instrumental variables approach in which we instrument the size of the bilateral ethnic community in the year 1996, M_{ij}, with the log of the number of people of country i who register at destination j in the year 1988. The underlying hypothesis is that historical bilateral migration flows correlate with the migrant stocks in Spain even after a relatively long period of time, but not with the unobserved determinants of the recent immigration boom.[25] We use the square of the historical bilateral

[23] Note that this more encompassing model does not allow us to identify the coefficient of the bilateral investment term because data on investment are only available at the regional level.

[24] Notice that the full network elasticity includes the effects operating through the multilateral resistance term. In what follows, we assume that these effects are negligibly small when we are referring to the network elasticity.

[25] The year 1988 is the first year for which such detailed information are available. It is well before the start of the Spanish immigration boom. Our instrument includes all people with a foreign nationality registering at Spanish municipalities in 1988, irrespective of their country of birth and their last place of residence. Hence, in contrast to the definition of our migrant flow variable, it includes internal migration in Spain. We add one to the number of people before taking the log in order to keep observations with zero migrant

migration flows as a second excluded instrument. This allows us to perform tests on overidentifying restrictions and check for instrument exogeneity.

3.2 Skill Structure of Immigration Flows

Aggregate migration data with reliable information on the skill structure of immigration can only be constructed at the level of Spanish regions instead of provinces. Hence, the second model for the skill structure of immigration flows, given by equation (15), cannot be estimated at the level of provinces. In principle, there are two alternative ways to estimate the model at the more aggregate level of Spanish regions. The first is to rule out regions as secondary clusters from the very beginning, and to consider the set of Spanish regions to form the set of final migration destinations within the primary cluster of Spain. In terms of our model, this is equivalent to setting κ_r equal to unity for all r and letting each Spanish region be a final migration destination $j, j \in A_{iz}$, where country z is Spain.[26] The second way is to derive the migration function for migration into Spanish regions from the existing three-level nesting structure of the NMNL migration model. The starting point is to use equations (8) and (9) to compute the probability $P_i^o(j^o \in A_{izr}) = P_i^o(j^o \in A_{izr} | j^o \in A_{iz}) P_i^o(j^o \in A_{iz})$. It is easy to show, then, that the two alternative approaches lead to two different migration functions, because they are derived from two different models which are not fully compatible with each other. In what follows, we lay out our estimation strategy for the first approach and report the corresponding results in the next section. We have checked for robustness of our results using the second approach, but abstain from providing detailed estimation results.[27]

In principle, the parameters in equation (15) are consistently estimated in a fixed effects model which applies the within-transformation to wipe out all country-specific fixed effects, μ_i^*. The dependent variable, $\ln\left(\frac{m_{ij}^h}{m_{ij}^l}\right)$, measures the skill content of migration. It is defined as the log ratio of the number of new high-skilled immigrants over the number of new low-skilled immigration from country i in region j, aggregated over the five-year period from 2002 to 2006. These information are obtained by aggregating micro-level data from the National Immigrant Survey 2007 (NIS). The NIS defines immigrants as individuals aged 16 years or older who were born abroad and have lived in Spain for more than a year, or at least intended to stay for more than a year at the time the survey was conducted.[28] Importantly, this definition is independent of the individual's legal status, such that the data again include documented and undocumented migrants. The survey gathers unique information on a total of 15,465 migrants through field interviews conducted between November 2006 and February 2007. The sample was obtained through a relatively complex three-stage sampling scheme,

flows.

[26]Notice that this approach acknowledges the similarity among all Spanish regions (measured by $1-\lambda_z$) but rules out any similarities of Spanish regions at the sub-country level. This assumption will be tested in the next section.

[27]Subsection 4.2 includes a short description of these robustness checks.

[28]Foreign-born individuals with Spanish nationality from birth who migrated to Spain within two years after birth are not considered as immigrants.

which was designed to offer reliable and representative data to policy makers and researchers. More detailed information on the sampling can be found in Reher & Requena (2009) and INE (2007). In the survey, migrants report, inter alia, their year of arrival in Spain, their first destination in Spain, as well as their highest level of education they completed before migrating. We obtain skill-specific migrant flows by aggregating the number of individuals by country of birth and Spanish destination region, distinguishing between migrants with completed tertiary education before migrating (high-skilled) and those without (low-skilled) and applying the provided population weights. Although the data can be considered representative of immigrants who arrived shortly before the survey was taken, the numbers for earlier cohorts are less reliable due to the lack of information on immigrants who died, returned or migrated onward. We deal with the trade-off between a large number of individuals and data representativeness in that we consider only immigrants who arrived in Spain between 1 January 2002 and 31 December 2006.

The size of the ethnic community, M_{ij}, is measured by the migrant stock observed at the level of Spanish regions as of 1 January 2002. These data are again taken from the Spanish Municipal Register. The sum of bilateral import and export values, t_{ij}, is collected at the level of Spanish regions for the year 2001. Bilateral investment stocks as of 2001 are approximated by gross FDI inflows from the beginning of 1998 until the end of 2001. In this model for the skill structure of immigration flows, differences in the size of the ethnic community across country-region combinations are used as identifying variation. Consequently, the fixed effects model cannot control for country-and-region effects. We instead augment the model by observable bilateral factors which are considered part of the term ψ_{ir} in μ^*_{ir}. In particular, we control for the geographical distance between origin country i and Spanish region r[29], as well as for common language between source and destination through the inclusion of an indicator variable. This indicator variable takes on the value one if at least 80% of the Spanish region's total population are native speakers of a language spoken by at least 20% of the people living in the origin country, and zero otherwise. The information on native languages in Spanish regions are taken from a number of recent survey studies carried out in Spain.[30] Language information on the origin countries come from Mayer & Zignago (2006). As with the previous model on the scale of immigration flows, the influence of all terms indexed j, nested in μ^*_j, is absorbed by a full set of dummy variables for the different Spanish regions. The complete specification of our model furthermore controls for world region-and-region fixed effects, μ^*_{wj}.

