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H. Jayet, G. Rayp, I. Ruyssen and N. Ukrayinchuk

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Hubert Jayet[1], Glenn Rayp[2], Ilse Ruyssen*[3], and Nadiya Ukrayinchuk[4]

[1] *EQUIPPE, Université Lille 1, France*

[2] *SHERPPA, Ghent University, Belgium*

[3] *IRES, Université Catholique de Louvain, Belgium; SHERPPA, Ghent University, Belgium*

[4] *EQUIPPE, Université Lille 2, France*

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Abstract

This paper analyses migratory streams to Belgian municipalities between 1994-2007. The Belgian population register constitutes a rich and unique database of yearly migrant inflows and stocks broken down by nationality, which allows us to empirically explain the location choice of immigrants at municipality level. Specifically, we aim at separating the network effect, captured by the number of previous arrivals, from other location-specific characteristics such as local labor or housing market conditions and the presence of public amenities. We expect labor and housing market variables to operate at different levels and develop a nested model of location choice in which an immigrant first chooses a broad area, roughly corresponding to a labor market, and subsequently chooses a municipality within this area. We find that the spatial repartition of immigrants in Belgium is determined by both network effects and local characteristics. The determinants of local attractiveness vary by nationality, as expected, but for all nationalities, they seem to dominate the impact of network effects.

JEL Classification:

Keywords: International migration, Location choice, Network effects, Nested logit

1 Introduction

The upsurge of migration flows in the last two decades has placed international migration high on the policy agenda of many countries. There is a thorough academic and political debate concerning potential explanations for this rise and adequate policies to manage it. Temporary migration schemes, the design of selective entry policies and the necessity of amnesties are only some of the recent migration topics that have been studied. Another important issue relates to the spatial distribution of migrants once they

*Corresponding author: Ilse Ruyssen, Department of General Economics, Tweekerkenstraat 2, B-9000 Gent, Belgium. Email: Ilse.Ruyssen@Uclouvain.be.

arrive in the destination country. Their location pattern is conditioned by the distribution of natives (Le Bras and Labbé, 1993; Chiswick and Miller, 2004), but usually follows different dynamics that may exhibit a strong impact on the welfare of both natives and immigrants, on the spatial distribution of natives (Borjas, 1993, 2003; Friedberg and Hunt, 1995; Winkelman and Zimmerman, 1993) and also on the negative perception of immigrants to natives (Roux, 2004).

Both economic and sociological studies have analyzed the main characteristics of these patterns and their consequences. It is well established that immigrants of the same or similar ethnic origin tend to spatially concentrate much more than natives (see Carrington et al., 1996; Chau, 1997; Winters et al., 2001; Heitmueller, 2003; Bauer et al., 2002, 2005). This occurs because spatial nearness enables the formation of social networks, which tend to play a more important role for immigrants than for natives. By providing initial assistance to newcomers or help to face bureaucratic challenges in the destination country, social networks reduce some of the fixed initial costs that new immigrants come across. However, the presence of strong agglomerations of immigrants may have a negative effect on the assimilation and integration of both newcomers and second generations of immigrants.

Many surveys of international migration have shown that the existence of networks in the destination country has a positive effect on the propensity to migrate (Stark and Taylor, 1989; Massey and Denton, 1987; Mayda, 2010; Ruyssen et al., ress). Only a limited number of studies, however, empirically estimated the effect of social networks on the location of immigrants within the host country. To our knowledge, this analysis has been conducted only for the United States (Bartel, 1989; Bauer et al., 2002), for Australia (Chiswick and Miller, 2004, 2005) and for France (Jayet and Ukrayinchuk, 2007). For other countries of destination, the spatial repartition of immigrants has not yet been explored, mainly because the required data is not available. The Belgian population register, however, constitutes a rich and unique database of yearly migrant inflows and stocks with a detailed breakdown by nationality and age cohort, which proves ideal for a study of the location pattern of immigrants in Belgium.

Besides providing insight into the spatial distribution of immigrants in Belgium through a descriptive analysis, this paper contributes to the migration literature in two important ways. On the one hand, we develop a hierarchical (nested logit) model of the location choice of immigrants that is consistent with random utility maximization (but not necessarily with full information). Specifically, we expect labor and housing market variables to operate at different levels such that immigrants first select a region roughly corresponding to a labor market, and subsequently choose the municipality within this region maximizing their utility. On the other hand, we investigate the relative importance of social networks versus these labor and housing market variables as well as other location specific characteristics such as the presence of public amenities, geographical and cultural attractiveness or distance to the nearest border.

The remainder of the paper is structured as follows. Section 2 presents the main stylized facts concerning the location of immigrants in Belgium. Section 3 outlines the theoretical model of the location choice of immigrants and clarifies the choice for a nested structure. Section 4 elaborates on the econometric methodology, specification tests and the empirical specification. Section 5 reports the empirical results from the nested model of location choice, from the decomposition of immigration probabilities - demonstrating to what extent the location pattern is determined by locations characteristics versus network effects - and from the analysis of the determinants of the local effects. Section 6 concludes.

2 The data

Before turning to the theoretical model, we briefly explain our choice for Belgium to study the location pattern of immigrants and present the main stylized facts.

Belgium is one of the few countries that consistently maintained a population register and as such simultaneously keeps track of migrant inflows and stocks at the local level. Other countries derive statistics on immigrant flows from specific surveys or the issuance of resident permits. In the first case, the number of migrants is estimated based on a subsample of the population. Ireland and the United Kingdom, for instance, both rely on repeated surveys and periodically revise their estimates based on census data. Given the significant adjustments following the latest census in each of these two countries, survey-based estimates do not appear to constitute the most accurate source of information. In the second case, the annual inflow corresponds to the number of persons who were awarded residence permits of a certain minimum duration (one year in France and Switzerland and unlimited duration in Australia, Canada, New Zealand and the United States). The most important problem with permit data is that they only record the number of persons entering the country, without necessarily keeping track of their location *within* the country. Finally, some countries - like France - are bound to rely on census data in order to keep track of the size of the foreign population. These are typically conducted every six to twelve years and hence do not provide yearly information on changes in the location pattern of foreigners.

In Belgium, on the other hand, municipalities have maintained a local population register ever since the founding of the Belgian State in 1830. It is one of the few countries that consistently maintained a population register over such a long period of time, mainly for administrative purposes. The creation of a national centralized population register in 1983 and the digitalization in 1988 considerably improved the accuracy and efficiency of these local registers. Additionally, the local and national registers are compared and adjusted at every population census in order to remove any remaining inconsistencies.

Specifically, every foreigner who resides in Belgium for more than three months needs to apply for a permit for temporary stay from the Ministry of Justice. When granted, the immigrant needs to register in the municipality where he or she resides. Subsequently, local police is called in to verify whether proper registration has taken place. When an immigrant decides to leave the country for good, this has to be declared to the administration of his or her commune of residence. But also in case he or she fails to do so, a deregistration might take place following standard inquiries by the local police. In both cases, the deregistration is reported to the Belgian Directorate for General Statistics and Economic Information, that produces the international migration statistics. This approach allows to account for inflows as well as outflows and as such addresses one of the major issues generally affecting population register data.

By assigning an individual reference number to each person born or arriving in the country, the register is able to keep track of the residence of every legal citizen residing in Belgium. Illegal migrants, i.e. foreigners without a valid residence permit, do not appear in the immigration statistics as long as their situation has not been regularized.[1] Neither do asylum seekers, who are, as of 1995, enrolled in a special waiting register until they have been granted refugee status.[2]

Hence, the Belgian Directorate for General Statistics and Economic Information is able to produce very accurate data on the location of legal immigrants in Belgium. The in-dept breakdown in combination with the regular consistency checks and police control result in an unparalelled dataset which proves ideal for an empirical analysis of the location pattern of immigrants at municipality level.

In what follows, we take a closer look at the Belgian migration data and briefly describe the spatial distribution of immigrants across Belgian municipalities. We make use of the digitally available data on migrant inflows and stocks for the period 1994-2007[3], kindly provided by the Belgian Directorate for General Statistics and Economic Information. The data are broken down by nationality and age cohort, which allows us to distinguish immigrants at working age (age 20 to 64). Specifically, they comprise information on the number of immigrants arriving and living in each of the 588 municipalities for 97 different nationalities.

[1]Consequently, the database does not only record newcomers arriving from abroad but also migrants who already settled in a specific municipality and decide to move on to the next. It is thus not possible to distinguish internal migrants from international immigrants. Yet, we believe that our theoretical model applies to both types of migrants in the same manner: whether it concerns an internal or an international migrant, the choice for a certain location is expected to be made according to the same decision process.

[2]In fact, these refugees are not included in the immigrant streams as such but rather reported in a different category 'adjustments'. This procedure obscures the real migratory movements, as illustrated by the reduced inflows recorded between 1995 and 1998. Yet, although information on the number of asylum applicants and refugees is available, details on these persons are fairly limited, which prohibits a simple merge of refugees and migrants to obtain a more accurate picture of current migratory streams.

[3]Although the complete period for which the data are digitally available corresponds to 1990-2007, we limit our sample to the years 1994-2007, corresponding to the period for which all the explanatory variables in our empirical analysis are available.

It should be noted that fluctuations in the migrant stock are to some extent related to modifications in the Belgian nationality law. The amendments of 1984 and 1991, in particular, fostered the acquisition of Belgian citizenship leading to sharp drops of the migrant stock in the following years. In 1992, for instance, no less than 46 368 immigrants acquired the Belgian nationality compared to only 8 457 (16 376) in 1991 (1993). Most of them were Italians, with 25 377 (22 362) naturalizations in 1985 (1992), as opposed to only 7 637 (5 854) during the period 1986-1991 (1993-1995). Because there is no data on yearly naturalizations by country of origin at municipality level, we cannot correct the migrant stock for the occurrence of naturalizations. The empirical analysis is however robust to fluctuations in the migrant stock related to changes in the naturalization policy (such as the amendment of 2000) as long as the naturalization behavior of immigrants is homogenous across municipalities, such that the distribution of immigrants across districts and municipalities is not affected, which is likely to be the case.[4] Second, the empirical analysis is conducted separately for some of the most important nationalities in our sample. This serves as a final control since presumably not all nationalities in our sample respond equally to changes in the naturalization law. The largest response can be expected from Italians and immigrants from non-EU countries - Morocco, Poland and Turkey - whereas the response for immigrants from neighboring countries - France, Germany and the Netherlands - is likely to remain fairly limited.

Belgian migration streams have been ever growing during the sample period. Whereas previous rises in immigration flows could be related to temporarily favorable migratory conditions, following economic upsurges and labor shortages, the more recent migratory intensification can be linked to increased family reunification, European enlargement and rising asylum applications since 1994. Table 1 presents migrant stocks for the year 2007[5] for the nationalities included in our empirical analysis[6], together with their share in total migrant stocks as well as their growth rates between 1994-2007. In 1994, the foreign population in Belgium amounted to 862 747, i.e. 8.54 per cent of the total population. During the period 1994-2007, the migrant stock grew by nearly 4 per cent, reaching 863 222 migrants in 2007, who account for 8.21 per cent of the total population. The nationalities included in our sample add up to 67 per cent of the total foreign population in 2007.

[4]The reason is that we estimate only differences with respect to a reference district or municipality so that any impact of time specific law changes is cancelled out, as explained in Section 4.1.

[5]Given that the migrant stock is reported each year on January 1, it does not reflect changes in the migratory pattern which took place during the year of recording but rather captures the stock of migrants at the end of the preceding year.

