Dissecting Network Externalities in International Migration

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Abstract

Existing migrant networks play an important role in explaining the size and structure of immigration flows. They affect the net benefits of migration by reducing assimilation costs ('self-selection channel') and by lowering legal entry barriers through family reunification programs ('immigration policy channel'). This paper presents an identification strategy allowing to disentangle the relative importance of these two channels. Then, it provides an empirical analysis based on US immigration data by metropolitan area and country of origin. First, we show that the overall network externality is strong: the elasticity of migration flows to network size is around one. Second, only a quarter of this elasticity is accounted for by the policy channel. Third, the policy channel was stronger in the 1990s than in the 1980s as the family reunification programs became more effective with growing diasporas. Fourth, the overall diaspora effect and the policy channel are more important for low-skilled migrants.

JEL Classification: F22, O15

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1 Introduction

Even in an age of instant communication and rapid transportation, immigration to a new country is a risky endeavor. Migrants face significant legal barriers, social adjustment costs, financial burdens and uncertainties while they try to reach and settle in their destinations. By providing financial, legal and social support, existing diasporas[1] and other social networks increase the benefits and lower the costs faced by new migrants. As a result, diasporas are among the most important determinants of the size, skill structure and destination composition of migrant flows.

The goal of this paper is to identify and determine the relative importance of different channels through which diasporas influence migration patterns. These channels may be divided into two general categories. The first channel is the lowering of assimilation costs which generally matter *after* the migrant crosses the border. Assimilation costs cover a wide range of hurdles faced by the migrants in finding employment, deciphering foreign cultural norms and adjusting to a new linguistic and economic environment. All of these obstacles tend to be local in nature and the support provided by the existing local network can be crucial.[2] The second channel,

[1]Diaspora (in ancient Greek, "a scattering or sowing of seeds") refers to dispersion of any people or ethnic population from their traditional homelands and the ensuing cultural developments in the destination. In the economic sense, the diaspora refers to migrants who gather in a particular destination country or region.

[2] Bauer et al. (2007) or Epstein (2008) argued that network effects might reflect 'herd behavior' in the sense that migrants with imperfect information about foreign locations follow the flow of other migrants, based on the (wrong or right) supposition that they had better informa-

referred to as the ’policy’ channel, is the overcoming of legal entry barriers and they help the migrant at the border *before* she/he arrives at the final destination. More specifically, diaspora members who have already acquired citizenship or certain residency rights in the destination countries become eligible to sponsor their immediate families and other relatives. These family reunification programs are the main routes for many potential migrants in most OECD countries.

Even though these two rather distinct roles of diasporas - lowering of assimilation costs and overcoming policy induced legal barriers - are recognized in the literature, there has been no attempts to empirically decompose their relative importance. A natural approach is to directly use micro data on the various entry paths migrants use as well as their individual characteristics. Appropriate use of indicators on migration policies along with diaspora characteristics could provide information on the relative importance of family-based admission of new migrants. Unfortunately, there is, to the best of our knowledge, no large micro database providing detailed information on the various entry tracks migrants from different countries use as well as the corresponding flows for each track . Furthermore, information on changes in immigration laws might not be enough to gauge the importance of family reunification policies over time. For example, many undocumented migrants became legal residents after amnesty programs took place in the US in the 1990s. Those regularized migrants, in turn, became eligible to bring their close relatives to the US over the next decade. This results in a rapid increase in the number of migrants coming through family reunification programs in spite of no significant change in US migration laws. Another issue is that a significant number of highly skilled US migrants used kinship-based tracks for convenience while they were fully eligible to use economic migration tracks such as H1B or special talent visas. Ascribing their migration pattern only to the family reunification track would give a distorted picture of the importance of each migration channel.

As an alternative to the use of individual data on immigration paths, this paper develops a differ-

tion.

ent identification strategy using aggregate data available at the city level for the United States.[3] As mentioned earlier, the role of the diasporas in overcoming legal entry barriers operates at the border before the migrant settles in a given city. Thus, the probability for a migrant to obtain legal entry and residence permit through a family reunification program depends on the *total size* of the network already present in the United States, not on the distribution of this diaspora across different cities. On the other hand, the assimilation effect is mostly local and matters after the migrant chooses a city to settle. For example, if a migrant lives in Chicago, the diaspora in Los Angeles is less likely to be of much help to him in terms of finding a job or a school for his children, especially relative to the network present in Chicago. This is the distinction we exploit to identify the relative importance of these two channels. We develop a simple theoretical model showing that, under plausible functional homogeneity of the network externalities, the two different channels can be identified using bilateral data by country of origin of migrants and by metropolitan area of destination. We then provide several extensions based on educational differences, time dimension, alternative migrant definitions or geographic areas and control of potential sources of endogeneity.

We first show that the overall network effect is strong; the elasticity of migration flows to networks is around one, a result in line with Bin Yu (2007) and Beine et.al. (2011). Second, only a quarter of this elasticity is accounted for by the policy channel; the rest is due to the assimilation effect. Each immigrant sponsors 0.25-0.30 relatives within ten years, a result which is in line with the earlier results of Jasso and Rosenzweig (1986, 1989) who focus only on the policy multiplier. This shows the difficulty for host country government to curb the dynamics of immigration and confine the multiplier effects. Third, the policy-selection channel was higher in the nineties than in the eighties due to more generous family reunion programs. Fourth, the

[3] The US Census data is actually disaggregated at the metropolitan area level which might include multiple cities or a city and its surrounding areas. For simplicty, we use the phrase ”city” instead of ”metropolitan area.”

global elasticity and its policy contribution are greater for low skilled migrants. Finally, these results are extremely robust to the specification, to the choice of the dependent variable, to the definition of the relevant network and to the instrumentation of network sizes.

The critical role of diasporas on migration patterns have been clearly recognized in the sociology, demography and economics literatures and extensively analyzed over the last twenty years (such as Boyd, 1989). Regarding assimilation costs, Massey et al. (1993) provided one of the earliest papers, showing show diasporas reduce moving costs, both at the community level (e.g. inflow of people from the same nation helps creating subcultures), and at the family level (increase utility of friends and relatives). As shown by Carrington, Detragiache and Viswanath (1996), this explains why the size and structure of migration flows gradually change over time. In addition, networks provide information and assistance to new migrants before they leave and when they arrive; this facilitates newcomers' integration in the destination economy and reduces uncertainty. Based on a sample of individuals originating from multiple communities in Mexico and residing in the U.S., Munshi (2003) showed that an individual is more likely to be employed and earn higher wage when her network is larger.[4] Beine et al. (2010) used a bilateral data set on international migration by educational attainment from 195 countries to 30 OECD countries and explored how diasporas affect the size and human capital structure of future migration flows. They find that the diasporas are by far the most important determinant, explaining over 70 percent of the observed variability of the size of flows. Regarding educational selection, diasporas were found to benefit the migration of low-skilled relative to the highly-skilled, thus exerting a negative effect and explaining over 45 percent of the variability of the selection ratio. Using micro-data from Mexico, the earlier study of McKenzie and Rapoport (2007) find the same effect, which is also supported by Winters et.al (2001).