For some combinations of origin countries and destination regions we lack information on the skill ratio, so that the variable $\ln\left(\frac{m^h_{ij}}{m^l_{ij}}\right)$ is unobserved. This raises concerns of endogenous sample selection. It can be shown that the probability of observing the skill ratio is an increasing function of the total number of bilateral immigrants over the period considered. We follow Beine et al. (2011) in implementing a two-step Heckman

[29]Distances are constructed using the STATA module GEODIST by Picard (2010). Latitudinal and longitudinal data of origin countries are taken from Mayer & Zignago (2006). Coordinates for the Spanish regions are obtained from the Spanish Wikipedia/GeoHack webpage.

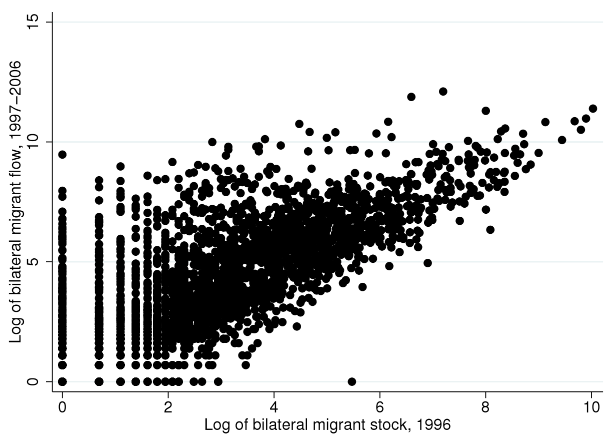
[30]See table A.1 in the appendix for a list of surveys.

procedure which goes back to the seminal work by Heckman (1976). The first step of this procedure estimates a probit model for the probability of observing $\ln\left(\frac{m_{ij}^h}{m_{ij}^l}\right)$ on the full sample including observations for which data on the skill ratio are missing (selection equation). The selection equation includes all explanatory variables of equation (15) as right-hand side variables, plus the number of new bilateral immigrants from country i in region j over the period from 1 January 2002 to 31 December 2006. We thus apply a single exclusion restriction to equation (15) (the structural equation). The second step uses all observations for which the dependent variable is actually observed to estimate the structural equation, augmented by the inverse Mills ratio obtained from the first step as an explanatory variable. As a further robustness check, we apply the instrumental variables approach to this model for the skill structure of immigration flows, by analogy to the model for the scale of immigration flows.

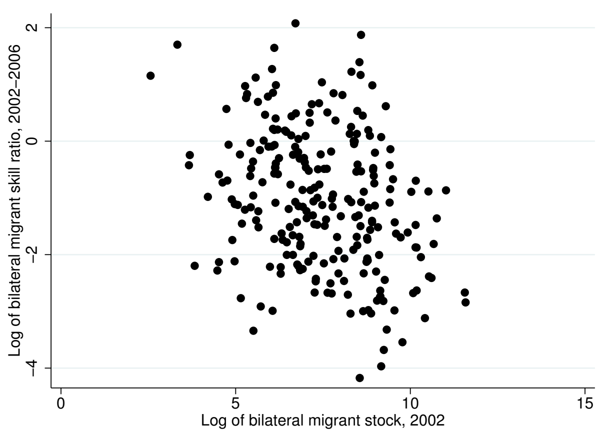
4 Estimation Results

This section presents and discusses our estimation results. We start out with a descriptive look at the relationship between the scale and skill structure of immigration flows and the size of ethnic communities in final migration destinations in Spain. Figure 2(a) is a scatter plot for immigration between 1997 and 2006 versus ethnic communities in 1996, where each dot stands for a combination of origin country and destination province in Spain. We observe a positive correlation between the two variables. Figure 2(b) is a scatter plot for the skill content of immigration between 2002 and 2006 versus ethnic communities at the beginning of 2002, where now each dot represents a combination of origin country and destination region in Spain. The figure suggests a weak negative correlation between the two variables. Hence, both figures give tentative support for the first part of propositions 1 and 2. In what follows, we test whether these correlations reflect a causal relationship running from ethnic communities to the scale and skill structure of immigration.

Figure 2: Ethnic Communities and the Scale and Skill Structure of Subsequent Immigration Flows



(a) $\ln(m_{ij})$ plotted against $\ln(1+M_{ij})$, provincial level



(b) $\ln(S_{ij})$ plotted against $\ln(1+M_{ij})$, regional level

4.1 Results for the Scale of Immigration Flows

This subsection presents the estimation results of the first model for the scale of immigration flows as specified in equation (14). We first abstract from a key feature of this model, viz. that the network elasticity may vary across Spanish regions due to cross-regional differences in the degree of substitutability between any two final migration destinations located in the same region.[31] Hence, we first estimate an *average* network elasticity in Spain which can be compared to the results reported by Beine et al. (2012), who use comparable data for the US and estimate a model similar to ours.[32] Tables 1 and 2 show the results from the fixed effects model and the two stage least squares (2SLS) fixed effects model, respectively. In columns (a) and (b) of both tables, we eliminate country fixed effects via an adequate within-transformation. The number of observations is equal to 2,592, which is the result of having 55 origin countries, 50 provinces, and 158 undefined values for the dependent variable due to zero migrant flows ($55 \times 50 - 158 = 2,592$). In columns (c) to (f), we modify the within-transformation so as to eliminate country-and-region fixed effects. The number of observations is reduced to 2,209, given that this approach must exclude seven regional destinations in Spain, each consisting of a single province.[33]