[6]The selection of nationalities has been made based on two criteria. First, all the nationalities in our sample feature in the top ten of sending countries. Second, considering that we merely intend to find out whether the location choice differs depending on a person's nationality, we consider only a few nationalities, namely those with the least empty cells in the migration data. As such, we do not consider origins like Portugal, Spain and the UK that also appear in the top ten of sending countries but whose emigrants are not substantially spread across the Belgian territory. The last column of Table 1 reveals the percentage of municipalities with non-zero migrant stocks in 2007 for the nationalities in our sample.

Table 1: Migrant stocks: main nationalities, 2007

Origin	Units	Share (%)	Growth (%)	Coverage (%)
Total population	10 511 300		4.79	
All foreigners	863 222	100.00	3.96	100.00
Italy	175 561	20.34	-19.29	97.45
France	120 698	13.98	26.83	99.32
Netherlands	110 513	12.80	58.53	98.64
Morocco	80 613	9.34	-44.40	89.63
Turkey	39 665	4.59	-55.06	71.60
Germany	37 014	4.29	26.25	95.24
Poland	18 032	2.09	274.73	85.54
Total sample	582 096	67.43	-10.42	100.00

Notes: Authors' calculations based on data obtained from the Belgian Directorate for General Statistics and Economic Information. *Share* denotes the share of the total migrant stock in Belgium. *Growth* reflects the growth rate of migrant stocks between 1994 and 2007. *Coverage* indicates the percentage of municipalities with non-zero migrant stocks by nationality in 2007.

The most striking observation is that not the closest neighbors but Italians still form the largest foreign community in Belgium. Although their number systematically decreased since the 1990s, no less than one in five foreign residents still has the Italian nationality. Other important communities originate from France and the Netherlands. Their share in the total foreign population kept growing, and reached 14 and 13 per cent in 2007, respectively. The largest non-European foreign communities are the Moroccan and Turkish communities with 80 613 and 39 665 residents, respectively. Their share in the total migrant stock, nevertheless, severely dropped since 1994 (by 44 and 55 per cent respectively), following the 1991, 1995 and 2000 amendments to the naturalization law, which facilitated acquisition of the Belgian nationality[7]. An overview of yearly migrant stocks by nationality can be found in appendix Table A-1.

Focussing on immigrant flows, on the other hand, we get a very different picture. Table 2 illustrates absolute and relative numbers together with growth rates for immigrant flows in 2007 for both the total immigrant population and the working age subgroup (immigrants aged 20 to 64) as well as correlation coefficients between flows of working age and retired immigrants. Immigrant flows from the nationalities in our sample represent 47 per cent of the overall immigrant flow to Belgium in 2007. Proportionally, these countries sent out slightly more working age immigrants than other countries as their share in the

[7]The largest impact on the number of naturalizations stems from the amendment of March 1, 2000, leading to 61 878 and 62 881 naturalizations in 2000 and 2001, respectively.

overall immigrant flow to Belgium reaches 49 per cent.

Table 2: Immigrant flows by type of activity: main nationalities, 2007

	Total (working age and retired)			Working age			Working age vs. Retired
Origin	Units	Share (%)	Growth (%)	Units	Share (%)	Growth (%)	Correlation (%)
All foreigners	10 6576	100	70.09	78 655	100.00	73.91	62.68
France	12 269	11.51	99.50	9 100	11.57	108.91	67.14
Netherlands	11 370	10.67	75.54	7 922	10.07	65.59	92.18
Poland	9 393	8.81	1 084.49	7 930	10.08	1 176.97	66.38
Morocco	7 831	7.35	64.24	6 065	7.71	67.68	68.21
Germany	3 385	3.18	10.51	2 532	3.22	12.58	41.08
Turkey	3 180	2.98	-11.00	2 494	3.17	10.94	25.45
Italy	2 708	2.54	-1.67	2 131	2.71	14.57	77.03
Total sample	50 136	47.04	81.80	38 174	48.53	93.43	62.50

Notes: see Table 1. *Correlation* denotes the correlation coefficient between immigrants at working age and immigrants age 65 and older.

Most migrants arriving in Belgium in 2007 came from neighboring countries France and the Netherlands, i.e. around 22 per cent of the total flow. Also Poland and Morocco turn out important sending countries, together covering another 16 per cent of total Belgian immigration in 2007. In addition, Polish migrant flows in 2007 were over 10 times their size in 1994, whereas 2007 inflows from Morocco grew by 60 per cent compared to those in 1994. Immigrant flows from Turkey and Italy, on the other hand, both decreased during the sample period. Whereas Italy was the most important sending country as far as concerns the total number of foreigners in Belgium, immigration from Italy represented only a small share, i.e. less than 3 per cent, of Belgium's most recent inflows.

The correlation coefficients of working age versus retired immigrant flows are usually quite modest, with specifically low values for German and Turkish immigrants. Only the Dutch inflow appears quite balanced across age groups. Consequently, in our empirical analysis, we will focus on immigrants at working age only, rather than considering the immigrant population as a whole. A summary of yearly migrant flows by nationality can be found in appendix Tables A-2 and A-3 for all age groups and for working age migrants, respectively.

The maps in Figure 1 depict the spatial distribution of immigrants across municipalities in 1994 and 2007. Total migrant stocks reported in 1994 range from 0.2 to 53.2 per cent, compared to 0.3 to 48.9 per cent in 2007. A quick glance at the figures reveals that the majority of municipalities in Flanders has lower relative migrant stocks than Wallonia. Focussing on the situation in 2007, it seems that in many municipalities in the North, less than 1.5 per cent of the population is foreign, whereas in the South these percentages vary between 1.5 and 8. In municipalities in and around Brussels, on the other hand, relative migrant stocks typically account for 8 to 45 per cent of the population.

In terms of immigrant flows, as illustrated in Figure 2, recent 2007 immigrant streams reveal more or less the same pattern as those in 1994, indicating a great deal of persistence in the migratory process. In 2007 (1994), immigrant flows amounted up to 5 (3) per cent of the local population. Whereas new immigrants still tend to locate in and around Brussels, along the French, Dutch and German border as well as in the Southern tip of Belgium neighboring Luxembourg, the former mining districts in the Mid-West and North-East attract far less immigrants. Moreover, in comparison with relative migrant stocks, new immigrant streams appear to be less concentrated and more scattered across the country.

Figure 1: Total migrant stocks in thousands of the population by municipality, 1994 and 2007

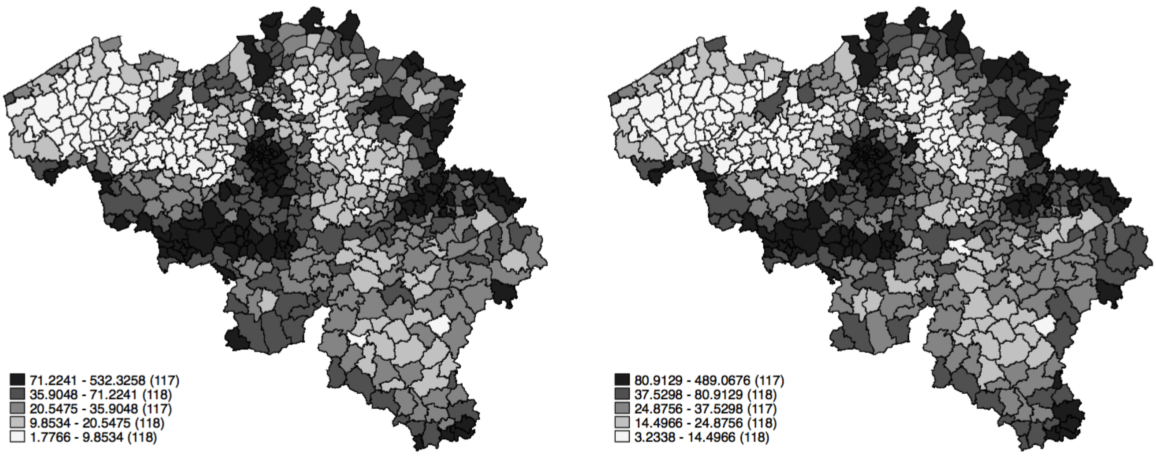
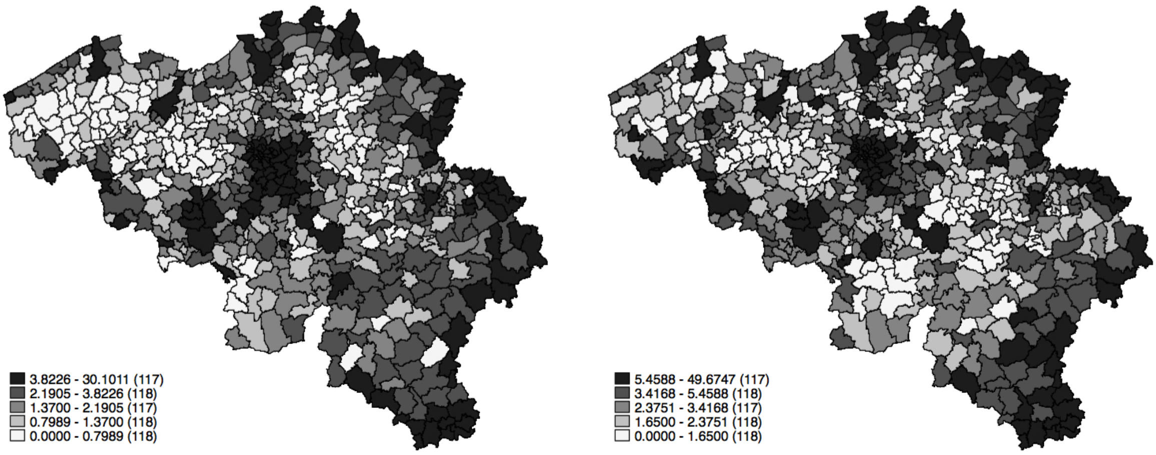


Figure 2: Total flows of working age immigrants in thousands of the population by municipality, 1994 and 2007



The spatial distribution of immigrants according to their country of origin can be found in appendix Figures A-1 and A-2. In general, immigrants from neighboring countries tend to be located close to the border of their country of origin. Yet, the French can also be found in the municipalities close to Luxembourg, Germans favor also municipalities in Antwerp and, not surprisingly, Italians can be found especially in former mining districts. The Dutch are also located in Brussels, though to a lesser extent than the latter three nationalities, as well as in the Northern Ardennes. Moroccan, Turkish and Polish immigrants, finally, are spread more equally across the country, with slightly higher concentrations in mid Belgium and the former mining districts.

3 A nested logit model of location choice

Consider a migrant who has decided to move to a certain destination country and who is supposed to choose a specific location i within this country. Our starting point is a standard choice model in which the migrant chooses the location that maximizes his or her utility at time t, net of moving costs, i.e. $U_{i,t}$. This utility may be measured using an indirect utility function: after choosing a location i, the migrant sells his or her labor and buys goods and services on local markets and simultaneously benefits from local externalities or publicly provided goods. As such, $U_{i,t}$ depends upon three types of location-specific characteristics: (i) expected labor market conditions and prices of goods, (ii) the presence of externalities such as amenities and public goods and (iii) migration costs. Information on local prices or wages is usually unavailable. As a proxy for these indicators, we might however use variables determining the equilibrium on the corresponding local markets. If information on local housing rent, for example, would be unavailable, we could use information on the transactions of housing premises. The second type of location factors encompasses climatological conditions, the social environment, and the quality and quantity of infrastructure and public services in education and health. Standard proxies for migration costs, finally, are distance to the country of origin as well as the presence of a border or a common language.