[4] On the contrary, Piacentini (2010) used data on migration and education from a rural region of Thailand to show that networks negatively affect the propensity of young migrants to pursue schooling while in the city.

In terms of the effect of diasporas in overcoming policy induced migration restrictions, family reunification is the main legal route for many potential migrants in the United States and most continental European countries. Even in one of the most selective country such as Canada, about 40 percent of immigrants obtain legal residence under the family reunification and refugee programs, rather than selective employment or skill-based programs. Jasso and Rosenzweig (1986, 1989) estimate that each U.S. labor-certified immigrant generated a first-round multiplier around 1.2 within ten years (i.e. sponsored 0.2 relatives). Using a longer perspective, Bin Yu (2007) shows that each newcomer generates an additional inflow of 1.1 immigrants.

The remainder of this paper is organized as following. Section 2 uses a simple labor migration model to explain our identification strategy. Data are described and econometric issues are discussed in Section 3. Results are provided in Section 4. Finally, Section 5 concludes.

2 Model and identification strategy

We use a simple model of labor migration where inviduals with heterogeneous skill types s ($s = 1, ..., S$) born in origin country i ($i = 1, ..., I$) decide whether to stay in their home country i or emigrate to location j ($j = 1, ..., J$) in the destination country. In the estimation, the set of destination locations are different cities in the same country, the United States, and, therefore share the same national immigration policy but they differ in other local attributes. As advocated by Grogger and Hanson (2011), the individual utility is linear in income and includes possible migration and assimilation costs as well as characteristics of the city of residence. The utility of a type-s individual born in country i and staying in country i is given by

$$u_{ii}^s = w_i^s + A_i^s + \varepsilon_{ii}$$

where w_i^s denotes the expected labor income in location i, A_i denotes country i's characteristics (amenities, public expenditures, climate, etc.) and ε_{ii} is an individual-specific iid extreme-value distributed random term. The utility obtained when the same person migrates to location j is given by

$$u_{ij}^s = w_j^s + A_j^s - C_{ij}^s - V_{ij}^s + \varepsilon_{ij}$$

where w_j^s, A_j^s and ε_{ij} denote the same variables as above. In addition, two types of migration costs are distinguished as in Beine et al. (2011). On the one hand, C_{ij} captures moving and assimilation costs that are borne by the migrant. C_{ij}^s, together with $(w_j^s + A_j^s) - (w_i^s + A_i^s)$, would determine the net benefit of migration in a world without any policy restrictions on labor mobility and the self-selection of migrants into destinations. We will assume below that C_{ij} depends on the network size in location j. The network outside j, on the other hand, has no effect on the migrants moving to j. Next, V_{ij}^s represents policy induced costs borne by the migrant to overcome the legal hurdles set by the destination country's government's (policy channel). Since family reunion programs are implemented at the national level, V_{ij}^s depends on the network size at the country level, not at the city level. Obviously, the main motivation to differentiate between these two types of costs is to identify the role of immigration policy on the size and structure of migration flows.

For simplification, we slightly abuse the terminology and refer to C_{ij}^s as *local moving/assimilation costs* and to V_{ij}^s as *national visa/policy costs*. It is worth noting that we allow both of these costs to vary with skill type. It is well documented that high-skill workers are better informed than the low skilled, have higher capacity adapt to assimilate or have more transferrable lingusitic, technical and cultural skills. In short, high skilled workers face lower assimilation costs. In addition, the skill type also affects visa costs if there are selective immigration programs (such as the point-system in Canada or the H1-B program in the U.S.) that specifically target highly educated workers and grant them special preferences.

Let N_i^s denote the size of the native population of skill s that is within migration age in country i. When the random term follows an iid extreme-value distribution, we can apply the results in McFadden (1974) to write the probability that a type-s individual born in country i will move to location j as

$$\Pr\left[u_{ij}^s = \max_k u_{ik}^s\right] = \frac{N_{ij}^s}{N_i^s} = \frac{\exp\left[w_j^s + A_j^s - C_{ij}^s - V_{ij}^s\right]}{\sum_k \exp\left[w_k^s + A_k^s - C_{ik}^s - V_{ik}^s\right]},$$

and the bilateral ratio of migrants in city j to the non-migrants is given by

$$\frac{N_{ij}^s}{N_{ii}^s} = \frac{\exp\left[w_j^s + A_j^s - C_{ij}^s - V_{ij}^s\right]}{\exp\left[w_i^s + A_i^s\right]}$$

Hence, the log ratio of emigrants in city j to residents of i (N_{ij}^s/N_{ii}^s) is given by the following expression

$$\ln\left[\frac{N_{ij}^s}{N_{ii}^s}\right] = \left(w_j^s - w_i^s\right) + \left(A_j^s - A_i^s\right) - \left(C_{ij}^s + V_{ij}^s\right) \tag{1}$$

Let us now formalize network externalities. As stated above, both C_{ij}^s and V_{ij}^s depend on the existing network size. Local moving/assimilation costs depend on origin country and host location characteristics (denoted by c_i^s and c_j^s respectively), increases with bilateral distance d_{ij} between i and j, and decreases with the size of the diaspora network at destination, M_{ij} (captured by the number of people living in location j and born in country i) at the time of migration decision of our individual. In line with other empirical studies, we assume logarithmic form for distance and diaspora externality, and add one to the network size to get finite moving costs to destination where the network size is zero. This leads to

$$C_{ij}^s = c_i^s + c_j^s + \delta^s \ln d_{ij} - \alpha^s \ln\left(1 + M_{ij}\right) \tag{2}$$

where all parameters ($c_i^s, c_j^s, \delta^s, \alpha^s$) are again allowed to vary with skill type s.