In the most parsimonious specification of the fixed effects model in column (a) of table 1, the estimated coefficient of the migrant stock variable is equal to 0.686. This value is impressively close to the value reported by Beine et al. (2012). The coefficient is estimated with very high precision (robust standard error equal to 0.021) and thus statistically significant at the 1% level. Augmenting the model by bilateral FDI and trade flows in column (b), we see that the coefficient of the FDI variable is positive and highly significant. Yet, the point estimate of this coefficient is equal to 0.012 and thus implies a moderate quantitative importance only. Bilateral trading relations, instead, do not seem to have a significant impact on the scale of migration. Maybe more importantly, the estimates of the network elasticity are virtually unchanged in this version of the model. What does change the estimates is controlling for country-and-region fixed effects in columns (c) and (d). We see a drop in the coefficient of the migrant stock variable down to 0.533, which corresponds to a decrease by roughly 20%. We see a further reduction by more than 10% once we take out the variation that is constant for each combination of world regions and Spanish provinces via dummy variables. Our results point towards a sizeable upward bias in the estimation of the family and friends effect in specifications (a)-(c) due to unobserved heterogeneity.

[31] Of course, this applies to the elasticities of the migration inflow with respect to FDI and trade flows as well.

[32] Beine et al. (2012) distinguish between local and national network externalities. Our estimates of the family and friends effect can be compared to their local assimilation effect, which is given by their estimate of the parameter α in table 1 on page 16 of Beine et al. (2012) ($\hat{\alpha} \approx 0.7$).

[33] Applying the within-transformation to such observations yields all zeros.

Table 1: Scale of Immigration Flows – Fixed Effects Model†

	Dependent Variable: Migration Inflow (Province-Level 1997-2006)					
	(a)	(b)	(c)	(d)	(e)	(f)
Stock of Migrants	0.686***	0.680***	0.533***	0.534***	0.467***	0.467***
(Province-Level 1996)	(0.021)	(0.022)	(0.027)	(0.027)	(0.031)	(0.031)
FDI Flow		0.012***				
(Region-Level 1997)		(0.004)				
Trade Flow		0.006		0.004		0.009
(Province-Level 1996)		(0.006)		(0.006)		(0.007)
Constant	-0.040	-0.064	-0.082	-0.079	-0.125	-0.120
	(0.102)	(0.102)	(0.073)	(0.073)	(0.079)	(0.079)
Province Effects	Yes	Yes	Yes	Yes	Nested	Nested
Country Effects	Yes	Yes	Nested	Nested	Nested	Nested
Country-and-Region Effects	No	No	Yes	Yes	Yes	Yes
World Region-and-Province E.	No	No	No	No	Yes	Yes
Observations	2,592	2,592	2,209	2,209	2,209	2,209
Within R^2	0.786	0.786	0.660	0.660	0.755	0.755

† All variables are in natural logs. Heteroskedasticity-robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively. The regressions include all countries with at least 630 nationals residing in Spain in the year 1996 (55 origin countries). See section 3 for a detailed description of all variables.

The 2SLS fixed effects estimations in table 2 substantially strengthen our interpretation of a quantitatively important and causal effect of ethnic communities on the scale of immigration. They report a somewhat larger role for the family and friends effect, with an elasticity ranging between 0.776 and 0.986. As before, the coefficient of the migrant stock variable is lowest when we control for country-and-region effects as well as for world region-and-province effects. This result gives further credit to our earlier interpretation regarding the effects of omitted variables. The loss in precision from using the 2SLS fixed effects approach is fairly small if interpreted relative to the fixed effects model. The effects of both trade and FDI on the scale of immigration flows are essentially zero.

The IV diagnostics are all encouraging. The first-stage F statistic for the joint significance of the excluded instruments is relatively high and thus points to the relevance and strength of the instruments. It exceeds the critical value of 10 in all specifications, which is required for reliable inference in the case of a single endogenous regressor; see Stock et al. (2002). Wooldridge's robust score χ^2 test of overidentifying restrictions checks for instrument exogeneity. The null hypothesis (exogeneity) of this test can never be rejected at any reasonable significance level. This suggests that our instruments are uncorrelated with the structural error term, and that our structural equation is correctly specified. We also report the results from two exogeneity tests for the migrant stock variable. Wooldridge's robust score χ^2 test and the robust regression-based F test both reject the null hypothesis that the stock variable is exogenous at the 1% level. The migrant stock variable should thus indeed be treated as endogenous.

Table 2: Scale of Immigration Flows – 2SLS Fixed Effects Model†

	Dependent Variable: Migration Inflow (Province-Level 1997-2006)					
	(a)	(b)	(c)	(d)	(e)	(f)
Stock of Migrants	0.986***	0.985***	0.831***	0.834***	0.776***	0.778***
(Province-Level 1996)	(0.037)	(0.037)	(0.055)	(0.055)	(0.071)	(0.071)
FDI Flow		0.003				
(Region-Level 1997)		(0.004)				
Trade Flow		0.004		0.006		0.009
(Province-Level 1996)		(0.006)		(0.007)		(0.006)
Constant	0.110	0.098	0.110	0.115	0.075	0.081
	(0.113)	(0.113)	(0.084)	(0.084)	(0.087)	(0.088)
Province Effects	Yes	Yes	Yes	Yes	Nested	Nested
Country Effects	Yes	Yes	Nested	Nested	Nested	Nested
Country-and-Region Effects	No	No	Yes	Yes	Yes	Yes
World Region-and-Province E.	No	No	No	No	Yes	Yes
Observations	2,592	2,592	2,209	2,209	2,209	2,209
Within R^2	0.759	0.759	0.621	0.621	0.726	0.726
Robust first-stage F test	211.2	205.9	71.85	72.04	38.61	38.61
Test on Overidentifying R.						
Robust score χ^2 test	0.044	0.060	0.165	0.153	2.201	2.109
- p-value	0.834	0.807	0.685	0.695	0.138	0.146
Exogeneity Test						
Robust score χ^2 test	73.26	73.80	29.30	29.79	18.40	18.63
- p-value	0	0	0	0	0	0
Robust regression F test	81.96	82.75	30.45	31.01	16.73	16.95
- p-value	0	0	0	0	0	0

† All variables are in natural logs. Heteroskedasticity-robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively. The regressions include all countries with at least 630 nationals residing in Spain in the year 1996 (55 origin countries). The (log) stock of migrants in 1996 is instrumented with the (log) flow of foreign nationals in the year 1988 as well as with the square of this variable. See section 3 for a detailed description of all variables.