In addition to these location-specific factors, also social networks are expected to have an impact on the utility - and hence also the location choice - of immigrants. As mentioned in the introduction, immigrants have a tendency to develop social and economic networks within their country of destination, which might help newcomers to find jobs and housing, to keep in touch with the culture of the origin country, and to alleviate liquidity constraints. From the migration literature, we know that these networks have both a strong local and ethnic dimension: immigrants tend to be involved in social relations with migrants of the same country of origin and typically locate close to each other. Because of their strong local dimension, currently existing national networks serve as a pull for newcomers: new immigrants are drawn to locations where previously arrived migrants of the same origin have developed local networks that can positively affect their utility.

Consider again the location factors of the first type, which in fact reflect labor and housing market conditions. These location factors are likely not to operate at the same level: we expect that immigrants look for a job in a fairly broad area - covering several municipalities - and subsequently look for housing in a municipality within this area. This hypothesis implies a two stages process, which can be expressed using a nested logit model of location choice.

More precisely, let us consider a set of I locations. Each location belongs to a higher-level area roughly corresponding to a labor market. Location i belongs to area $k = \kappa(i)$. The location choice involves a two-stage process: (i) choosing an area k and (ii) choosing a location i within area k. The utility of choosing location i is

$$U_{i,t} = (z_{i,t})' \beta + \left(z^*_{\kappa(i),t}\right)' \beta^* + \alpha_i + \zeta_{\kappa(i),t} + \varepsilon_{i,t} \tag{1}$$

where $z_{i,t}$ is a vector of location factors varying across locations and periods, while $z^*_{\kappa(i),t}$ varies across areas and periods, but is common to all locations within the same area. The parameter α_i is a local effect measuring the impact of all the time invariant location factors while $\zeta_{\kappa(i),t}$ and $\varepsilon_{i,t}$ are random terms capturing the influence of all the unknown time varying area and location characteristics. The local effect measuring the impact of all the time invariant location factors can be rewritten as

$$\alpha_i = (x_i)' \theta + \left(x^*_{\kappa(i)}\right)' \theta^* + \eta_i \tag{2}$$

where x_i a vector of location factors specific to location i and $x^*_{\kappa(i)}$ a vector of location factors common to all the locations included in the area $\kappa(i)$.

Both random terms, $\zeta_{\kappa(i),t}$ and $\varepsilon_{i,t}$, are assumed iid, following Gumbel probability distributions. More precisely, for every k, the cdf of $\zeta_{k,t}$ is $F_1(\zeta) = \exp(-\exp(-\zeta/\mu_1))$ whereas, for every i, the cdf of $\varepsilon_{i,t}$ is $F_2(\varepsilon) = \exp(-\exp(-\varepsilon/\mu_2))$. Equivalently, both ζ/μ_1 and ε/μ_2 share the cdf $F(\xi) = \exp(-\exp(-\xi))$. Our utility function being defined up to a multiplicative constant, we can normalize without loss of generality, by choosing the identification restriction $\mu_1 + \mu_2 = 1$. The moment that the agent is choosing an area k, he knows the value of the random terms $\zeta_{1,t}, \ldots, \zeta_{K,t}$, but he does not know the value of the random terms $\varepsilon_{1,t}, \ldots, \varepsilon_{I,t}$. The value of the random terms $\varepsilon_{i,t}$ is revealed only once an area k has been chosen.

In the second stage, after the agent has chosen area k, he can only choose between alternative locations in area k. Within area k, $\left(z^*_{k,t}\right)' \beta^*$, $\zeta_{k,t}$ and $(x^*_k)' \theta^*$ do not differ across locations, so that the choice of a location maximises the reduced utility

$$U^2_{i,t} = (z_{i,t})' \beta + \alpha^2_i + \varepsilon_{i,t} = V_{i,t} + \varepsilon_{i,t} \tag{3}$$

where

$$V_{i,t} = (z_{i,t})' \beta + \alpha^2_i \tag{4}$$

$$\alpha^2_i = (x_i)' \theta + \eta_i \tag{5}$$

As such, the probability of the migrant choosing location i within area k, $p_{i,t}^2$, has a logit form,

$$p_{i,t}^2 = \frac{\exp\left(V_{i,t}/\mu_2\right)}{\sum_{j,\kappa(j)=k}\exp\left(V_{j,t}/\mu_2\right)} = \exp\left(V_{i,t}/\mu_2 - \overline{V}_{k,t}/\mu_2\right) \tag{6}$$

where the inclusive value $\overline{V}_{k,t} = \mu_2 \ln\left(\sum_{j,\kappa(j)=k}\exp\left(V_{j,t}/\mu_2\right)\right)$ equals the expected indirect utility of the migrant settling in location i within area k at date t: $E\left[\max_{i,\kappa(i)=k} U_{i,t}^2\right] = \overline{V}_{k,t}$.

In the first stage, as the migrant does not know the final location he will choose in the second stage, he only chooses the area maximizing the expected utility,

$$\begin{aligned} E\left[U_{i,t}|\kappa(i)=k\right] &= \left(z_{k,t}^*\right)'\beta^* + \left(x_k^*\right)'\theta^* + E\left[\max_{i,\kappa(i)=k} U_{i,t}^2\right] + \zeta_{k,t} \\ &= \left(z_{k,t}^*\right)'\beta^* + \left(x_\kappa^*\right)'\theta^* + \overline{V}_{k,t} + \zeta_{k,t}. \end{aligned} \tag{7}$$

Consequently, the probability of the migrant choosing area k, $p_{k,t}$, has a logit form,

$$p_{k,t}^1 = \frac{\exp\left(\frac{\left(z_{k,t}^*\right)'\beta^* + \left(x_k^*\right)'\theta^* + \overline{V}_{k,t}}{\mu_1}\right)}{\sum_n \exp\left(\frac{\left(z_{n,t}^*\right)'\beta^* + \left(x_n^*\right)'\theta^* + \overline{V}_{n,t}}{\mu_1}\right)}. \tag{8}$$

It should be mentioned that - despite some obvious parallels - our model is not completely identical to the nested logit model developed by McFadden (1978). Both models satisfy the independence of irrelevant alternatives (IIA) property when the choice is restricted to alternative locations situated within the same area. The property however no longer holds when alternatives are located in different areas. There is yet an important difference: in McFadden's nested logit model, the agent always chooses the best alternative, i.e. the location from the set I that offers the highest utility. McFadden (1978) defines $p_{k,t}^1$ as the probability that the best alternative is a location within area k, while $p_{i,t}^2$ is the probability that the best alternative is location i, knowing that it is situated in area $\kappa(i)$. The choice process in McFadden (1978) thus assumes that immigrants are fully informed. Our model, on the other hand, relaxes this assumption and acknowledges that immigrants do not have full information and as such cannot make completely rational decisions. It is an actual two-stage decision model with uncertainty in which the agent chooses, in the first stage, the area maximizing his expected utility and, in the second stage, the best alternative within this area. There is no guarantee, however, that this is also the location with the highest utility among all locations in the set I. Contrary to McFadden's model, the agent is thus not necessarily choosing the best location: if the best alternative is situated in an area where the other locations are bad enough for the expected utility to be low, the agent does not choose this area in the first stage and subsequently cannot choose the best alternative in the second stage. We believe that this more realistically reflects an immigrant's decision making process.

4 Empirical analysis

4.1 Estimation method

Although the estimation follows standard methods for nested logit models with fixed effects, our empirical analysis stumbles across some additional complications. We first maximize the reduced utility from equation (3), i.e. the second stage in our nested logit model. There are three points to note, however. First, given that alternatives to the choice of location i are other municipalities included in area $\kappa(i)$, the set of available alternatives depends upon the area. Second, given that the choice problem is invariant with respect to the scale factor μ_2, we can only estimate the scaled coefficients, β/μ_2 and α_i^2/μ_2. Third, because the choice problem within an area is invariant with respect to an additive constant, the local factors α_i^2 are not identified and we can only estimate the scaled difference $\left(\alpha_i^2 - \alpha_{r(\kappa(i))}^2\right)/\mu_2$ where, for every area k, $r(k)$ is an arbitrarily chosen reference location.[8] Specifically, in the second stage, we maximize the following log likelihood:

$$LL = \sum_{i,t} n_{i,t} \ln p_{i,t}^2 \tag{9}$$

where

$$p_{i,t}^2 = \frac{\exp\left((z_{i,t})' b + a_i^2\right)}{\sum_{j,\kappa(j)=k} \exp\left((z_{j,t})' b + a_j^2\right)} \tag{10}$$

with $b = \beta/\mu_2$ and $a_i^2 = \left(\alpha_i^2 - \alpha_{r(\kappa(i))}^2\right)/\mu_2$. The maximum likelihood estimates $\hat{b}$ of b and $\hat{a}_i^2$ of a_i^2 can then be used to calculate the estimated inclusive value for every area k and year t as

$$\hat{V}_{k,t} = \ln\left(\sum_{j,\kappa(j)=k} \exp\left((z_{i,t})' \hat{b} + \hat{a}_i^2\right)\right). \tag{11}$$

Note that $\hat{V}_{k,t}$ is not an estimator of the true unknown inclusive value,

$$\begin{aligned} \overline{V}_{k,t} &= \mu_2 \ln\left(\sum_{j,\kappa(j)=k} \exp\left(\frac{V_{j,t}}{\mu_2}\right)\right) = \mu_2 \ln\left(\sum_{j,\kappa(j)=k} \exp\left((z_{i,t})' b + a_i^2 + \frac{\alpha_{r(k)}^2}{\mu_2}\right)\right) \\ &= \mu_2 \ln\left(\sum_{j,\kappa(j)=k} \exp\left((z_{i,t})' b + a_i^2\right)\right) + \alpha_{r(k)}^2. \end{aligned} \tag{12}$$

$\overline{V}_{k,t}$ may thus be estimated as $\mu_2 \hat{V}_{k,t} + \alpha_{r(k)}^2$ with μ_2 and $\alpha_{r(k)}^2$, however, still unknown.

Subsequently, we proceed to the estimation of the first stage. Replacing $\overline{V}_{k,t}$ in (7) by its estimated value, we get

$$E\left[U_{i,t} | \kappa(i) = k\right] = \left(z_{k,t}^*\right)' \beta^* + (x_k^*)' \theta^* + \mu_2 \hat{V}_{k,t} + \alpha_{r(k)}^2 + \zeta_{k,t}. \tag{13}$$

[8] Consequently, as argued in Section 2, the analysis is robust to fluctuations in the migrant stock related to changes in the naturalization policy as long as they do not affect the distribution of immigrants across districts and municipalities, which is likely to be the case.