Regarding national visa costs, we stated earlier that all cities share the same national migration and border policy which, in many cases, are specific to the origin country i. For example, migrants from certain countries might have preferential entry, employment or residency rights that are not granted to citiziens of other countries. An individual migrant's ability to use the diaspora network to cross the border (for example, via using the family reunification program) depends on the aggregate size of the network in the destination country,

$$M_i \equiv \sum_{j \in J} M_{ij}.$$

Assuming the same logarithmic functional form for the network externality, the visa cost to each particular location j can be written as

$$V_{ij}^s = v_i^s - \beta^s \ln (1 + M_i) \tag{3}$$

where v_i^s stands for origin country characteristics, and extent of the network externality β^s is allowed to vary with skill type. Inserting (2) and (3) into (1) leads to

$$\ln N_{ij}^s = \mu_i^s + \mu_j^s - \delta^s \ln d_{ij} + \alpha^s \ln (1 + M_{ij}) + \beta^s \ln (1 + M_i) \tag{4}$$

where $\mu_i^s \equiv \ln N_{ii}^s - w_i^s - A_i^s - c_i^s - v_i^s$ and $\mu_j^s \equiv w_j^s + A_j^s - c_j^s$ are, respectively, origin country i's and destination location j's characteristics which will be captured by fixed effects in the estimation.[5] (α^s, β^s) are the relative contributions of the network externality through the local assimilation and national policy channels.

Estimating (4) with data on bilateral migration flows from the set I of origin countries to the set J of locations (sharing common immigration policies) cannot be used to identify the magnitude of the policy channel since $\ln (1 + M_i)$ is common to all destinations in set J for a given origin country i. The coefficient will simply be absorbed by the country fixed effects. However, we take advantage of the identical functional form of the assimilation and policy channels to solve this problem. Focusing on the set of destinations J, the aggregate stock can be rewritten as

[5] In principle, N_{ii}^s should be treated as an endogenous variable. We disregard this problem by assuming that each bilateral migration flow N_{ij}^s is small relative to N_{ii}^s.

$M_i = M_{ij} + \sum_{k \neq j} M_{ik}$. It follows that $\ln(1 + M_i)$ in (4) can be expressed as

$$\ln(1 + M_i) \equiv \ln(1 + M_{ij}) + \ln(1 + \Pi_{ij})$$

where $\Pi_{ij} \equiv (1 + M_{ij})^{-1} \sum_{k \neq j} M_{ik}$. Since we have both the bilateral migration and diaspora data available for the full set of locations in set J for every country in set I, Π_{ij} can be constructed for each (i, j) pair. Assuming both externalities are linear (as in Pedersen et al., 2008, or McKenzie and Rapoport, 2010) or follow an homogenous function of degree a (e.g. M^a), we are able to perform this transformation. As a result, we can rewrite (4) as

$$\ln N_{ij}^s = \mu_i^s + \mu_j^s - \delta^s \ln d_{ij} + (\alpha^s + \beta^s) \ln(1 + M_{ij}) + \beta^s \ln(1 + \Pi_{ij}) \tag{5}$$

Now β^s can be properly idenditified since Π_{ij} is a real bilateral variable. μ_i^s and μ_j^s capture all origin country and destination specific fixed effects. As mentioned earlier, d_{ij} measures the physical pairwise distance between i and j. We can only properly estimate coefficients $\alpha^s + \beta^s$ and β^s from the above equation. However, the assimilation mechanism α^s might be recovered by substracting β^s from $\alpha^s + \beta^s$.

3 Data and econometric issues

The data in this paper come from the 5% samples of the U.S. Censuses of 1980, 1990 and 2000, which include detailed information on the social and economic status of foreign-born people in the United States. Of this array of information, we utilize characteristics such as gender, education level, country of birth and geographic location of residence in the U.S. identified by metropolitan area. For the diaspora variable, we use all migrants in a given metropolitan area as reported in the 1990 census (or the 1980 census in the relevant sections). For the migration flow variable, we use the number of migrants (depending on the relevant definition) who arrived between 1990 and 2000 according to the 2000 census (or who arrived during 1980-1990 according to 1990 census).

We re-group the educational variable provided by the U.S. Census (up to 15 categories in the 2000 Census) to account for only 3 categories. These are are (i) low skilled migrants with less than 11 schooling years; (ii) medium skilled migrants with more than 11 schooling years up to high school degree; (iii) the high skilled migrants who have some college degree or more. An indicator of the location of education is not available in the U.S. census so we infer this from the information on the age at which the immigrant reports to have entered the U.S. More specifically, we designate individuals as "U.S. educated" if they arrived before they would have normally finished their declared education level. For example, if a university graduate arrived at the age of 23 or older, then he/she is considered "home educated." On the other hand, if the age of arrival is above 23, we assume the education was obtained in the U.S. We also construct data on geographic distances between origin countries and U.S. metropolitan areas of destination. The spherical distances used in this paper were calculated using STATA software based on geographical coordinates (latitudes and longitudes) found on the web: www.mapsofworld.com/utilities/world-latitude-longitude.htm, for country capital cities and www.realestate3d.com/gps/latlong.htm as well as Wikipedia for US cities.

The identification strategy of this paper rests on the implicit assumption that migrants settle down on a permanent basis taking the network externality into account. This might be undermined if a large proportion of migrants are registered first in some particular metropolitan area (basically an entry area) and move afterwards within the 10 year period to another location. One reason for thus could be that families host their relatives from abroad first, and then send them to another state for the purpose of risk diversification at the family level. Unfortunately, the Census data do not yield a precise estimate of the mobility rate. Nevertheless, using information at hand for the 1990-2000 period suggests that the internal mobility issue is not too serious. Over the 1990-2000 period, out of 12.78 millions new migrants, 5.26 millions came from abroad after 1995. It can be expected that a very large share did not change location in the US after arriving. For the 7.52 millions remaining who arrived between 1990 and 1995, the Census data give their location in 1995. 5.93 millions turned out to stay in the same metropolitan area. Out of the 1.59 millions remaining, respectively 0.75 and 0.84 moved to respectively another county (but not to another state) and to another state. Nevertheless, some metropolitan areas include multiple counties so it is possible that those people remained in the same metropolitan area. And the same holds for states since some large metropolitan areas like Chicago, New Jersey or New York are spread over different states. All in all, those figures cannot be used to provide a direct measure of the metropolitan area mobility and assumptions have to be made. Let's assume that the migrants coming after 1995 did not move internally. If all people changing of county moved also to another metropolitan area, one obtains that the internal mobility rate is 11.1%. If we assume that people changed of MA only when moving to another state, this rate falls to 6.6%. Nevertheless, because some metropolitan areas include multiple counties or multiple states, this rates should be seen as upper bounds of internal mobility. All in all, those figures suggest that our identification strategy is not undermined by large internal mobility rates of migrants within the 10 year period under investigation.