Our next specification allows for cross-regional differences in the parameter κ_r. These should be reflected in differences in the quantitative importance of the family and friends effect across Spanish regions. The specification employed is equivalent to the one reported in column (f) of table 1, except for the fact that we now interact the migrant stock variable with dummy variables for the different Spanish regions. Table 3 reveals substantial heterogeneity in the size of the network elasticity across Spanish regions. The elasticity value is largest for Cataluña (0.781) and smallest for Extremadura (0.144).[34] According to our theoretical model, the heterogeneity in the estimated network elasticity must be due to cross-regional differences in the degree of dissimilarity of final migration destinations located in the same Spanish region, captured by the parameter κ_r. Hence, individuals seem to consider the provinces in Cataluña (Barcelona, Girona, Lleida, and Tarragona)

[34]In the estimation, Cataluña serves as the reference region. The differences between the elasticities estimated for Cataluña and for either of the other regions (except for Comunitat Valenciana) are statistically significant at least at the 10% level according to t-tests.

to be very similar, relative to the provinces in Extremadura (Badajoz and Cáceres). This result accords with the pronounced autonomy of Cataluña in terms of its political and cultural life. At any rate, the large and significant cross-regional differences in the estimated network elasticity implies a strong violation of the IIA assumption for final migration destinations located in different Spanish regions.

Table 3: Network Elasticity, by Spanish Region†

Spanish Region r	Estimate of $\theta\gamma/(\lambda_z\kappa_r)$	Spanish Region r	Estimate of $\theta\gamma/(\lambda_z\kappa_r)$
Cataluña	0.781	Aragón	0.500
Comunitat Valenciana	0.699	Castilla y León	0.452
Galicia	0.562	País Vasco	0.316
Canarias	0.524	Castilla-La Mancha	0.179
Andalucía	0.500	Extremadura	0.144

† This table reports region-specific estimates of the elasticity of the migration inflow variable with respect to the migrant stock variable. The specification employed is equivalent to that reported in column (f) of table 1, except that we interact the migrant stock variable with dummy variables for the different Spanish regions. According to F tests for the joint significance of the coefficients of the migrant stock variable and of either of the interaction terms (not reported), the above-reported elasticities are all significant at the 1% level. The number of observations is 2,209, and the within R^2 is 0.763.

4.2 Results for the Skill Structure of Immigration Flows

Tables 4 and 5 report, respectively, the results from fixed effects and Heckman estimations of our second model for the skill structure of immigration flows as specified in equation (15). Recall that we define Spanish regions as final migration destinations and employ regional data instead of provincial data in the following estimations. The fixed effects estimator is applied to 241 observations with non-missing values for the migrant skill ratio (the dependent variable). The full matrix contains 935 combinations of 55 origin countries and 17 destination regions. Throughout all specifications employed in table 4, we find a robustly significant negative impact of ethnic migrant communities on the skill ratio of immigration flows, as suggested by theory. The estimated elasticity varies between -0.399 and -0.354, but the differences are never statistically significant at any reasonable level of confidence. Neither the trade nor the FDI variable turn out to be statistically significant. This finding is not surprising in light of the poorly suggestive evidence in favor of a positive effect of trade or FDI on the scale of immigration flows. Maybe surprisingly, the effects of a common language and geographical proximity are also estimated to be zero, but one should keep in mind here that identification comes only from within-cluster variation.

Table 4: Skill Structure of Immigration Flows – Fixed Effects Model†

	Dependent Variable: Migrant Skill Ratio (Region-Level 2002-2006)					
	(a)	(b)	(c)	(d)	(e)	(f)
Stock of Migrants	-0.399***	-0.395***	-0.390***	-0.380***	-0.374***	-0.354***
(Region-Level 2002)	(0.069)	(0.069)	(0.071)	(0.096)	(0.097)	(0.100)
FDI Flow			-0.007			-0.017
(Region-Level 1997-2001)			(0.017)			(0.019)
Trade Flow			-0.013			0.040
(Region-Level 2001)			(0.078)			(0.103)
Language		0.302	0.297		0.178	0.268
(Region-Level)		(0.198)	(0.198)		(0.403)	(0.403)
Distance		-0.411	-0.449		-0.155	-0.175
(Region-Level)		(0.350)	(0.365)		(0.483)	(0.506)
Constant	0.545**	0.529**	0.560**	0.514*	0.494*	0.463
	(0.233)	(0.236)	(0.253)	(0.267)	(0.273)	(0.301)
Region Effects	Yes	Yes	Yes	Nested	Nested	Nested
Country Effects	Yes	Yes	Yes	Yes	Yes	Yes
World Region-and-Region E.	No	No	No	Yes	Yes	Yes
Observations	241	241	241	241	241	241
Within R^2	0.201	0.213	0.214	0.383	0.384	0.387

† All variables except for the language dummy are in natural logs. Heteroskedasticity-robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively. See section 3 for a detailed description of all variables.