Again, three points are worth noting. First, because θ^* and the vector of local effects $\left(\alpha^2_{r(1)}, \ldots, \alpha^2_{r(K)}\right)$ are not identified independently of each other, we can only estimate the "area effects" $\alpha^1_k = (x^*_k)' \theta^* + \alpha^2_{r(k)}$. Second, when no identification condition is specified, only the scaled coefficients, $b^* = \beta^*/\mu_1$, $\lambda = \mu_2/\mu_1$ and α^1_k/μ_1 are identified[9]. Third, the "area effects" themselves are not fully identified. Only the scaled differences to a reference area (say area K), $a^1_k = \left(\alpha^1_k - \alpha^1_K\right)/\mu_1$ can be estimated. Specifically, in the first stage of the nested logit model, we maximize the following log likelihood:

$$LL = \sum_{k,t} N_{k,t} \ln p^1_{k,t} \tag{14}$$

where

$$N_{k,t} = \sum_{i,\kappa(i)=k} n_{i,t} \tag{15}$$

$$p^1_{k,t} = \frac{\exp\left(\left(z^*_{k,t}\right)' b^* + a^1_k + \lambda \hat{V}_{k,t}\right)}{\sum_m \exp\left(\left(z^*_{m,t}\right)' b^* + a^1_m + \lambda \hat{V}_{m,t}\right)} \tag{16}$$

which gives maximum likelihood estimates $\hat{\lambda}$ of λ, $\hat{b}^*$ of b^* and $\hat{a}^1_k$ of a^1_k. Subsequently using the equalities $\lambda = \mu_2/\mu_1$ and $\mu_1 + \mu_2 = 1$, we get estimates for μ_1 and μ_2:

$$\hat{\mu_1} = \frac{1}{\hat{\lambda} + 1} \tag{17}$$

$$\hat{\mu_2} = \frac{\hat{\lambda}}{\hat{\lambda} + 1}. \tag{18}$$

Then, combining

$$\alpha_i = (x_i)' \theta + \left(x^*_{\kappa(i)}\right)' \theta^* + \eta_i \tag{19}$$

$$\alpha^2_i = (x_i)' \theta + \eta_i \tag{20}$$

$$\alpha^1_k = (x^*_k)' \theta^* + \alpha^2_{r(k)} \tag{21}$$

gives

$$\alpha_i = \alpha^1_{\kappa(i)} + \alpha^2_i - \alpha^2_{r(\kappa(i))} \tag{22}$$

$$\alpha_{r(K)} = \alpha^1_K + \alpha^2_{r(K)} - \alpha^2_{r(K)} = \alpha^1_K \tag{23}$$

for any location i and reference location $i = r(K)$ within the reference area K, respectively. Now, using the fact that

$$\mu_2 a^2_i = \alpha^2_i - \alpha^2_{r(\kappa(i))} \tag{24}$$

$$\mu_1 a^1_k = \alpha^1_k - \alpha^1_K \tag{25}$$

[9] Note that, contrary to McFadden's nested logit model, λ is not restricted to the unit interval for the model to be consistent with utility maximization, it only needs to be non-negative.

we get

$$a_i \equiv \alpha_i - \alpha_{r(K)} = \alpha_i - \alpha_K^1 = \left(\alpha_{\kappa(i)}^1 - \alpha_K^1\right) + \left(\alpha_i^2 - \alpha_{r(\kappa(i))}^2\right) = \mu_1 a_{\kappa(i)}^1 + \mu_2 a_i^2 \tag{26}$$

which may be estimated as

$$\hat{a}_i = \hat{\mu_1} \hat{a}_{\kappa(i)}^1 + \hat{\mu_2} \hat{a}_i^2 = \frac{\hat{a}_{\kappa(i)}^1 + \hat{\lambda} \hat{a}_i^2}{\hat{\lambda} + 1}. \tag{27}$$

These estimated local effects can then be used to estimate θ and θ^* in

$$a_i = \alpha_i - \alpha_{r(K)} = \left(x_i - x_{r(K)}\right)' \theta + \left(x_{\kappa(i)}^* - x_K^*\right)' \theta^* + \eta_i - \eta_{r(K)} \tag{28}$$

which, using the estimated values for a_i, transforms to

$$\hat{a}_i = \left(x_i - x_{r(K)}\right)' \theta + \left(x_{\kappa(i)}^* - x_K^*\right)' \theta^* + \eta_i - \eta_{r(K)} + u_i \tag{29}$$

with u_i a random error term.

This equation may be estimated using standard least squares (OLS) methods. One must however account for potential autocorrelation generated by the nested and spatial structure of locations that are situated in the same area or spatially correlated, respectively. Both spatial lag models (SAR) and spatial error models (SEM) have been used to capture this geographic interdependence (Anselin, 1988). In fact, the spatial econometrics literature provides both theoretic and econometric motivations for the use of spatial regression models. Theoretic motivations refer to the formal specification of the theoretical model in which spatial interaction is assumed. The most important econometric motivations involve (i) bilateral flows describing a diffusion process over space with a time lag, which show up in a cross-sectional model in the form of a SAR model, and (ii) omitted latent influences that are spatial in nature, which lead to a spatial Durbin model (SDM) with spatial lags of both the dependent and explanatory variables (LeSage and Pace, 2009).

We do not a priori assume spatial dependence but rather use ordinary and robust Lagrange Multiplier (LM) tests to evaluate its presence (in the form of a spatial lag or spatial error) in the local effects. Subsequently, we follow the approach of LeSage and Pace (2008), LeSage and Pace (2009) and Elhorst (2010), which starts from a spatial Durbin model, the most general model of spatial dependence, and relies on specification tests to determine whether this model can be simplified to a SAR or SEM model. LeSage and Pace (2009) show that the SDM is less affected by omitted variable bias than a model that ignores spatial dependence. This holds when the omitted variable is truly involved in the data generating process, but also when it is not, its inclusion does not lead to bias in the estimates. Consequently, the authors suggest relying on a model that includes spatial lags of the dependent and explanatory variables even if this seems counterintuitive at first.

It should be noted that our estimation method is robust to zero flows. More precisely, even though the time dimension is quite large (our sample has 13 years), some locations never received an immigrant (from a specific nationality) during the period. For these locations, the flow is zero every year, which implies that the estimated probability of receiving a migrant is zero and that the estimator of the local fixed effect, $\hat{\alpha}_i$, is minus infinity. Consequently, these observations are dropped from our sample. Yet, this does not bias our results because of the following reason. In the first stage, the IIA property holds within every area, so that restricting the choice set within an area still results in consistent estimates. Analogously, in the second stage, the IIA property holds for the choice across areas, so that again restricting the choice set still leads to consistent estimates.

The estimation approach outlined above allows us to carry out several specification tests. A first series of tests looks at the value $\hat{\lambda}$, the coefficient of the inclusive value. First, in order to ensure that our model is compatible with the random utility function from which it is derived, $\hat{\lambda}$ should be non-negative. When it moreover falls in the interval [0,1], our model is equivalent to the nested logit model developed by McFadden (1978). Second, if $\hat{\lambda} = 1$ (or, equivalently, $\hat{\mu}_1 = \hat{\mu}_2$), our model reduces to the standard logit model. Note however that even if the true model is a standard logit one, our first stage estimation provides consistent estimates of the parameters b and a_i^2. Consistency is a straightforward consequence of the IIA property: for every location, restricting the choice set to the locations of the same area leads to a standard logit choice model where the IIA property holds. As such, estimating the model using these restricted choice sets still leads to consistent parameter estimates. Restricting the choice set, however, leads to a loss in information, reducing efficiency. Third, when $\hat{\mu}_1 = 0$, there is no uncertainty in the first stage, i.e. the choice of an area, so that all immigrants concentrate in the same area. However, within this area, they may still spread across different locations. Equivalently, when $\hat{\mu}_2 = 0$, there is no uncertainty in the second stage, i.e. the choice of a location within an area: within each area, all the immigrants concentrate in the same location. However, at the area level, they may spread across different areas.

4.2 Empirical specification

4.2.1 Time varying variables

In order to empirically investigate the relative importance of network effects and location characteristics, we need to identify arguments for $z_{i,t}$ and $z^*_{k,t}$. The vector of location-specific factors, $z_{i,t}$, includes a measure of the size of the local network. Following standard practice, the latter is approximated by the local stock of migrants from the same origin country as a share of the local population at the end of the previous period, $s_{i,t-1}$. Yet, we believe that not only the network effect of the location itself but also that of neighboring locations might act as a pull towards newcomers. As argued above, the choice for a specific location might be linked to the spatial nearness of the social network, but this does not necessarily require the network is situated in the exact same location. Therefore, our empirical specification includes also the average migrant stock in the direct neighbors to each location (whether or not they belong to the same area) relative to the population in those neighboring locations, denoted $sn_{i,t-1}$.[10]

In order to capture housing market conditions, we include average prices and the number of transactions for both houses (i.e. $hp_{i,t}$ and $ht_{i,t}$) and apartments (i.e. $ap_{i,t}$ and $at_{i,t}$) at the local level. To control for scale effects, the number of transactions is taken as a share of the local population. In addition, house and apartment prices are expressed in differences with respect to the cross-sectional mean to eliminate any potential effect of rising housing prices during the sample period. We have no a priori expectations about the sign of average housing prices: a negative sign suggests immigrants prefer locations where housing is relatively cheap, whereas a positive sign might signal that immigrants from a certain country prefer locations with a higher social standard. More precisely, theory suggests that the value that agents attach to local amenities and local public goods is capitalized in property prices in these localities. This results in a positive correlation between the prices of real estate on the one hand, and amenities and local public goods on the other hand. If we would dispose of a full set of covariates providing an extensive description of local amenities and public goods, the coefficient of the price would be negative, as in every negatively sloped demand function. However, the set of covariates available for describing locations is fairly limited, so that many amenities are omitted in our empirical specification, leading to a positive sign of housing prices. The latter indicates that, when households need to choose between locations with poor amenities and low housing prices and locations with ample amenities where land prices are higher, they will opt for the later because the price difference generated by the market remains below their willingness to pay for a higher level of amenities. This positive sign is more likely to be observed when the population is more sensitive to the level of amenities. For the number of housing transactions we expect a positive sign in line with the idea that a more active housing market facilitates the acquisition of accommodation in the destination.

As argued above, labor market conditions are expected to play at the area level rather than the local level. As such, we use the foreign employment rate at the area level, $e_{k,t}$, as a proxy for area-specific job opportunities for immigrants, $z^*_{k,t}$.[11] It is obtained as the sum - over all sectors - of the product of (i) the sectoral share by nationality in national employment and (ii) the share of the sector in total employment

[10] In order to avoid taking the log of zero, we add unity to the migrant stock variables before calculating population shares.

[11] Ideally, we would also include a measure of average wages to capture expected income opportunities. Unfortunately, data on average wages is unavailable. One solution would be to proxy for it using average income declarations per inhabitant. The latter is however severely correlated with housing prices suggesting that it captures also other effects besides average income opportunities. Consequently, we do not include this measure in our empirical specification.

at the area level. Hence, assuming a logarithmic utility function, we define

$$
\begin{aligned}
(z_{i,t})' \beta = \beta_1 \ln(s_{i,t-1}) + \beta_2 \ln(sn_{i,t-1}) \\
+ \beta_3 \ln hp_{i,t} + \beta_4 \ln ap_{i,t} + \beta_5 \ln ht_{i,t} + \beta_6 \ln at_{i,t}
\end{aligned} \tag{30}
$$

$$
(z^*_{k,t})' \beta^* = \beta^*_1 e_{k,t}. \tag{31}
$$

4.2.2 Time invariant variables

Furthermore, recall that α_i is considered to capture all the time invariant location factors, such as overall capacity, migration costs or the presence of public amenities. It is straightforward to see that larger locations are able to host more immigrants. Popular proxies for the size of locations and as such also their hosting capacity are surface (sf_i) and population density (pd_i). In order to control for these size effects, we include both measures in our empirical specification. Migration costs are often proxied by the distance to the origin country or the presence of a common border. Both indicators have proven to influence monetary expenses as well as non-monetary opportunity costs (such as foregone earnings while traveling and finding a job) incurred by the migrant (see e.g. Karemera et al., 2000; Gallardo-Sejas et al., 2006; Lewer and Van den Berg, 2008; Pedersen et al., 2008; Mayda, 2010). Given the relatively small size of the locations in our sample, there is not much variation in the distance between origin country and destination location and, as such, its inclusion in the empirical specification does not make much sense.[12] The spatial concentration of immigrants from neighboring countries along the border of their country of origin, however, suggests that the presence of a common border positively influences migration to those locations. Yet, this positive effect is not confined to the strict set of locations actually situated along the border (see Figures 1 and 2), but rather seems decaying in nature. To capture this, we incorporate the minimal distance to the nearest border, dbo_i on top of the minimal distance to Brussels, dbr_i, which is supposed to capture the relative attractiveness of the capital region as the principal transportation hub holding the largest international airport and train connections to international destinations and other locations within Belgium.