As far as the econometric methodology is concerned, equation (5), supplemented by an error term ϵ_{ij}^s, forms the basis of the estimation of the network effects. The structure of the error term can be decomposed in a simple fashion:

$$\epsilon_{ij}^s = \nu_{ij}^s + u_{ij}^s \tag{6}$$

where u_{ij}^s are independently distributed random variables with zero mean and finite variance, and ν_{ij}^s reflects unobservable factors affecting the migration flows.

There are a couple of estimation issues raised by the nature of the data and the specification. Some of those issues lead to inconsistency of usual estimates such as OLS estimates. One issue is the potential correlation of ν_{ij}^s with M_{ij}. This point is addressed in section 4.6. Another important concern is related to the high prevalence rate of zero values for the dependent variable N_{ij}^s which is, depending on the period (1980's or 1990's), between 50 and 70 percent of the total number of observations. Consistent with our model, distances and other barriers make migration prohibitive, especially between small origin countries and small metropolitan destinations.

The high proportion of zero observations appears in large numbers in many other bilateral contexts, such as international trade or military conflict, and creates similar estimation problems. The use of the log specification drops the zero observations which constraints the estimation to a subsample involving only the country-city pairs for which we observe positive flows. This in turn leads to underestimation of the key parameters α^s and β^s. One usual solution to that problem is to take $ln(1 + N_{ij}^s)$ as the dependent variable and to estimate (5) by OLS. This makes the use of the global sample possible. Nevertheless, this adjustment is subject to a second statistical issue, i.e. the correlation of the error term u_{ij}^s with the covariates of (5). Santos-Silva and Tenreyro (2006) specifically cover this problem and propose some appropriate technique that minimizes the estimation bias of the parameters. This issue has also been addressed by Beine et al. (2011) in the context of global migration flows.

Santos-Silva and Tenreyro (2006) show, in particular, that if the variance of u_{ij}^s depends on c_j^s, m_i^s, d_{ij} or M_{ij}, then its expected value will also depend on some of the regressors in the presence of zeros. This in turn invalidates one important assumption of consistency of OLS estimates. Furthermore, they show that the inconsistency of parameter estimates is also found using alternative techniques such as (threshold) Tobit or non linear estimates. In contrast, in case of heteroskedasticity and a significant proportion of zero values, the Poisson pseudo maximum likelihood (herefafter Poisson) estimator generates unbiased estimators of the parameters of (5).[6] Furthermore, the Poisson estimates is found to perform quite well under various heteroskedasticy patterns and under rounding errors for the dependent variable. Therefore, in the subsequent estimates of (5), we use the Poisson estimation techniques and report the estimates

[6] Unsurprinzingly, our estimates of α^s, β^s and δ^s using alternative techniques such as the threshold Tobit and OLS on the log of the flows (either dropping or keeping the zero values) turn out to be different from the Poisson estimates. In particular, they lead to much higher values for δ^s, which is exactly in line with the results obtained by Santos-Silva and Tenreyro (2006) for trade flows. Results are not reported here to save space but are unvailable upon request.

for α^s, β^s and δ^s.

4 Results

We first estimate (5) with Poisson pseudo maximum likelihood function. We use origin country and destination city fixed effects to capture the variables μ_i^s and μ_j^s respectively. We initially ignore skill and education differences by performing the estimation with aggregate migration flows. Then, we let coefficients vary by education level (sub-section 4.2) and account for income differences at origin that might lead to heterogeneity in the educational quality and other characteristics of the migrant flows (sub-section 4.3). Finally, we present a large set of robustness checks.

4.1 Local and national network externalities

In the first benchmark estimation, we do not differentiate between education levels and assume that the coefficients $\left(\mu_i^s, \mu_j^s, \delta^s, \alpha^s, \beta^s\right)$ are identical across different edcuation groups. The dependent variable N_{ij} in (5) measures the total migration flows from country i to U.S. metropolitan area j between 1990 and 2000. As explained above, the Poisson estimator addresses the issues created by the presence of large number of zeros for the migration flows. We use robust estimates, which is important with the Poisson estimator. Indeed, failure to do that often lead to underestimated standard errors and unrealistic t-statistics above 100. The standard errors are not reported to save space but they usually lead to estimates of δ^s, α^s and β^s with t-statistics lower than 10.[7]

The use of the full sample involves the inclusion of micro-states with idiosyncratic migration

[7] Results are available upon request.

patterns. Many of these countries have fewer than a total of 500 migrants in the United States and their distribution across the U.S. cities is not properly captured in the census data due to imperfect sampling. We adjust the initial sample and leave out micro states which we define in terms of the total size of their migrant stock in the U.S. We use different threshold values of this criterion : 1040, 2900, 7300 and 10000 migrants in the U.S. which correspond to 135, 113, 104 and 99 source countries, respectively. These samples account between 98.8 and 99.9 percent of all migrants and the respective results are reported in columns (1)-(4) of Table 1.

The estimate of the national diaspora effect is in line with previous results, such as in Beine et al. (2011). The key parameters are quite stable across subsamples which is mainly due to the fact that we capture almost all of the migrants in the U.S., although we leave out a number of origin countries. We find that a one percent increase in the initial stock of diaspora leads to approximately one percent increase in the bilateral migration flow over a period between 1990 and 2000, given by the coefficient of $\alpha + \beta$. The results further suggest that the diaspora effect is composed of about one fourth by the national policy effect ($\frac{\beta}{\alpha+\beta}$) and the rest by the local assimilation effect ($\frac{\alpha}{\alpha+\beta}$). Our implied multiplier associated with the policy effect is in line with the one obtained by Jasso and Rozenzweig (1986, 1989). Finally, the effect of the distance is also quite consistent with a coefficient of around -0.5, regardless of the sample size.

All of the results in columns (1)-(4) were based on the flows of migrants aged over 15 at time of arrival, regardless of current or arrival age. Next, we use alternative definitions of migration flows and show that our estimates are quite similar. In column (5), the migrants are restricted to ages between 15 and 65 at the time of their arrival and are in the U.S. as of 2000, so it excludes elderly immigrants. In column (6), we take only male migrants between 15 and 65 at the time of their arrival between 1990 and 2000. In both of these cases, the results are fairly robust to the choice of alternative measures of the migration flows. The main difference is that the national policy effect is found to be slightly higher for men, indicating the local assimilation effect might influences male migration less strongly when compared to women.