We have argued above that the fixed effects estimator may deliver biased estimates due to endogenous sample selection. Table 5 therefore reports the results from the two-step Heckman model with fixed effects. These results confirm our concerns about endogenous sample selection regarding the dependent variable. In all specifications considered, the coefficient estimate of the inverse Mills ratio is positive and statistically significant at the 5% level, which suggests that the fixed effects estimations indeed suffer from sampling bias.[35] Recall that the selection equation (first step; not reported) employs the log of the number of new bilateral immigrants from country i in region j over the period from 2002 to 2006 as a single exclusion restriction. As expected, its estimated coefficient is also highly significant and positive.

[35]The inverse Mills ratio is defined as the ratio of the standard normal probability density function to the standard normal cumulative distribution function, both evaluated at the linear prediction from the first stage estimates.

Table 5: Skill Structure of Immigration Flows – Two-Step Heckman Model with Fixed Effects†

	Dependent Variable: Migrant Skill Ratio (Region-Level 2002-2006)					
	(a)	(b)	(c)	(d)	(e)	(f)
Stock of Migrants	-0.379***	-0.375***	-0.370***	-0.351***	-0.336***	-0.317***
(Region-Level 2002)	(0.063)	(0.062)	(0.063)	(0.073)	(0.074)	(0.076)
FDI Flow			-0.006			-0.019
(Region-Level 1997-2001)			(0.015)			(0.015)
Trade Flow			-0.008			0.057
(Region-Level 2001)			(0.072)			(0.076)
Language		0.282	0.278		0.344	0.445
(Region-Level)		(0.217)	(0.217)		(0.430)	(0.436)
Distance		-0.398	-0.430		-0.163	-0.165
(Region-Level)		(0.360)	(0.372)		(0.480)	(0.486)
Inverse Mills Ratio	0.229**	0.233**	0.232**	0.257**	0.282**	0.282**
	(0.102)	(0.101)	(0.101)	(0.110)	(0.111)	(0.111)
Constant	0.331	0.312	0.338	0.269	0.208	0.158
	(0.224)	(0.223)	(0.241)	(0.220)	(0.232)	(0.257)
Region Effects	Yes	Yes	Yes	Nested	Nested	Nested
Country Effects	Yes	Yes	Yes	Yes	Yes	Yes
World Region-and-Region E.	No	No	No	Yes	Yes	Yes
Observations	241	241	241	241	241	241

† All variables except for the language dummy are in natural logs. Heckman-corrected standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively. The regressions include all countries with at least 630 nationals residing in Spain in the year 1996 (55 origin countries). The selection equation of the two-step Heckman procedure is augmented by the total number of new bilateral immigrants over the period from 2002 to 2006. The structural equation is supplemented by the inverse Mills ratio obtained from the first step and uses all observations for which the dependent variables is actually observed. See section 3 for a detailed description of all variables.

This evidence in favor of endogenous sample selection notwithstanding, our conclusions in terms of the family and friends effect on the skill structure of immigration flows remain virtually unchanged both qualitatively and quantitatively. The point estimates of the elasticity of the migrant skill ratio with respect to the size of the migrant community at destination are found to be only slightly smaller in absolute terms in the Heckman estimations compared to the fixed effects estimations, ranging between -0.379 and -0.317. As with the fixed effects model, the migrant stock variable is the only structural explanatory variable whose effect is statistically different from zero.

We have checked the robustness of our results and the validity of some underlying assumptions in various ways. First, we have applied the least squares correction for selectivity bias proposed by Olsen (1980) to the data. The Olsen-correction employs a linear probability model (LPM) in the first step instead of a non-linear Probit model, as does the Heckman model. The results obtained from this alternative selection correction (not reported) are fully in line with those from our Heckman estimations. Second, we have pursued a 2SLS fixed effects approach by complete analogy to the model for the scale of immigration flows. The results are reported in table A.3 in the appendix. They do not alter our causal interpretation in any significant way. Third, following the methodology proposed by Grogger & Hanson (2011, 53-54), we have excluded the possibility that individuals group Spanish regions into clusters at the sub-country level.[36] To do so, we have repeatedly estimated the scale model as given in equation (14), using regional data instead of provincial data and each time excluding the observations for one Spanish region.[37] The estimated network elasticity is very stable across regressions, ranging between 0.681 and 0.742.

Finally, we have estimated a migration function which describes migration into Spanish regions but which derives from the three-level NMNL model featuring Spanish provinces instead of regions as final migration destinations; see also the discussion at the beginning of subsection 3.2. A complication in this framework is that this migration function depends, among other things, on the number of provinces in each regional cluster and the within-cluster distribution of ethnic communities across provinces. This last argument is part of a highly non-linear term, which collapses to zero, however, if we look at regions consisting of a single province. Hence, we have estimated the model excluding all regions consisting of more than one province.[38] In spite of the reduced number of observations, our estimates (not reported) continue to reflect a negative and statistically significant impact of ethnic communities on the skill structure of immigration.[39]

5 Conclusion

Considering data from the recent Spanish immigration experience, we have shown that existing ethnic migrant communities in Spanish provinces or regions spur further migration to these destinations, and cause the skill content of this subsequent migration to decline. Both effects are economically significant and robust across different specifications. We have used the variation in the data across combinations of a large number of origin countries and Spanish provinces or regions, in order to identify the causal effects of ethnic communities on the scale and skill structure of immigration. Unlike previous studies on network effects in migration, we have allowed for final migration destinations within the same country or region to be similar from the perspective of prospective migrants. This implies a partial relaxation of the IIA assumption. Our approach is corroborated by the significant degree of cross-regional heterogeneity in our estimates of the network elasticity, which points towards rich substitution patterns among final migration destinations. Furthermore, from our estimates of the average network elasticity in Spain we deduce that previous estimates are upward-biased due to unobserved heterogeneity.