Besides geographical proximity, also externalities such as the presence of amenities and public goods are expected to foster the genuine attractiveness of locations. To proxy for these externalities, we include the number of hospitals, ho_i, secondary schools, sc_i, and sport clubs, sp_i, in percentage of the local population. Furthermore, we account also for the size of the motorway network as a share of the total surface, mw_i, and for the touristic attractiveness of municipalities, i.e. hotel occupancy in nights per inhabitant, to_i.

[12] The same holds for variables capturing environmental conditions: given the small size of Belgian municipalities and Belgium as a whole, there is not much climatological variation across locations which renders its inclusion uninformative.

Finally, we expect that also cultural proximity, captured by the presence of a common language, cl, facilitates adaptation and integration in the new environment which in turn reduces the costs of migration and increases migration to those locations (see also Karemera et al., 2000; Gallardo-Sejas et al., 2006; Lewer and Van den Berg, 2008; Pedersen et al., 2008). As such, the local effect, α_i, can be written as

$$\begin{aligned}\alpha_i = \gamma_0 &+ \gamma_1 \ln sf_i + \gamma_2 \ln pd_i + \gamma_3 \ln dbo_i + \gamma_4 \ln dbr_i \\ &+ \gamma_5 \ln ho_i + \gamma_6 \ln sc_i + \gamma_7 \ln sp_i + \gamma_8 \ln mw_i + \gamma_9 \ln to_i + \gamma_{10} cl_i. \end{aligned} \tag{32}$$

Consequently, combining equations (30), (31) and (32) we can rewrite equation (1) as

$$\begin{aligned} U_{i,t} = \gamma_0 &+ \beta_1 \ln(s_{i,t-1}) + \beta_2 \ln(sn_{i,t-1}) \\ &+ \beta_3 \ln hp_{i,t} + \beta_4 \ln ap_{i,t} + \beta_5 \ln ht_{i,t} + \beta_6 \ln at_{i,t} + \beta_1^* e_{k,t} \\ &+ \gamma_1 \ln sf_i + \gamma_2 \ln pd_i + \gamma_3 \ln dbo_i + \gamma_4 \ln dbr_i \\ &+ \gamma_5 \ln ho_i + \gamma_6 \ln sc_i + \gamma_7 \ln sp_i \\ &+ \gamma_8 \ln mw_i + \gamma_9 \ln to_i + \gamma_{10} cl_i + \zeta_{\kappa(i),t} + \varepsilon_{i,t}, \end{aligned} \tag{33}$$

which corresponds to the empirical specification of location choice that will be estimated in the next section. Note that equation (33) encompasses two sources of persistence: at date t, location i might be attractive because of (i) the effect of the time invariant location factors, measured by α_i, or (ii) because it has attracted immigrants in the past, who developed a local network, the size of which is measured by $s_{i,t-1}$ and $sn_{i,t-1}$.

Furthermore, equation (33) ignores spatial dependence in the location decision. The strong spatial concentration of immigrants, however, suggests that the error terms, and specifically the local effects, are likely to exhibit spatial dependence. In fact, the empirical literature on location decisions often explicitly acknowledges the presence of spatial dependence and makes use of spatial econometric techniques. In the migration context, however, only Jayet et al. (2010) and Ukrayinchuk and Jayet (2011) explicitly address spatial dependence in the location decision of immigrants in the destination country and find a highly significant coefficient for the spatial terms suggesting a great deal of spatial interconnection between the location of immigrants across Italian provinces and Swiss regions, respectively. In what follows, we do not impose a specific form of spatial dependence but rather rely on specification tests to determine its presence and structure. Starting from the most general specification of spatial dependence, i.e. a spatial Durbin model, we can write equation (32) as

$$\alpha_i = \gamma_0 + \rho W \alpha_i + \gamma_m X_i + \sigma_m W X_i \tag{34}$$

with $\gamma_m = (\gamma_1, ..., \gamma_{11})$, $X_i = (\ln sf_i, \ln pd_i, \ln dbo_i, \ln dbr_i, \ln ho_i, \ln sc_i, \ln sp_i, \ln mw_i, \ln to_i, cl_i)$ and W a row-normalized spatial weight matrix of inverse distances.

Most of the data for the explanatory variables has been collected from the Belgian Directorate for General Statistics and Economic Information. This is the case for migration statistics but also for housing, labor market and geographical variables as well as information on the motorway network, hotel occupancy, urbanization and the local official language. For apartment prices, part of the data is missing. To deal with this, we plug in zeros for all missing observations and include a dummy variable coded one if data in the original value was missing and zero otherwise. This procedure however does not affect our estimation results (the results for the remaining variables are not affected by the inclusion of apartment prices in the empirical specification). Other sources include the Belgian Hospitals Association for the number of hospitals, the Federation Wallonia-Brussels for data on the number of secondary schools and sport clubs in the French speaking community and the German community ministry for the same data in the German speaking districts. For the Flemish speaking region, these data have been obtained from the Flemish Ministry of Education and Training and Bloso, the sport administration of the Flemish government, respectively. Whereas the data on the number of secondary schools are reasonably compatible, this is not true for the number of sport clubs. In order to guarantee consistency, we subtract the regional mean from the number of sport clubs for each municipality.

Table A-4 displays descriptive statistics for immigrant flows and stocks at district level and municipality level. Pairwise correlation coefficients for time varying and time invariant explanatory variables can be found in Tables A-5 and A-6, respectively. Because of the panel data nature of the first step explanatory variables, the correlation coefficients presented in Table A-5 correspond to within correlation, i.e. the pairwise correlation between the explanatory variables after having demeaned the variables over time. Overall, pairwise correlations are fairly limited.

4.3 Endogeneity issues

Before presenting the results, a number of endogeneity problems that may be generated by our network variables should be mentioned. In the analysis of social interactions, two major sources of endogeneity prevail. First, the behavior of the reference population used to develop the social interaction variables may be influenced by the behavior of the individuals included in the sample. Second, both the sampled population and the reference population may be influenced by the same unobserved factors. The first source of endogeneity does not affect our analysis: at year t, our sample includes all the migrants entering Belgium during year t, while our network variables are local stocks of migrants who entered Belgium prior to the year t. The location choice of migrants who arrived before t is unlikely to be influenced by the location choice of those arriving at year t, i.e. future migrants.

The fact that the location choice of immigrants arriving during the year t and the stock of migrants present at the beginning of year t is influenced by the same location factors seems more of a concern at first. Note, however, that in order to influence both the stock of migrants who made their location choice prior to t and the flow of migrants making their location choice during year t, a location factor must be permanent. The impact of these location factors is measured by our local fixed effects, α_i, and does not appear in the random terms $\zeta_{\kappa(i),t}$ and $\epsilon_{i,t}$. Furthermore, the local fixed effects, α_i, are estimated parameters, which preserves our analysis from being affected by the second source of endogeneity. More precisely, at date t, the only random terms influencing the location choice of the stock of migrants are the random terms for previous years, $\zeta_{\kappa(i),t-1}, \zeta_{\kappa(i),t-2}, \ldots$ and $\epsilon_{i,t-1}, \epsilon_{i,t-1}, \ldots$. But, all the random terms being i.i.d., $\zeta_{\kappa(i),t}$ and $\epsilon_{i,t}$ are not correlated with $\zeta_{\kappa(i),t-1}, \zeta_{\kappa(i),t-2}, \ldots$ and $\epsilon_{i,t-1}, \epsilon_{i,t-1}, \ldots$ so that time-variant location factors do not generate endogeneity. As such, the network variables in our analysis are not subject to endogeneity problems.

5 Estimation results

The estimations are carried out for the total population of immigrants and for the seven most important national origins: France, Germany, Italy, Morocco, The Netherlands, Poland and Turkey. The locations are the 588 Belgian municipalities. Areas (i.e. groups of municipalities) are defined as the 43 Belgian districts. Given that labor market variables are a crucial element in our theoretical model of the location decision, the analysis focusses on immigrants at working age only.

In what follows, we present results from the hierarchical nested logit model and from a decomposition of the immigration rate to evaluate the relative importance of the two sources of persistence: network effects and location factors. Finally, we regress the estimated local effects on the time invariant location characteristics in order to investigate their role in the location decision.

5.1 Time-varying determinants of immigrants' location choice

Table 3 presents the estimation results of the nested logit model described above. The model systematically converges and the results are robust to changes in the initial value of the coefficients in the maximization algorithm.

First of all, reffering to the specification tests discussed in Section 4.1, we find a positive significant coefficient for the inclusive value (i.e. $\hat{V}_{k,t}$) for all nationalities in our analysis. For three of the seven nationalities considered, the coefficients for the inclusive value do not fall within the $[0, 1]$ interval as would be expected from McFadden's (1978) nested logit model.

Table 3: Time varying determinants of immigrants' location choice - Nested logit

Variable	TOT	DE	FR	IT	MA	NL	PL	TR
$\hat{V}_{k,t}$	0.372***	1.199***	0.585***	1.917***	0.767***	1.086***	0.658***	0.943***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln s_{i,t-1}$	−0.086***	0.059	0.246***	0.022	0.195***	0.134***	0.071***	0.296***
	(0.000)	(0.244)	(0.000)	(0.786)	(0.000)	(0.002)	(0.002)	(0.000)
$\ln sn_{i,t-1}$	−0.340***	0.446***	0.060	0.465**	0.169***	−0.452***	0.047	0.138**
	(0.000)	(0.000)	(0.562)	(0.016)	(0.009)	(0.000)	(0.334)	(0.010)
$\ln ph_{i,t}$	0.077***	0.038	0.383***	0.010	−0.351***	0.458***	−0.764***	0.032
	(0.001)	(0.691)	(0.000)	(0.947)	(0.000)	(0.000)	(0.000)	(0.835)
$\ln pa_{i,t}$	0.010	−0.066**	−0.005	0.001	−0.022	0.001	−0.070	−0.145***
	(0.137)	(0.012)	(0.783)	(0.979)	(0.555)	(0.959)	(0.105)	(0.002)
$\ln th_{i,t}$	0.040***	0.071*	−0.014	−0.061	0.170***	0.152***	−0.102**	0.012
	(0.000)	(0.066)	(0.594)	(0.245)	(0.000)	(0.000)	(0.011)	(0.837)
$\ln ta_{i,t}$	0.006	0.031	0.007	−0.066**	0.037	0.044***	−0.006	0.022
	(0.269)	(0.187)	(0.661)	(0.033)	(0.125)	(0.000)	(0.831)	(0.461)
$\ln e_{k,t}$	1.111***	1.991***	2.206***	−0.250	0.603***	−0.310	2.793***	−0.028
	(0.000)	(0.002)	(0.000)	(0.675)	(0.000)	(0.446)	(0.000)	(0.783)
$\hat{\mu}_1$	0.729***	0.455***	0.631***	0.343***	0.566***	0.479***	0.603***	0.515***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\hat{\mu}_2$	0.271***	0.545***	0.369***	0.657***	0.434***	0.521***	0.397***	0.485***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wald $\hat{\mu}_1 = \hat{\mu}_2$	107.868***	1.748	9.501***	45.515***	6.037**	1.604	5.272**	0.275
P-val	(0.000)	(0.186)	(0.002)	(0.000)	(0.014)	(0.205)	(0.022)	(0.600)
LL_1	-1600308	-66339	-175393	-50252	-117620	-174903	-66439	-40006
LL_2	-2079377	-75121	-210232	-65756	-135346	-204820	-74839	-72306