Table 1. Overall Network Effects - per sub-samples

	Different Diaspora Sizes				Alternative Migrant Definitions		Geog. Area
Parameters	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\alpha + \beta$	0.964	0.964	0.965	0.965	0.876	0.912	0.875
β	0.259	0.254	0.250	0.247	0.190	0.263	0.164
δ	-0.510	-0.498	-0.490	-0.483	-0.488	-0.507	-0.442
Tot U.S. diaspora	1040	2900	7300	10000	10000	10000	10000
# obs	32912	27346	25168	23958	23958	23958	23958
# incl countries	135	113	104	99	99	99	99
% incl U.S. mig.	99.9	99.7	99.2	98.8	98.8	98.8	98.8
Migrant Definition	All 15+	All 15+	All 15+	All 15+	All 15-65	Male 15-65	All 15+
Country FE	yes	yes	yes	yes	yes	yes	yes
City FE	yes	yes	yes	yes	yes	yes	yes

Notes: ML Poisson estimates of equation (1). All parameters significant at the 1 percent level; otherwise mentioned; robust estimates; Estimation carried out on migrants aged 15 and over, on the 1990-2000 period; threshold in terms of the size of the total diaspora at destination (across all U.S. metropolitan areas).

Our identification strategy rests on the definition of metropolitan areas used by the U.S. Census bureau which defines the location of our local network/diaspora. In other words, we assume the migrant and his local diaspora network are located within the same US metropolitan area. In order to test the robustness of this particular assumption, we modify the definition of the geographic area corresponding to the local network. We consider that the M_{ij} variable is composed by the number of migrants from country i living in metropolitan area j as well as in neighboring metropolitan areas that are located within 100 miles from the center of j.[8] In about 50 percent of the cases, this leads to an increase in the size of the network. Column (7) provides the estimation results of this change in the geographic area definition. We find that both effects are roughly similar with the estimates of the comparable regression, presented in column (4). The

[8] When we modify M_{ij} , we end up naturally modifying Π_{ij} in (5) as well. More specifically an increase (resp. decrease) in M_{ij} implies a decrease (resp. increase) in Π_{ij} .

assimilation/network effect is relatively stronger and but the policy effect is somewhat lower than in the benchmark regression.

4.2 Education level

The strength of the diaspora effect tends to decline with the education and the skill levels of the migrant flows. The main reason is that unskilled migrants face higher assimilation costs and policy restrictions in the U.S. Hence they rely more on their social networks to overcome these barriers. Among recent papers in the literature, McKenzie and Rapoport (2010) use individual data from Mexico and Beine et.al (2011) use bilateral data at the country level to confirm these patterns.

In line with the existing literature, we differentiate between migrant flows based on their education levels to identify different skill categories. There is a certain level of imperfection in the census data since the education level is given by the number of years of completed education as reported by the migrants who come from different countries with different education regimes. Comparison across origin countries is difficult, but, we aggregate these into three different categories as is usually done in the literature (Docquier, Lowell and Marfouk, 2009). These categories are (i) low skilled migrants with less than 11 schooling years; (ii) medium skilled migrants with more than 11 schooling years up to high school degree; (iii) the high skilled migrants who have some college degree or more.

We estimate (5) for these three education levels separately and the results are presented in Columns (1)-(3) of Table 2. We specifically focus on the migrants who completed their education prior to migration and did not receive any further education in the United States in order to separate out migrants who entered as children with their families or who entered for education purposes under special student visas. In line with previous results, we find that the total diaspora effect ($\alpha + \beta$) decreases with the education level of migrants, from 1.146 for low skilled to 0.884 for high skilled migrants. Comparing skilled and unskilled migrants, we find the local assimilation effect, given by α, is higher for low skilled migrants relative to high skilled migrants - at 0.763 vs. 0.655. The difference in the policy effect of the diaspora is, however, much more significant - 0.383 vs. 0.229. These results indicate that the diasporas are more important for the low skilled migrants but the effect is even stronger in overcoming national policy barriers in both relative and absolute terms.

These educational distinctions do not fully take into account the heterogeneity in the quality of education across origin countries. Migrants from different countries will nominally have the same education levels but a university diploma obtained in Canada would, on average, imply higher human capital level than a diploma obtained in poorer and less developed countries. Such educational quality differences will be especially severe since the results are only for migrants who have completed their education at home.

In an innovative paper, using some measures of the observed skills for immigrants in Canada that obtained their education at home, Coulombe and Tremblay (2009) are able to estimate some skill-schooling gap. This approach provides some measure of the quality relative to the national education quality in Canada. They show that the average gap with Canada can amount to more than 4 years of education for some countries.[9] If the quality of education differs among migrants with the same nominal education levels, the ability to migrate outside family reunification programs or other legal channels might be low. In that case, one could expect the national visa and the local assimilation effects of diasporas to be stronger.

There is no common measure of quality of education by origin country. Nevertheless, Coulombe

[9] See also Mattoo, Neagu and Ozden's (2008) exploration of the brain waste effect where migrants with seemingly similar education levels but from different countries end up at jobs with varying levels of quality in terms of human capital requirements. They conclude that differences in educational quality in the origin country and selection effects explain a large portion of these differences.

and Tremblay (2009) show that the skill-schooling gap is highly correlated with the level of GDP per head in the origin country. In line with this approach, we estimate (5) following the World Bank income classification while continuing to use the thresholds in terms of size of the U.S. diaspora. These groups are (i) low income countries, (ii) middle income countries and (iii) high income countries.

Table 2. Results - Education level and quality

	Education levels			Income Level		
	Low	Medium	High	Low	Middle	High
Parameters	skilled	skilled	skilled	Income	Income	Income
	(1)	(2)	(3)	(4)	(5)	(6)
$\alpha+\beta$	1.146	0.905	0.884	1.905	1.126	0.968
β	0.383	0.149	0.229	1.173	0.439	0.211
δ	-0.778	-0.452	-0.493	-1.364	-0.883	-0.171
# obs	25168	25168	25168	2904	12826	10164
# Countries	104	104	104	12	53	42
Country FE	yes	yes	yes	yes	yes	yes
City FE	yes	yes	yes	yes	yes	yes

Notes: ML Poisson estimates of (5) on countries with less than 7300 migrants All parameters significant at the 1 percent level, otherwise mentioned; robust estimates.