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[36] Notice that this additional clustering would lead to a misspecified migration function due to a violation of the IIA assumption for the different destination regions in Spain.

[37] In these estimations, we eliminate country fixed effects via an adequate within-transformation, and we control for fixed effects for each combination of world regions and Spanish destination regions in addition to bilateral trade flows.

[38] This is a valid approach as long as individuals do not group Spanish regions into clusters at the sub-country level, which we have shown to be true above.

[39] We have also experimented with two alternative estimation approaches following Quigley (1976) and Lerman (1976). Both include the full set of regions in Spain and are summarized in McFadden (1978, 547-550). Again, we have obtained a robustly significant, negative impact of ethnic communities on the skill structure of immigration.

Our findings add to the understanding of the recent immigration phenomenon in Spain. Arguably, this immigration has gained momentum through Spain's strong economic growth in the years prior to the Global Financial Crisis. However, our analysis has revealed that it has also been reinforced by existing ethnic ties between source and destination. This immigration has in turn led to a change in the size and composition of the country's population and labor supply, with potentially important effects on a number of key macroeconomic variables such as wages, unemployment, and production, as well as on the national welfare state. On top of the substantial challenges deriving from immigration, the Spanish economy has been affected severely by the global economic downturn in 2007/08, with national output plummeting and unemployment, especially youth unemployment, hitting record levels. Recent numbers suggest that this is reflected in a sharp decline in new immigration and a significant amount of return migration in the very short run. The conjoint analysis of the structural relationships among past migration, future migration, wages, and employment involves non-trivial dynamics. Attempts to study these dynamics in a unified framework seem to appear as a challenging yet promising avenue for future research.

References

[1] Anderson, James E., "The Gravity Model," *Annual Review of Economics*, 3 (2011), 133–160.

[2] Anderson, James E., and Eric van Wincoop, "Gravity with Gravitas: A Solution to the Border Puzzle," *American Economic Review*, 93:1 (2003), 170–192.

[3] Baghdadi, Leila, "Mexico-U.S. Migration: Do Spatial Networks Matter?," Universite Paris I. mimeograph (2005).

[4] Bartel, Ann P., "Where Do the New U.S. Immigrants Live?," *Journal of Labor Economics*, 7:4 (1989), 371–391.

[5] Bauer, Thomas, Gil S. Epstein, and Ira N. Gang, "Enclaves, Language, and the Location Choice of Migrants," *Journal of Population Economics*, 18:4 (2005), 649–662.

[6] Bauer, Thomas, Gil S. Epstein, and Ira N. Gang, "Measuring Ethnic Linkages among Migrants," *International Journal of Manpower*, 30:1/2 (2009).

[7] Beine, Michel, Frédéric Docquier, and Çağlar Özden, "Diasporas," *Journal of Development Economics*, 95:1 (2011), 30–41.

[8] Beine, Michel, Frédéric Docquier, and Çağlar Özden, "Dissecting Network Externalities in International Migration," University of Luxembourg mimeograph (2012).

[9] Beine, Michel, and Sara Salomone, "Migration and Networks: Does Education Matter more than Gender?," *Scandinavian Journal of Economics* (forthcoming).

[10] Belot, Michèle V. K., and Timothy J. Hatton, "Immigrant Selection in the OECD," *Scandinavian Journal of Economics* (forthcoming).

[11] Bertoli, Simone, "Networks, Sorting and Self-selection of Ecuadorian Migrants," *Annals of Economics and Statistics*, 2010:97/98 (2010), 261–288.

[12] Bertoli, Simone, and Jesús Fernández-Huertas Moraga, "Multilateral Resistance to Migration," IZA Discussion Paper No. 5958 (2011).

[13] Borjas, George J., "Self-Selection and the Earnings of Migrants," *American Economic Review*, 77:4 (1987), 531–553.

[14] Buch, Claudia M., Jörn Kleinert, and Farid Toubal, "Where Enterprises Lead, People Follow? Links Between Migration and German FDI," *European Economic Review*, 50:8 (2006), 2017–2036.

[15] Card, David and Ethan G. Lewis, "The Diffusion of Mexican Immigrants During the 1990s: Explanations and Impacts," in George J. Borjas (Ed.), *Mexican Immigration to the United States* (Chicago: University of Chicago Press, 2007), chapter 6, 193–227.

[16] Carrington, William J., Enrica Detragiache, and Tara Vishwanath, "Migration with Endogenous Moving Costs," *American Economic Review*, 86:4 (1996), 909–930.

[17] Chau, Nancy, "The Pattern of Migration with Variable Migration Cost," *Journal of Regional Science*, 37:1 (1997), 35–54.

[18] Chiquiar, Daniel, and Gordon H. Hanson, "International Migration, Self-Selection, and the Distribution ofWages: Evidence from Mexico and the United States," *Journal of Political Economy*, 113:2 (2005), 239–281.

[19] Chiswick, Barry R., "Are Immigrants Favorably Self-Selected?," *American Economic Review: Papers and Proceedings*, 89:2 (1999), 181–185.

[20] Chiswick, Barry R., and Paul W. Miller, "Where Immigrants Settle in the United States," *Journal of Comparative Policy Analysis*, 6:2 (2004), 185–197.

[21] Clark, Ximena, Timothy J. Hatton, and Jeffrey G. Williamson, "Explaining U.S. Immigration, 1971-1998," *Review of Economics and Statistics*, 89:2 (2007), 359–373.

[22] Dolfin, Sarah, and Garance Genicot, "What Do Networks Do? The Role of Networks on Migration and 'Coyote' Use," *Review of Development Economics*, 14:2 (2010), 343–359.