Note: P-values between brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Furthermore, for all seven nationalities, both scale factors $\hat{\mu}_1$ and $\hat{\mu}_2$ are positive and significantly differ from zero. This finding suggests that there is uncertainty in the choice of both the area and the location within the area so that we can exclude spatial concentration of immigrants in one district or in one municipality within the district. The scale factors strongly differ across nationalities, but are close to 0.5 for Germans, Dutch and Turks, implying that the variance of the random term at the area level is approximately the same as the variance of the random term at the municipal level. In fact, a Wald test reveals that for these nationalities, the estimated scale effects are not significantly different (or equivalently $\hat{\lambda}$ is not significantly different from one). For the remaining nationalities, however, we can reject the null hypothesis that our model may be reduced to a standard non nested logit model.[13]

For the total immigrant population, the size of the network in a particular municipality as well as that in neighboring municipalities seems to discourage settlement in that municipality. This is not

[13] This implies that for three nationalities, we could reduce the model to a conditional logit model and that the nested structure is redundant. Other specification tests, however, (i.e. a log-likelihood test, as suggested by (Börsch-Supan, 1987)) give conflicting results. Given that, as mentioned above, the nested logit model produces consistent estimates even if the nested structure is not required, we prefer to keep the nested logit model for all the nationalities. Comparing the results from the nested logit model with those obtained for the conditional logit model - as presented in Table A-7 - we see the estimates for Germans, Dutch and Turkish immigrants do not substantially differ.

surprising given that the overall immigrant flow and stock group a multitude of nationalities, rendering the notion of a national network inapplicable. Only when network effects could be interpreted as some kind of herd effect (as is often the case in a context of imperfect information), we would expect a positive coefficient (see e.g. Bauer et al., 2007; Epstein, 2008). Considering nation specific networks, on the other hand, renders a completely different picture. The estimated network effect is positive and highly significant for all nationalities except for Germans and Italians. For these immigrants, however, we find evidence for a strong pull effect from average stocks in neighboring municipalities. To a lesser extent, also Moroccans and Turks seem attracted to municipalities with large Moroccan and Turkish communities in those surrounding them. Against expectations, the estimated parameter for average stocks in neighboring municipalities appears significantly negative for the Dutch, although the size of the network in the municipality itself has a highly significant positive impact. The largest influence of the own network effect is, nevertheless, found for Turks and the French.

As far as concerns the housing market variables, we find a significantly positive impact of house prices for immigrants from neighboring countries. The coefficient appears negatively significant for Moroccans and Poles. The prices of apartments are only significant with a negative sign for Germans and Turks, and insignificant for the remaining nationalities. French and Dutch often locate close to the border, which suggest that they move to Belgium for housing reasons. As such, they are likely to be highly sensitive to the level of local amenities and local public goods, which, as noted in section 4.2.1, explains the positive sign. On the contrary, immigrants from poor and distant countries, like Moroccans and Poles, move mainly for labor market reasons and do not have enough resources for accepting to pay for higher levels of amenities, hence the negative sign of the housing price variable.

When significant, the coefficients of house (apartment) transactions are generally positive, except for Poles (Italians). This confirms that immigrants favor municipalities where the acquisition of housing is relatively less challenging.[14]

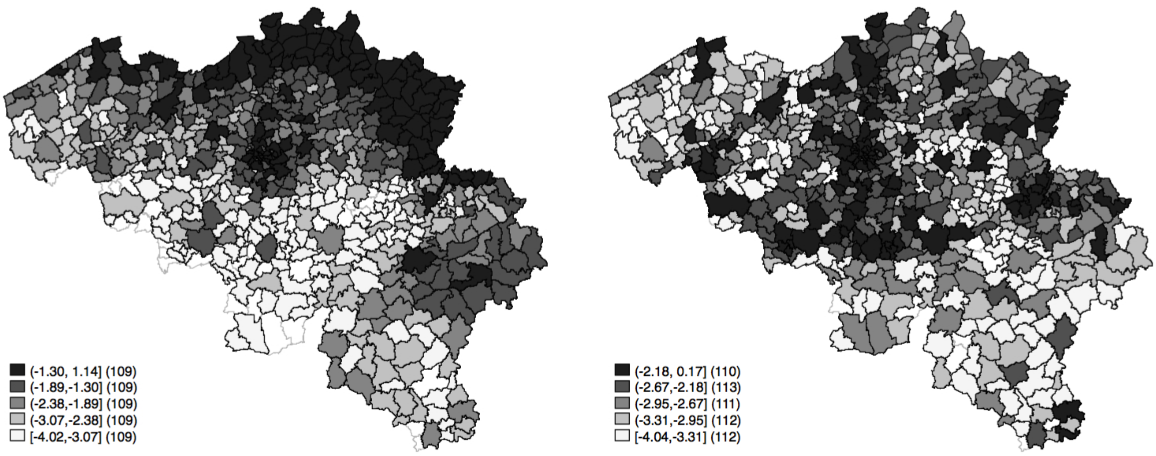
With respect to the employment rate, we find that significant effects are always positive in line with our expectations. The largest effect is observed for Polish immigrants, followed by French and Germans. Employment opportunities within the district do not seem to play a significant role in shaping the location pattern of Italians, Turks and the Dutch.

Finally, as they are too numerous to be tabulated, estimated "local effects", $\hat{a}_i$, are illustrated in Figure

[14]It might be argued that a large inflow of immigrants in a municipality might create pressure on the housing market, driving up housing prices and the number of transactions. Given that we consider bilateral immigrant flows, however, the effect of migration on housing prices and transactions is likely to be minor. In order to test for potential reverse causality, we re-estimated the model using the first, second or third lag of housing prices. Though not reported here for brevity, the results appear robust to whether these variables are lagged or not. The results are available upon request from the authors.

3, for two representative cases, i.e. Dutch and Moroccan immigration.[15] The maps indicate to which municipalities immigrants are drawn once network effects and other time varying location determinants have been neutralized. For the Dutch case, we find important local effects in municipalities located along the Dutch border, in and around Brussels and in the South-East. In the Moroccan case, on the other hand, attractive municipalities are more spread and especially situated along a North-South line, from Antwerp to Charleroi through Brussels. The importance of these location effects relative to networks is explored below.

Figure 3: Local effects for Dutch and Moroccan immigrants



5.2 Networks versus local effects

In this section we examine to what extent the current location pattern of immigrants in Belgium is determined by the genuine attractiveness of locations (captured by the local effects) relative to the network effect. In other words, we want to examine which source of persistence is the most powerful. This question can be answered by decomposing the number of immigrants in each location into a part explained by the network effect, the local effect and a residual. This allows us to define the number of immigrants who would be choosing a certain location if there were no network (local) effects and to single out the direct consequence of network (local) effects.

To calculate the immigrant rates predicted by the different models, let us rewrite the probability equations (6) and (8) by replacing $z_{i,t}$ and $z_{k,t}$ by their functional form in (30) and (31) and the parameters $\beta = (\beta_0, ..., \beta_6)$, β_1^* and α_i by their estimated values . Specifically, the probability that a migrant chooses

[15] The location effects could not be estimated for a small number of municipalities, namely those that did not receive any migrant of a specific nationality during the sample period.

a certain location i at time t, i.e. $\hat{p}_{i,t}$, becomes

$$\hat{p}_{i,t} = \hat{p}^2_{i,t}\hat{p}^1_{\kappa(i),t} \tag{35}$$

$$\hat{p}^2_{i,t} = \frac{\exp\left(\hat{b_1}(\ln s_{i,t-1}+1)+\hat{b_2}(\ln sn_{i,t-1}+1)+\Omega_{i,t}+\hat{a}^2_i\right)}{\sum_{j,\kappa(j)=k}\exp\left(\hat{b_1}(\ln s_{j,t-1}+1)+\hat{b_2}(\ln sn_{j,t-1}+1)+\Omega_{j,t}+\hat{a}^2_j\right)} \tag{36}$$

$$\hat{V}_{k,t} = \log\left(\sum_{j,\kappa(j)=k}\exp\left(\hat{b_1}(\ln s_{j,t-1}+1)+\hat{b_2}(\ln sn_{j,t-1}+1)+\Omega_{j,t}+\hat{a}^2_j\right)\right) \tag{37}$$

$$\hat{p}^1_{k,t} = \frac{\exp\left(\hat{b^*_1}\ln u_{i,t}+\hat{a}^1_k+\hat{\lambda}\hat{V}_{k,t}\right)}{\sum_m \exp\left(\hat{b^*_1}\ln u_{m,t}+\hat{a}^1_m+\hat{\lambda}\hat{V}_{m,t}\right)} \tag{38}$$

with $\Omega_{i,t}$ the vector of all time varying location factors except network effects, namely

$$\Omega_{i,t} = \hat{b_3}\ln hp_{i,t} + \hat{b_4}\ln ap_{i,t} + \hat{b_5}\ln ht_{i,t} + \hat{b_6}\ln at_{i,t}. \tag{39}$$

If there were no network effects, the parameters $\hat{b_1}$ and $\hat{b_2}$ would be zero, so that the estimated probability without network effects becomes

$$\hat{p}^{'}_{i,t} = \hat{p}^{2'}_{i,t}\hat{p}^{1'}_{\kappa(i),t} \tag{40}$$

$$\hat{p}^{2'}_{i,t} = \frac{\exp\left(\Omega_{i,t}+\hat{a}^2_i\right)}{\sum_{j,\kappa(j)=k}\exp\left(\Omega_{i,t}+\hat{a}^2_j\right)} \tag{41}$$

$$\hat{V}^{'}_{k,t} = \log\left(\sum_{j,\kappa(j)=k}\exp\left(\Omega_{i,t}+\hat{a}^2_j\right)\right) \tag{42}$$

$$\hat{p}^{1'}_{k,t} = \frac{\exp\left(\hat{b^*_1}\ln u_{i,t}+\hat{a}^1_k+\hat{\lambda}\hat{V}^{'}_{k,t}\right)}{\sum_m \exp\left(\hat{b^*_1}\ln u_{m,t}+\hat{a}^1_m+\hat{\lambda}\hat{V}^{'}_{m,t}\right)}. \tag{43}$$

Without local effects, on the other hand, the parameters $\hat{a}^2_i$ and $\hat{a}^1_k$ are set to zero which results in the following estimated probabilities

$$\hat{p}^{''}_{i,t} = \hat{p}^{2''}_{i,t}\hat{p}^{1''}_{\kappa(i),t} \tag{44}$$

$$\hat{p}^{2''}_{i,t} = \frac{\exp\left(\hat{b_1}(\ln s_{i,t-1}+1)+\hat{b_2}(\ln sn_{i,t-1}+1)+\Omega_{i,t}\right)}{\sum_{j,\kappa(j)=k}\exp\left(\hat{b_1}(\ln s_{j,t-1}+1)+\hat{b_2}(\ln sn_{j,t-1}+1)+\Omega_{j,t}\right)} \tag{45}$$

$$\hat{V}^{''}_{k,t} = \log\left(\sum_{j,\kappa(j)=k}\exp\left(\hat{b_1}(\ln s_{j,t-1}+1)+\hat{b_2}(\ln sn_{j,t-1}+1)+\Omega_{j,t}\right)\right) \tag{46}$$

$$\hat{p}^{1''}_{k,t} = \frac{\exp\left(\hat{b^*_1}\ln u_{i,t}+\hat{\lambda}\hat{V}^{''}_{k,t}\right)}{\sum_m \exp\left(\hat{b^*_1}\ln u_{m,t}+\hat{\lambda}\hat{V}^{''}_{m,t}\right)}. \tag{47}$$

Subsequently, we calculate the number of migrants in each location as predicted by the complete model and the models without networks and local effects, respectively. Let $n_{.,t}$ denote the total number of foreigners (from a certain origin country) in Belgium at date t and $N_{i,t}$ the total population of location

i at date t. Then $\tau_{i,t}$ is defined as the percentage of immigrants in the total population in location i at date t. This gives

$$\hat{\tau}_{i,t} = 100 * \hat{n}_{i,t}/N_{i,t} \text{ with } \hat{n}_{i,t} = n_{.,t}\hat{p}_{i,t} \tag{48}$$

$$\hat{\tau}^{'}_{i,t} = 100 * \hat{n}^{'}_{i,t}/N_{i,t} \text{ with } \hat{n}^{'}_{i,t} = n_{.,t}\hat{p}^{'}_{i,t} \tag{49}$$

$$\hat{\tau}^{''}_{i,t} = 100 * \hat{n}^{''}_{i,t}/N_{i,t} \text{ with } \hat{n}^{''}_{i,t} = n_{.,t}\hat{p}^{''}_{i,t} \tag{50}$$

for the complete model, the model without network effects and the model without local factors, respectively. Hence, we can define three residual immigration rates, i.e. the difference between (i) the observed immigration rate and the one predicted by the complete model, i.e. $d_{i,t} = \tau^{obs}_{i,t} - \hat{\tau}_{i,t}$, (ii) the immigration rate predicted by the complete model and the model without network effects, i.e. $d^{'}_{i,t} = \hat{\tau}_{i,t} - \hat{\tau}'_{i,t}$, and (iii) the immigration rate predicted by the complete model and the model without local factors, i.e. $d^{''}_{i,t} = \hat{\tau}_{i,t} - \hat{\tau}''_{i,t}$.