There is no common measure of quality of education by origin country. Nevertheless, Coulombe and Tremblay (2009) show that the skill-schooling gap is highly correlated with the level of GDP per head in the origin country. In line with this approach, we estimate (5) following the World Bank income classification while continuing to use the thresholds in terms of size of the U.S. diaspora. These groups are (i) low income countries, (ii) middle income countries and (iii) high income countries.

Income levels of the origin countries of course capture many effects in addition to the quality of education, such as the level of development of financial markets, ability to finance migration expenses, domestic political conditions, quality of economic institutions and various other push factors. Results of this estimation exercise are reported in Columns (4)-(6) of Table 2. We find that the overall diaspora effect decreases with income level from 1.905 for low income countries to 0.968 for high income countries. In line with the previous estimates of columns (1)-(3), we find that most of the variation is driven by the national visa/policy effects. The effect of the diaspora size through the visa effect for high-income countries is a minuscule 0.211. On the other hand, it is 0.439 for middle income and 1.173 for low income countries. These results show clearly that the diaspora plays an important role in providing migrants from low income countries legal access to the U.S. On the other hand, the assimilation effect shows almost no variation - it is 0.732 for low income countries and 0.757 for high income countries. Finally, low-skill migrants are much more sensitive to distance as seen with the sharp decline in the coefficient of distance with income levels.

4.3 Flows in the 90's vs 80's

Our analysis in the previous sections focused on the effect of the 1990's diaspora level on the migration flows between 1990 and 2000. Our dataset includes parallel measures for the migration patterns in the 1980's. It is useful to perform the same estimation on the flows observed in the 1980's to check if there has been any important changes in the patterns and the relative effects. One possibility is to combine observations from the 1980's with those from the 1990's and adopt a panel approach by pooling the data from the two cross section. Nevertheless, it is very likely that the expected effects (α and β) will be different over time and prevent us from pooling our data.

While it is unclear if there has been any significant cultural shift in the U.S. to alter the assimilation effect (α), the U.S. immigration policy has experienced several important changes between the 1980s and the 1990s. The main change is the strengthening of the family reunification between the 1980's and the 1990's with the 1990 US Immigration Act which clearly expanded opportunities for family reunification. This leads to two additional aspects that are not directly modified with the 1990 law but exert important effect on the extent of family reunification in the aftermath.

Table 3. Flows in the 1990's vs 1980's

	1990's			1980's		
Parameters	All	Low Skill	High Skill	All	Low Skill	High Skill
$\alpha+\beta$	0.965	1.146	0.884	0.829	0.935	0.768
β	0.247	0.383	0.229	0.083	0.199	0.137
δ	-0.483	-0.778	-0.493	-0.580	-0.971	-0.527
Nobs	23958	25168	25168	20230	20300	20300
Country FE	yes	yes	yes	yes	yes	yes
City FE	yes	yes	yes	yes	yes	yes

Notes: All = ALl skill types; LS = low skilled; HS = high skilled.ML Poisson estimates of (5) on countries with more than 7300 migrants.All parameters significant at the 1 percent level. Robust estimates. Estimation carried out on migration flows of individuals aged 15 and over.

The first feature is that the immediate relatives of US citizens are not limited or capped under the law. Therefore, quotas for family reunification can be exceeded in practice if the applications by immediate family members are above the estimated number by the law for a given year. As a result, as more immigrants obtain US citizenship, there is a natural upward trend in the number of people coming under the family reunification scheme *sensu lato*.The second important feature is related to the amnesty or legalization programs undertaken in 1986 via the Immigration Reform and Control Act. As large numbers of undocumented migrants obtain legal resident status, they become eligible to bring additional family members through the legal channels. Those who became citizens were even able to bring their relatives through the uncapped channel. Therefore, these policy developments suggest that the estimated β coefficient has increased between the 1980's and 1990's.

Table 3 reports the estimates obtained for the 1990's and the 1980's. For each period, we perform three estimations: for all migrants, for those with low education level, and for those with high education. Our estimates suggest that the national policy effects are uniformly stronger for the 1990's than for the 1980's for all immigrant categories. Naturally, the change is more important for unskilled migrants, more than doubling within a decade. This is in line with the impacts associated with the legalization programs which primarily effect undocumented migrants. In short, the comparison between the 1980's and the 1990's shows that our estimation of the policy effect is in line with what is expected from the evolution of the U.S. immigration policy as the role of the family reunification program increased. On the other hand, the coefficient of α stays around 0.75 for low skilled and 0.65 for high-skilled migrants across both decades, indicating the local assimilation effect did not change considerably over time.

4.4 Distance thresholds

Table 4. Close versus remote countries

	All skill types		Low skilled		High skilled	
Parameters	Close (1)	Far (2)	Close (3)	Far (4)	Close (5)	Far (6)
$\alpha + \beta$	0.970	1.060	1.152	0.952	0.890	1.115
β	0.218	0.368	0.336	0.067^n	0.231	0.513
δ	-0.331	-1.065	-0.648	0.308^n	-0.330	-1.490
Log likelihood						
# Obs	14762	10406	14278	9680	14278	9680
Country FE	yes	yes	yes	yes	yes	yes
City FE	yes	yes	yes	yes	yes	yes

Notes: ML Poisson estimates of (5) on the flow of migrants aged 15 and over from countries with more than 10,000 migrants in the U.S. All parameters significant at the 1 percent level, except those superscripted n (non significant). If not mentioned, robust estimates. Cut off value to define far and close: 6790 kilometers.

Distance plays a key role in migration patterns as one of the critical barriers. Furthermore, it has differential impact on migrants with varying skill levels and, as a result, operates as a selection mechanism. This differential impact is reflected in the distance coefficients in the earlier estimations in Table 2. Even though we have country fixed effects which may control for bilateral distances in many gravity estimations, due to the sheer size of the United States, there is still significant variation in terms of the distance and accessibility from origin countries to different American cities. For instance, the Caribbean countries that are close to the U.S. are likely to send more migrants to cities in the southeast compared to the northwest. In the subsequent estimations, we define far and close countries on the basis of the minimal distance to the U.S. border with a cutoff of 6790 kilometers which is the median distance in terms of pairs of origin countries and US metropolitan areas. We also consider the effect of distance for different education levels - low and high skilled.