[23] Fernández-Huertas Moraga, Jesús, "New Evidence on Emigrant Selection," *Review of Economics and Statistics*, 93:1 (2011), 72–96.

[24] Gould, David M., "Immigrant Links to the Home Country: Empirical Implications for U.S. Bilateral Trade Flows," *Review of Economics and Statistics*, 76:2 (1994), 302–316.

[25] Grogger, Jeffrey, and Gordon H. Hanson, "Income Maximization and the Selection and Sorting of International Migrants," *Journal of Development Economics*, 95:1 (2011), 42–57.

[26] Hatton, Timothy J., "A Model of U.K. Emigration, 1870-1913," *Review of Economics and Statistics*, 77:3 (1995), 407–415.

[27] Heckman, James J., "The Common Structure of Statistical Models of Truncation, Sample Selection, and Limited Dependent Variables and a Simple Estimator for Such Models," *Annals of Economic and Social Measurement*, 5:4 (1976), 475–492.

[28] INE, "National Immigrant Survey 2007. Methodology," (2007).

[29] Javorcik, Beata S., Çağlar Özden, Mariana Spatareanu, and Cristina Neagu, "Migrant Networks and Foreign Direct Investment," *Journal of Development Economics*, 94:2 (2011), 231–241.

[30] Jayet, Hubert, Nadiya Ukrayinchuk, and Giuseppe De Arcangelis, "The Location of Immigrants in Italy: Disentangling Networks and Local Effects," *Annals of Economics and Statistics*, 2010:97/98 (2010), 329–350.

[31] Lerman, Steven R., "Location, Housing, Automobile Ownership, and Mode to Work: A Joint Choice Model," *Transportation Research Record*, 610 (1976), 6–11.

[32] Lewer, Joshua J., and Hendrik Van den Berg, "A Gravity Model of Immigration," *Economics Letters*, 99:1 (2008), 164–167.

[33] Mayda, Anna M., "International Migration: A Panel Data Analysis of the Determinants of Bilateral Flows," *Journal of Population Economics*, 23:4 (2010), 1249–1274.

[34] Mayer, Thierry, and Soledad Zignago, "Notes on CEPII's Distances Measures," (2006).

[35] McFadden, Daniel L., "Modelling the Choice of Residential Location," in Anders Karlqvist, Lars Lundqvist, Folke Snickars, and Jörgen W. Weibull (Eds.), *Spatial Interaction Theory and Planning Models* (Amsterdam: North-Holland, 1978), 75–96.

[36] McFadden, Daniel L., "Econometric Analysis of Qualitative Response Models," in Zvi Griliches and Michael D. Intriligator (Eds.), *Handbook of Econometrics, Vol. II* (Amsterdam: Elsevier Science Publishers, 1984), chapter 24, 1396–1457.

[37] McKenzie, David, and Hillel Rapoport, "Network Effects and the Dynamics of Migration and Inequality: Theory and Evidence from Mexico," *Journal of Development Economics*, 84:1 (2007), 1–24.

[38] McKenzie, David, and Hillel Rapoport, "Self-Selection Patterns in Mexico-U.S. Migration: The Role of Migration Networks," *Review of Economics and Statistics*, 92:4 (2010), 811–821.

[39] Mrázowá, Monika, and Peter Neary, "Selection Effects with Heterogeneous Firms," Discussion Paper 588, University of Oxford, Department of Economics (2011).

[40] Munshi, Kaivan, "Networks in the Modern Economy: Mexican Migrants in the U.S. Labor Market," *Quarterly Journal of Economics*, 118:2 (2003), 549–599.

[41] Neyman, J., and Elizabeth L. Scott, "Consistent Estimates Based on Partially Consistent Observations," *Econometrica*, 16:1 (1948), 1–32.

[42] Olsen, Randall J., "A Least Squares Correction for Selectivity Bias," *Econometrica*, 48:7 (1980), 1815–1820.

[43] Orrenius, Pia M., and Madeline Zavodny, "Self-Selection among Undocumented Immigrants from Mexico," *Journal of Development Economics*, 78:1 (2005), 215–240.

[44] Ortega, Francesc, and Giovanni Peri, "The Causes and Effects of International Labor Mobility: Evidence from OECD Countries 1980-2005," NBER Working Paper No. 14833 (2009).

[45] Pedersen, Peder J., Mariola Pytlikova, and Nina Smith, "Selection and Network Effects – Migration Flows into OECD Countries 1990-2000," *European Economic Review*, 52:7 (2008), 1160–1186.

[46] Peri, Giovanni, and Francisco Requena-Silvente, "The Trade Creation Effect of Immigrants: Evidence from the Remarkable Case of Spain," *Canadina Journal of Economics*, 43:4 (2010), 1433–1459.

[47] Picard, Robert, "GEODIST: Stata Module to Compute Geodetic Distances," Statistical Software Components, Boston College Department of Economics (2010).

[48] Quigley, John M., "Housing Demand in the Short Run: An Analysis of Polytomous Choice," in NBER (Ed.), *Explorations in Economic Research, Volume 3, Number 1* (NBER, 1976), chapter 3, 76–102.

[49] Rauch, James E., and Vitor Trindade, "Ethnic Chinese Networks In International Trade," *Review of Economics and Statistics*, 84:1 (2002), 116–130.

[50] Reher, David, and Miguel Requena, "The National Immigrant Survey of Spain: A New Data Source for Migration Studies," *Demographic Research*, 20:12 (2009), 253–278.

[51] Santos Silva, J. M. C., and Silvana Tenreyro, "The Log of Gravity," *Review of Economics and Statistics*, 88:4 (2006), 641–658.

[52] Stock, James H., Jonathan H. Wright, and Motohiro Yogo, "A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments," *Journal of Business and Economic Statistics*, 20:4 (2002), 518–529.