Table 4 provides standard deviations for the observed immigration rates, $\tau^{obs}_{i,t}$, the immigration rates estimated from the complete model, $\hat{\tau}_{i,t}$, the immigration rates estimated from the model without network effects, $\hat{\tau}^{'}_{i,t}$, the immigration rates estimated from the model without local factors, $\hat{\tau}^{''}_{i,t}$, and three residual terms: the difference between the observed and estimated immigration rates from the complete model, $d_{i,t}$, between the immigration rates estimated with and without the network effect, $d^{'}_{i,t}$, as well as with and without the local factors, $d^{''}_{i,t}$. In addition, the table includes correlation coefficients between the estimated immigration rates from the complete model and the observed immigration rates, the immigration rates estimated without network effects and those estimated without local factors, respectively.

We find that the predictive power of the complete model is fairly high, except for Italians. For the other nationalities, the estimated immigration rates predicted by the complete model are highly correlated with the observed immigration rates and their standard deviation mostly exceeds that of residual immigration rates.

Dropping network effects lowers the variance of estimated immigration rates, except for Italians and the Dutch. Apart from German and Turkish immigration, we find a strong correlation between estimated immigration rates from the complete model and the model without network effects. This finding indicates that networks play a more important role for Germans and Turks compared to other nationalities in our sample. Dropping location factors, on the other hand, clearly reduces the variance of the estimated immigration rates for all nationalities, except for German immigrants. Unsurprisingly, we also find very low correlations between immigrant rates estimated by the complete model and the model without location factors, except for German immigrants for whom the correlation remains as high as 0.7.

These findings suggest that, except for German and Turkish immigrants, the role for network effects

Table 4: Decomposition of immigration rates

Immigration rate	TOT	DE	FR	IT	MA	NL	PL	TR
Standard deviation of								
$\eta_{i,t}$	0.344	0.100	0.134	0.032	0.097	0.162	0.053	0.037
$\hat{\eta}_{i,t}$	0.348	0.055	0.133	0.040	0.100	0.160	0.055	0.035
$\hat{\eta}^{'}_{i,t}$	0.330	0.030	0.116	0.046	0.076	0.179	0.053	0.027
$\hat{\eta}^{''}_{i,t}$	0.269	0.050	0.080	0.034	0.047	0.078	0.039	0.021
$d_{i,t}$	0.257	0.063	0.082	0.044	0.064	0.110	0.044	0.022
$d^{'}_{i,t}$	0.115	0.044	0.026	0.020	0.042	0.044	0.006	0.025
$d^{''}_{i,t}$	0.448	0.043	0.149	0.056	0.109	0.185	0.064	0.035
Correlation between $\hat{\eta}_{i,t}$ *and*								
$\eta_{i,t}$	0.724	0.819	0.809	0.263	0.791	0.765	0.664	0.821
$\hat{\eta}^{'}_{i,t}$	0.944	0.617	0.986	0.903	0.919	0.972	0.994	0.699
$\hat{\eta}^{''}_{i,t}$	-0.039	0.666	0.085	-0.135	0.044	-0.106	0.086	0.276

is small. Local effects, on the other hand, seem to unambiguously dominate network effects for all nationalities in our sample.

5.3 Time invariant determinants of immigrants' location choice

Using the consistent local effects estimates from the first step, $\hat{\alpha}_i$, we can finally estimate the parameters of the time invariant location factors defined in (32). As mentioned above, we do not a priori impose any specific form of spatial dependence in the local effects. Rather, the model is estimated first using OLS in order to detect its presence and structure. We use a row-normalized inverse distance spatial weight matrix, W, for both the spatial lag and the spatial error.

OLS estimates and LM test statistics for the presence and structure of spatial dependence can be found in Table A-8. Specifically, the table reports five LM tests: ordinary and robust LM tests for the spatial lag model developed by Anselin (1988) and Kelejian and Robinson (1992) respectively; ordinary and robust LM tests for the spatial error model developed by Burridge (1981) and Kelejian and Robinson (1992) respectively; and an LM test for the joint model incorporating both a spatial lag and a spatial error term. The test statistics always confirm the presence of spatial correlation in the residuals and the presence of a spatial lag in the dependent variable. Consequently, we proceed by estimating an SDM model and report Wald and Likelihood Ratio (LR) tests to see whether the SDM can be simplified to a SAR or SEM model. The test statistics, presented in in the lower panel of Table A-8, reveal that these hypotheses can be rejected at the 1 per cent significance level for all nationalities. As such, the model is estimated using maximum likelihood techniques that account for the presence of a spatial lag in both the local effects and the explanatory variables. This spatial structure has the important advantage that it controls for any omitted variables that exhibit spatial dependence.

Table 5 displays SDM parameter estimates. Overall, we find evidence for a strong and significant spatial lag in the local effects.[16] With a few exceptions, our findings are in line with the predictions of the theoretical model.[17]

Focussing first on the impact of the municipality's genuine location factors (as opposed to their spatially lagged counterparts), surface and population density appear to be the most robust time-invariant location determinants for immigrants. In line with our expectations, the estimated effects are always positive and highly significant for all nationalities in our sample.

As far as concerns the proxies for the migration cost, our results confirm that immigrants from neighboring countries prefer locations close to the border of their home country. Specifically, the effects are always negative except for Turks, but we find significant effects only for Dutch, French, Italian and Polish immigrants. Minimal distance to Brussels appears insignificant for all nationalities.

The relative number of hospitals has a predominant positive effect on migration. The influence of the number of secondary schools as a share of the local population, on the other hand, is mostly insignificant except for French and Italian immigrants with the expected sign. The impact for sport clubs, on the other hand, is significantly positive only for Dutch and Polish immigrants but negatively significant for the French. In general, however, these findings confirm the hypothesis that public amenities may act as a pull for immigrants, once other location factors have been taken into account.

Also the highway network mostly appears with a positive sign, though directly significant only for French immigrants. Touristic attractiveness, measured by hotel occupancy, nonetheless, plays an unambiguous positive role in attracting new immigrants. Besides actual touristic attractiveness, this variable might also capture other characteristics of the municipality that add to its general appeal. The presence of a common language, finally, is always highly significant with the expected sign.

Although the spatially lagged explanatory variables are not our major concern, it is interesting to see that so many of them appear significant, often counterbalancing the impact of the genuine municipality

[16] An implication of accounting for spatial dependence is that - unlike in the case of the independent data model - SDM parameter estimates also contain information about feedback effects: the extent to which a change in an explanatory variable in one location affects the dependent variable in all other locations (see Anselin and Le Gallo, 2006; Kelejian et al., 2006; LeSage and Pace, 2009). Calculating the direct and indirect effects summary measures suggested by LeSage and Pace (2009), however, reveals that the same qualitative results are obtained from both the parameter estimates presented in Table 5 as the direct effects estimates. For most nationalities, however, the spatial lag is close to one, resulting in fairly large indirect effects estimates, which casts doubt on the validity of this summary measure in the current framework. Keeping in mind that in the final step of the estimation procedure we do not aim to provide an in-depth analysis of the role played by each of the location characteristics in shaping the geographical spread of immigrants, but rather present an indication of the relative importance of other factors at work besides network effects, we present only actual parameter estimates. The summary measures are available upon request from the authors.

[17] A comparison of these results with those obtained using the local effects estimated by the conditional logit model - presented in Table A-11 - confirm that the qualitative results hold so that we can safely rely on the nested logit estimates to draw qualitative conclusions about the relative importance of location determinants.