First, we find that distance plays a much more important role for migrants coming from far away countries(columns (1) and (2) in table 4). The coefficient of the distance variable is significantly lower in absolute value when the origin countries are closer to the U.S. and these tend to be Latin American and Caribbean countries. Second, the overall diaspora effect is slightly higher when origin countries are far away but this is not statistically significant. However, there is a difference in terms of the composition. The national policy effect is higher for distant countries while the local assimilation effect is more important for closer countries.

We obtain more nuanced results when we compare the importance of distance for different education levels in columns (3) to (6). For unskilled migrants, distance seems to be a very significant deterrent to the extent that it becomes prohibitive. We find that for the unskilled migrants from distant countries, the policy effect is almost non-existing. On the other hand, for skilled migrants from far away countries, the visa effect is much stronger when compared to nearby countries. Finally, we see that the difference in the local assimilation effect between distant and nearby countries becomes small when we control for the skill level. The earlier difference in Columns (1)-(2) is simply due to the skill composition of migrants. In other words, once the migrants pass the border and enter the U.S., the local assimilation effect of the diaspora does not differ based on the country of origin.

4.5 Dropping small cities

In order to assess the robustness of our results, it might also be desirable to measure the extent of our findings that are driven by the inclusion of small cities which we define as metropolitan areas with a low number of migrants. One of the reasons of that concern is that small cities have large number of zero observations at the dyadic level for $\ln(1+M_{ij})$ and $\ln(1+\Pi_{ij})$, leading in turn to spurious correlation between the two variables. Therefore, we reestimate equation (5) with dropping small countries and small cities. In particular, we drop countries with less than 7300 or 10000 migrants in the U.S. and small cities with less than 2900 migrants or less than 7000 migrants. Combining the two cut off values yields four alternative regressions (reported in Table 5) with highly robust results. The value of the assimilation and of the policy effect are hardly affected by the exclusion of small countries and small cities.

Table 5. Dropping small cities

	Minimal size of total US diaspora			
	7300	10000	7300	10000
	Minimal size of city			
Parameters	2900	2900	7000	7000
$\alpha+\beta$	0.965	0.964	0.965	0.965
β	0.249	0.245	0.249	0.245
δ	-0.532	-0.481	-0.486	-0.482
# observations	23716	22748	18634	18392
Country FE	yes	yes	yes	yes
City FE	yes	yes	yes	yes

Notes: Poisson estimates. All parameters significant at the 1 percent level; otherwise mentioned; robust estimates; Estimation carried out on migrants aged 15 and over, on the 1990-2000 period; threshold in terms of the size of the total diaspora at destination (across all U.S. metropolitan areas).

4.6 Accounting for unobservable bilateral factors

Another potential econometric issue is generated by the presence of unobserved bilateral factors ν_{ij}^s influencing the bilateral migration flows N_{ij}^s. In absence of observations for those factors, their effect will be included in the composite error term given by $\nu_{ij}^s + u_{ij}^s = \eta_{ij}^s$.[10] If those factors also influence the diaspora M_{ij}, this leads to some correlation between the error term

[10] Note that the non observation of ν_{ij}^s is also due to the fact that our data is of cross sectional nature. In fact, if one could introduce the time dimension in (5), one could estimate ν_{ij}^s through

and one covariate, invalidating the use of OLS (and Poisson) estimators. This is known as the correlated effect problem (Manski, 1993).

A traditional approach to take care of the correlated effect bias is to use instrumental variables to predict value of M_{ij} using a variable that is uncorrelated with N_{ij}. Given that we estimate model (5) in a Poisson set-up, the solution is not straightforward here. Tenreyro (2007) proposes a method to combine Poisson estimators with instrumental variables estimator which can be done in the GMM context. Dropping the s subscript for convenience of exposition and aggregating all explanatory variables c_j^s, m_i^s, d_{ij} and M_{ij} into the x_{ij} vector, the Poisson estimator γ solves the following moment condition:

$$\sum_{ij}^{n}[N_{ij} - exp(x_{ij}\gamma)]x_{ij} = 0. \tag{7}$$

In order to instrument x_{ij}, one can use as an alternative the following GMM estimator denoted by ψ:

$$\sum_{ij}^{n}[N_{ij} - exp(x_{ij}\psi)]z_{ij} = 0 \tag{8}$$

in which z_{ij} represent the vector of instruments, i.e. variables that are supposed to be correlated with M_{ij} but uncorrelated with N_{ij}. In this robustness analysis, we rely on the GMM estimator ψ using two potential instruments. Those instruments are the variables $ln(1 + M_{ij})$ and $ln(1 + \Pi_{ij})$ observed in 1950, i.e. about 40 years before the observed diaspora in the benchmark regression. Those variables are well correlated with their values in 1990 (a tiny part of the stock of 1990 was already present in 1950). In contrast, the network and policy effects on the flows

bilateral fixed effects. In our case, the use of time through a panel data framework is not possible because of the clear rejection of the pooling assumption. In fact, it is obvious that some parameters such as the one capturing the visa effect (β^s) are not constant over time. In the robustness analysis, we document the change in the US migration policy and show that the β^s parameter changes between the 1980's and the 1990's.

during the 1990's associated with the migrants already present in 1950 are supposed to be quite limited.

One key question is the validity of the exclusion restriction of the instruments. Here, this mainly depends on whether the unobservable components are highly persistent over time. If it is the case, our instrument (correspond variables in 1950) are likely to be correlated with ν_{ij}^s, invalidating the exclusion condition. One often quoted unobserved factor involves climate variables such as average temperature of average rain falls in the sense that they will affect the choice of migrants coming from some countries. It is claimed that contemporaneous migrants (i.e. the N_{ij}^s variable) and the previous ones (i.e. the M_{ij} variable) follow the same climatic pattern. Nevertheless, the data shows that it is not the case. Mexican migrants in the 1950's had obviously a strong preference for nearby metropolitan areas with similar climatic conditions. This is not the case anymore since Mexican migrants have spread out all over the U.S. Another counterexample involves the Porto Rican migrants who tend to concentrate in New York where the climate is quite different from the one prevailing in Porto Rico. Shortly, the IV results should be mainly seen as some robustness check since they are valid under the condition that unobserved factors of N_{ij} should not be too much persistent over time.