[53] Zavodny, Madeline, "Welfare and the Locational Choices of New Immigrants," *Federal Reserve Bank of Dallas Economic Review*, (1997), 2–10.

[54] Zavodny, Madeline, "Determinants of Recent Immigrants' Locational Choices," *International Migration Review*, 33:4 (1999), 1014–1030.

Appendix

Table A.1: Data Sources†

Data	Source
Migrant Flows	http://www.ine.es/en/prodyser/micro_varires_en.htm, accessed on 10/05/2010
Migrant Skill Ratios	http://www.ine.es/prodyser/micro_inmigra.htm, accessed on 10/05/2010
Migrant Communities	http://www.ine.es/jaxi/menu.do?type=pcaxis&path=%2Ft20%2Fe245 &file=inebase&L=0, accessed on 10/07/2010
Trade Flows	http://datacomex.comercio.es/principal_comex_es.aspx, accessed on 10/20/2010
FDI Flows	http://datainvex.comercio.es/principal_invex.aspx, accessed on 10/20/2010
Historical Flows of Foreign Nationals	http://www.ine.es/en/prodyser/micro_varires_en.htm, accessed on 10/05/2010
Geographical Coordinates	http://es.wikipedia.org, accessed on 09/05/2011; Mayer & Zignago (2006)
Native Languages in Spanish Regions	Cataluña: Generalitat de Catalunya, Institut d'Estadística de Catalunya (2008). Enquesta d'usos lingüístics de la població 2008. Comunidad Foral de Navarra: Instituto de Estadística de Navarra (2001). Censo 2001 de Población y Viviendas en Navarra. Comunitat Valenciana: Universidad de Salamanca (2007). Estudio CIS No. 2.667. La identitad nacional en España. Galicia: Instituto Galego de Estatística (2008). Enquisa de condicións de vida das familias. Coñecemento e uso do galego. Edición 2008 Illes Balears: Villaverde i Vidal, J. A. (2003). L'Enquesta Sociolingüística 2003. Principals Resultats. País Vasco: Universidad de Salamanca (2007). Estudio CIS No. 2.667. La identitad nacional en España.

† See section 3 for the variable definitions and descriptions of how the considered micro-data have been aggregated.

Table A.2: List of the 55 Countries Considered in the Empirical Analysis, by World Regions

EAST ASIA & PACIFIC	Cuba	NORTH AMERICA	WESTERN EUROPE
China	Dominican Republic	& AUSTRALIA	Austria
Japan	Ecuador	Australia	Belgium
Korea	El Salvador	Canada	Denmark
Philippines	Honduras	United States	Finland
	Mexico		France
EASTERN EUROPE	Peru	SOUTH ASIA	Germany
& CENTRAL ASIA	Uruguay	India	Ireland
Bosnia and Herzegowina	Venezuela	Pakistan	Italy
Bulgaria			Netherlands
Poland	MIDDLE EAST	SUB-SAHARAN	Norway
Romania	& NORTH AFRICA	AFRICA	Portugal
Russia	Algeria	Angola	Sweden
	Egypt	Cape Verde	Switzerland
LATIN AMERICA	Iran	Equatorial Guinea	United Kingdom
& CARIBBEAN	Lebanon	Gamba	
Argentina	Morocco	Guinea	
Bolivia	Syria	Mauritania	
Brazil		Senegal	
Chile			
Colombia			

Table A.3: Skill Structure of Immigration Flows – 2SLS Fixed Effects Model†

	Dependent Variable: Migrant Skill Ratio (Region-Level 2002-2006)					
	(a)	(b)	(c)	(d)	(e)	(f)
Stock of Migrants	-0.458***	-0.459***	-0.448***	-0.517***	-0.516***	-0.501***
(Region-Level 2002)	(0.108)	(0.109)	(0.110)	(0.140)	(0.142)	(0.144)
FDI Flow			-0.004			-0.011
(Region-Level 1997-2001)			(0.017)			(0.017)
Trade Flow			-0.007			0.036
(Region-Level 2001)			(0.076)			(0.087)
Language		0.304	0.301		0.049	0.114
(Region-Level)		(0.189)	(0.189)		(0.357)	(0.362)
Distance		-0.392	-0.417		-0.107	-0.109
(Region-Level)		(0.333)	(0.351)		(0.428)	(0.443)
Constant	0.643**	0.632**	0.638**	0.740**	0.738**	0.699**
	(0.272)	(0.273)	(0.270)	(0.305)	(0.316)	(0.320)
Region Effects	Yes	Yes	Yes	Nested	Nested	Nested
Country Effects	Yes	Yes	Yes	Yes	Yes	Yes
World Region-and-Region E.	No	No	No	Yes	Yes	Yes
Observations	241	241	241	241	241	241
Within R^2	0.198	0.210	0.211	0.373	0.374	0.377
Robust first-stage F test	46.41	44.64	46.81	42.41	40.03	40.69
Test on Overidentifying R.						
Robust score χ^2 test	3.672	3.229	3.050	1.219	1.268	1.153
- p-value	0.055	0.072	0.081	0.270	0.260	0.283
Exogeneity Test						
Robust score χ^2 test	0.553	0.637	0.531	1.972	2.017	2.081
- p-value	0.457	0.425	0.466	0.160	0.156	0.149
Robust regression F test	0.512	0.587	0.486	1.410	1.428	1.456
- p-value	0.475	0.444	0.486	0.237	0.234	0.229

† All variables except for the language dummy are in natural logs. Heteroskedasticity-robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively. The (log) stock of migrants in 2002 is instrumented with the (log) flow of foreign nationals in the year 1988 as well as with the square of this variable. See section 3 for a detailed description of all variables.