Table 6. Instrumenting network sizes

	Poisson	Poisson+IV	
	(1)	(2)	(3)
$\alpha + \beta$	1.029	1.015	1.005
β	0.338	0.356	0.350
δ	-0.711	-0.750	-0.754
Nobs	23541	23541	23541
Country FE	yes	yes	yes
City FE	yes	yes	yes

Notes: First column : ML Poisson estimates of (5). Two last columns: GMM estimates. All parameters significant at the 1 percent level ; robust estimates. Estimation carried out on migration flows of individuals aged 15 and over. Instrument for IV estimates in col 2: local network size observed in 1950. Instruments for IV estimates in col 3: local and national network sizes observed in 1950.

One drawback of using such an instrument is that it leads to a change in the available sample. This is first due to the fact that the definitions of origin countries and US metropolitan areas have significantly changed between 1950 and 1990. A second reason is the independence of many former colonies during the 50's and 60's.[11] Therefore, in the robustness analysis, we use only comparable samples while relying on Poisson regressions that are not affected by the potential correlation between M_{ij} and ν^s_{ij}. In other terms, we show that the estimates for γ and for ψ are quite close in identical samples.

In practice, we first reestimate the Poisson regressions and use those estimates as a benchmark with respect to the IV (GMM) estimates. Table 6 report the estimates of the Poisson on the restricted sample in column **(**1), and of the combined Poisson and IV estimates la Tenreyro in columns (2) and (3). In column (2), we use one instrument only, i.e. $\ln(1 + M_{ij})$ observed in 1950 while in column (3) we supplement the instrument set with $\ln(1 + \Pi_{ij})$ observed in 1950.[12] The results show that our estimates are strikingly robust to the instrumentation procedure. Both the total diaspora effect and the estimated policy effect are very similar across estimation methods. They are also very similar regardless of the inclusion or not of $\ln(1 + \Pi_{ij})$ variable observed in 1950.

[11] For instance, all US migrants coming from former European colonies were identified as migrants coming from the colonizing country.

[12] Note that , we checked the robustness of the maximum likelihood estimator. Indeed, the use of the Pseudo Poisson Maximum Likelihood might lead to convergence problems and might generate spurious convergence. Following Santos Silva and Tenreyro (2010), the issue might be addressed through some iterative procedure dropping the insignificant fixed effects.

4.7 Influence of the homogeneity assumption

Our identification strategy assumes that the functional forms for the local assimilation and the national policy externalities of the diaspora networks are identical. In particular, we assume that both externalities are log-linear. It might also be desirable to assess whether this homogeneity assumption affects our results. One possibility is to estimate directly α and β in equation (4). Unfortunately, this is not possible if one accounts for unobserved heterogeneity across origin countries via inclusion of the fixed effects (μ_i^s) in the estimated equation. As an alternative, we can proceed to a two-step estimation of equation (4). In the first step, we estimate the following equation via Poisson maximum likelihood estimation:

$$\ln N_{ij}^s = \mu_i^s + \mu_j^s - \delta^s \ln d_{ij} + \alpha^s \ln\left(1 + M_{ij}\right) \tag{9}$$

This first estimation yields the coefficient for α for the 1990's. Interestingly, using a cut-off value of 7300 US migrants to exclude small countries, we get an estimated value for the coefficient of α equal to 0.719. This is strikingly close to the implied value of α in Table 1, i.e. 0.714. Then, in order to recover the coefficient of μ_i^s, we can estimate the value of β with the following country-level regression :

$$\mu_i = \gamma + \beta ln(1 + M_i) + \rho' X_{ik} + \omega_i \tag{10}$$

where ω_i is an error term and where X_{ik} are country-specific time-invariant factors that are supposed to be captured by the country fixed effect. The inclusion of the X_{ik} is supposed to account for the variability in the μ_i that is unrelated to the policy effect. We consider four potential factors : trade openness captured by the share of export to gdp, gdp per head in 1990, a dummy variable capturing whether the country speaks English of not and a regional dummy as defined by the World Bank official classification. In line with section 4.3., the sign of the GDP/head variable should be expected to be negative as rich countries are shown to have a lower value for the policy effect. The estimation tends to confirm this expectation.

The following exercise should be nevertheless seen as a sub-optimal procedure, aimed only at guessing the importance of the linearity assumption for both externalities. The reason is two-fold. First, the method is a two-step method, which is less efficient that the one step estimation methods like the one used before. Second, the inclusion of observable variables and the estimation of country fixed effects lead to small sample sizes.

Table 7 reports the estimation results. The results suggest that the impact of economic development is negative, as expected. The estimated value of β ranges between 0.36 and 0.57. This is slightly higher than in Table 1, leading to policy effect representing about 40% of the total network effect instead of the previously obtained 25%. Nevertheless, given that the procedure is quite different, the results are relatively similar and this robustness check procedure confirms that the local assimilation effect tends to dominate the global policy effect of the diaspora network. All in all, this exercise suggests that our identification strategy yields results that make sense, but that the linearity assumption might lead to a small underestimation of the value and the share of the policy effect.

Table 7. Assessing the linearity assumption: two-step estimation

Dep variable:		μ_i		
Constant	-2.670	-3.799	-4.203^c	-3.270
β	0.569^b	0.577^b	0.537^b	0.363^c
GDP/head	-0.119^a	-0.136^a	-0.119^a	-
Openness	-0.026	0.021	-	-
English	0.196	-	-	-
Region dummies	-0.267	-	-	-
R^2	0.182	0.163	0.128	0.030
Obs	97	97	100	105

Notes: First step estimation : see equation (4). Cut-off values of inclusion of origin countries: 7300 migrants. Second step estimated equation : $\mu_i = \xi + \beta ln(1 + M_i) + \rho X_i + u_i$. Note that the first step estimated α is 0.719. a, b, c: significant at 1%, 5% and 10% level respectively.

5 Conclusion

This paper deals with network externalities in international migration. In particular, it proposes a new approach aimed at disentangling the two main components of the network effect, i.e. the assimilation effect and the policy effect. Using migration data at the city level and at the country level, we are able to isolate the policy effect from the global network effect for the U.S.

We show that for the U.S., the average network elasticity is close to unity, with 25 % of it associated to the policy effect and 75% of it associated to the assimilation effect. This baseline result is in line with the existing literature (Jasso and Rosenzweig, 1986, 1989) suggesting that the medium-run migration multiplier associated to family reunification lies around 1.3.

Furthermore, we find that the size and the composition of the network effect vary across a set of characteristics of the migrants. The policy effect is larger for unskilled migrants and those coming from low income countries. Furthermore, the policy effect has significantly increased between the 80's and the 90's, reflecting a higher share of kinship based migration in the U.S., favored either by changes in the immigration laws or by other policies such as the legalization programs.

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