Table 5: Determinants of time-invariant local effects - SDM

	TOT	DE	FR	IT	MA	NL	PL	TR
Intercept	-6.652	-1.001	-5.462^{*}	7.985^{***}	-2.617	-11.802^{***}	-2.160^{**}	-12.941^{***}
	(0.350)	(0.504)	(0.055)	(0.000)	(0.110)	(0.000)	(0.036)	(0.000)
$\ln sf_i$	0.345^{***}	0.684^{***}	0.421^{***}	0.777^{***}	0.556^{***}	0.603^{***}	0.656^{***}	0.544^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln pd_i$	0.471^{***}	0.666^{***}	0.531^{***}	1.069^{***}	0.766^{***}	0.529^{***}	0.842^{***}	0.553^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln dbo_i$	-0.020^{***}	-0.006	-0.015^{***}	-0.035^{***}	-0.002	-0.050^{***}	-0.001^{***}	0.007
	(0.003)	(0.410)	(0.006)	(0.000)	(0.729)	(0.000)	(0.823)	(0.259)
$\ln dbr_i$	0.039	-0.025	0.058	-0.025	-0.012	-0.044	-0.034	0.031
	(0.486)	(0.653)	(0.204)	(0.744)	(0.755)	(0.500)	(0.468)	(0.555)
$\ln ho_i$	0.058	0.143^{***}	0.123^{***}	0.144^{*}	0.051	0.041	0.137^{***}	0.118^{**}
	(0.265)	(0.006)	(0.004)	(0.056)	(0.175)	(0.517)	(0.004)	(0.017)
$\ln sc_i$	-0.003	0.002	0.045^{***}	0.039^{***}	0.010	0.004	-0.004	0.003
	(0.746)	(0.866)	(0.000)	(0.005)	(0.260)	(0.851)	(0.659)	(0.760)
$\ln sp_i$	-0.064	-0.003	-0.087^{***}	0.018	-0.024	0.098^{**}	0.067^{*}	-0.020
	(0.103)	(0.943)	(0.008)	(0.801)	(0.456)	(0.043)	(0.082)	(0.604)
$\ln mw_i$	0.005	-0.003	0.014^{*}	0.007	-0.002	-0.008	0.002	-0.008
	(0.502)	(0.681)	(0.012)	(0.488)	(0.728)	(0.354)	(0.731)	(0.196)
$\ln to_i$	0.000	0.015^{***}	0.005	0.018^{***}	0.007^{**}	0.024^{***}	0.005	0.001
	(0.964)	(0.001)	(0.127)	(0.007)	(0.030)	(0.000)	(0.258)	(0.814)
cl_i		0.562^{**}	0.594^{***}		0.253^{***}	0.847^{***}		
		(0.015)	(0.000)		(0.002)	(0.000)		
Spatial lags								
$W \ln sf_i$	2.684^{***}	-1.446^{**}	0.224	-4.886^{***}	-0.513	1.461	-1.941^{**}	-0.251
	(0.006)	(0.026)	(0.694)	(0.000)	(0.245)	(0.129)	(0.011)	(0.659)
$W \ln pd_i$	0.886	-1.691^{*}	-1.130	-4.820^{***}	-1.165^{*}	-0.236	-1.171	-1.949^{**}
	(0.406)	(0.063)	(0.140)	(0.000)	(0.069)	(0.848)	(0.168)	(0.012)
$W \ln dbo_i$	-0.403^{***}	-0.228^{**}	-0.419^{***}	-0.217	-0.132^{**}	-0.306^{**}	-0.328^{***}	-0.027
	(0.000)	(0.024)	(0.000)	(0.112)	(0.049)	(0.016)	(0.003)	(0.757)
$W \ln dbr_i$	-0.613^{***}	-0.209	-0.010	-2.357^{***}	-0.209	-0.357	-0.969^{***}	0.754^{***}
	(0.007)	(0.494)	(0.954)	(0.000)	(0.259)	(0.201)	(0.002)	(0.004)
$W \ln ho_i$	1.425	1.498^{*}	5.692^{***}	-1.599	0.466	1.226	1.659^{**}	3.138^{***}
	(0.169)	(0.055)	(0.000)	(0.283)	(0.463)	(0.305)	(0.018)	(0.000)
$W \ln sc_i$	0.165^{***}	-0.097^{*}	-0.600^{***}	-0.233^{***}	0.315^{**}	-0.413	0.015	0.004
	(0.000)	(0.089)	(0.000)	(0.008)	(0.019)	(0.283)	(0.761)	(0.923)
$W \ln sp_i$	1.052^{**}	-0.837	-2.707^{***}	1.928	-0.070	1.971^{***}	-0.275	-1.516^{***}
	(0.014)	(0.140)	(0.000)	(0.104)	(0.848)	(0.000)	(0.625)	(0.001)
$W \ln mw_i$	1.140^{***}	0.157	0.543^{***}	0.059	-0.006	0.879^{***}	0.220	0.273^{*}
	(0.000)	(0.437)	(0.000)	(0.822)	(0.962)	(0.000)	(0.212)	(0.069)
$W \ln to_i$	0.239^{***}	0.036	0.072	0.239^{**}	0.041	0.393^{***}	0.100	0.079
	(0.000)	(0.584)	(0.150)	(0.011)	(0.406)	(0.000)	(0.106)	(0.140)
$W cl_i$		3.858	4.342^{***}		-2.357^{**}	-3.768		
		(0.292)	(0.000)		(0.032)	(0.220)		
$W \hat{\alpha}_i$	0.997^{***}	0.953^{***}	0.983^{***}	0.927^{***}	0.894^{***}	1.000^{***}	0.836^{***}	0.994^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Adj R^2	0.737	0.584	0.791	0.626	0.821	0.744	0.688	0.690
LL	-122.262	-100.702	3.773	-254.798	76.054	-196.031	-9.225	-75.857

Note: P-values between brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

characteristics. The latter is true for surface and population density, suggesting that immigrants might choose larger municipalities but prefer those that have smaller surrounding municipalities in terms of both surface and population. The genuine and spatially lagged effect of distance to the border and to Brussels, the motorway network and hotel occupancy, on the other hand, go in the same direction, intensifying the total effect. With a few exceptions, finally, also the impact of spatially lagged public amenities is mostly significant and positive. An insignificant or negative significant effect (as for schools), however, confirms the idea that people are more willing to commute for work than travel to get access to public goods.

6 Conclusions

This paper analyses migratory streams to Belgian municipalities between 1994-2007. Despite the renewed attention for the migration topic in the literature of the last two decades, the dynamics of the spatial distribution of immigrants remain poorly understood. For many European countries, their choice for a specific location within the destination country has not yet been explored, mainly because the required data has not been available. To fill this apparent gap in the literature, this paper provides a descriptive analysis of the spatial distribution of immigrants in Belgium and empirically investigates their location dynamics. The Belgian population register constitutes a rich and unique database of both migrant inflows and stocks with a detailed breakdown by nationality and age cohort, which allows us to distinguish the immigrants of working age.

Specifically, we aim at separating the network effect, captured by the number of previous arrivals, from other location-specific characteristics such as local labor or housing market conditions and the presence of public amenities. We expect labor and housing market variables to operate at different levels and develop a fixed effects nested logit model of location choice in which an immigrant first chooses a broad area, roughly corresponding to a labor market, and subsequently chooses a municipality within this area.

Our evidence suggests that, for most nationalities, this is a valid assumption and that immigrants' behavior is consistent with random utility maximization (though not necessarily with full information) for all nationalities. Although existing social networks usually act as a significant pull towards newcomers, both in the municipality itself and in those surrounding it, we find that the spatial distribution of Belgian immigrants is predominantly driven by location-specific characteristics such as housing and labor market variables.

A decomposition of predicted immigration rates reveals that the predictive power of our nested logit model is fairly high. We find that the genuine attractiveness of municipalities typically dominates the positive influence of social networks.

Finally, we estimate the parameters of the time invariant location determinants in our empirical model. We do not a priori assume a specific structure for spatial dependence in the local effects, but rely on a series of LM, Wald and LR tests to select the most appropriate specification. The test results reveal that a spatial lag for both the dependent and explanatory variables should be included in the regression. As such, we estimate an SDM model for the determinants of the local effects. The latter are found to vary by nationality, as expected, but with some noticeable parallels. The distance to the nearest border, for instance, is a significant determinant for immigrants from neighboring countries, as we would expect from the strong concentration of Dutch, French and German immigrants along the border of their origin country. But also the presence of public amenities and the municipality's touristic attractiveness act as a strong pull for immigrants.

In sum, our evidence suggests that the location choice of immigrants in Belgium is primarily determined by housing and labor market variables which vary in time, but also the genuine appeal of municipalities captured by the presence of public amenities and its geographical and cultural allure plays an important role in shaping the spatial repartition of immigrants.

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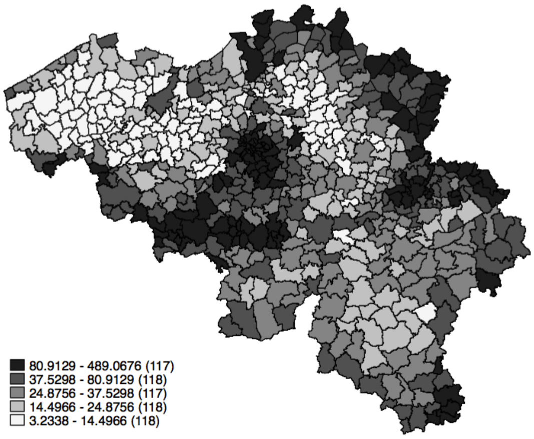
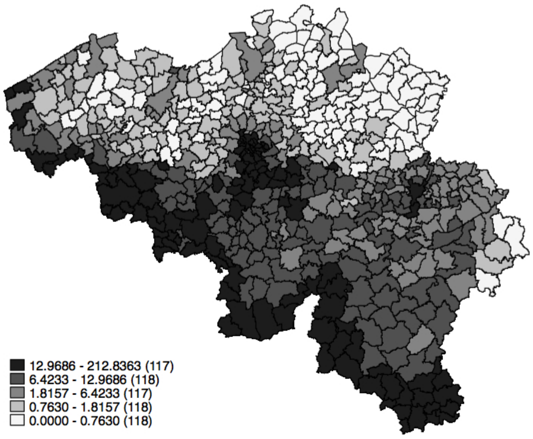
Appendix A Figures

Figure A-1: Migrant stocks in thousands of the population by municipality and origin, 2007



All origins



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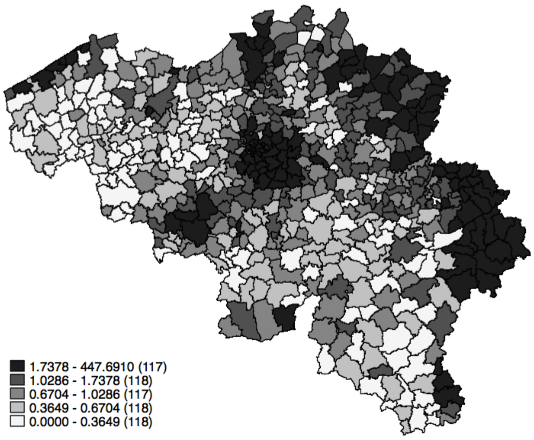

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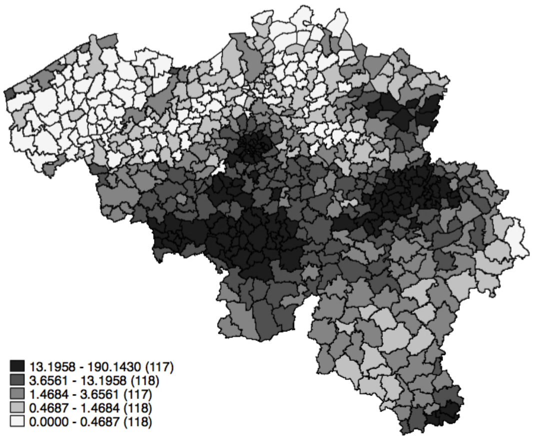

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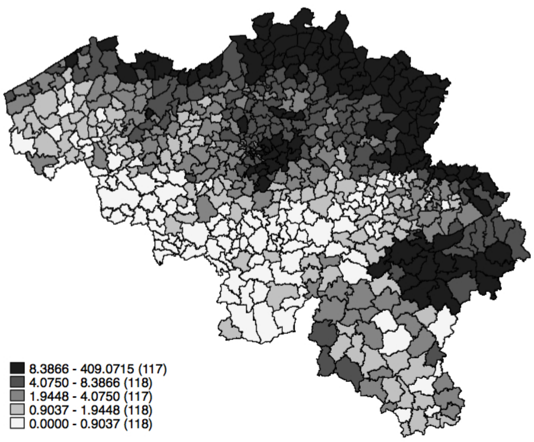

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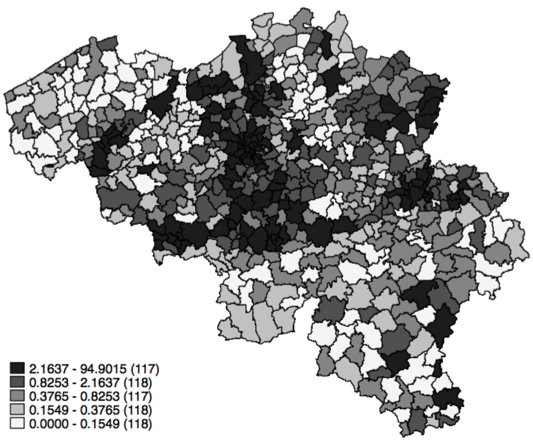

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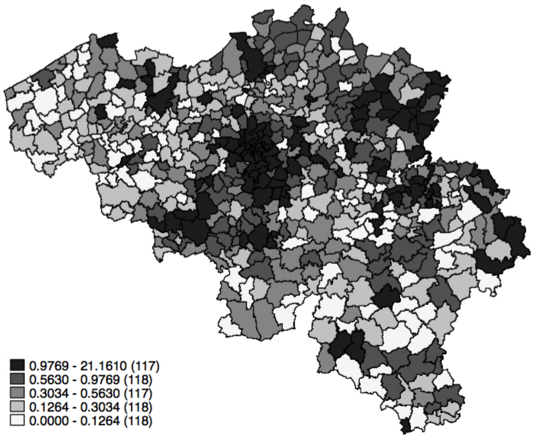

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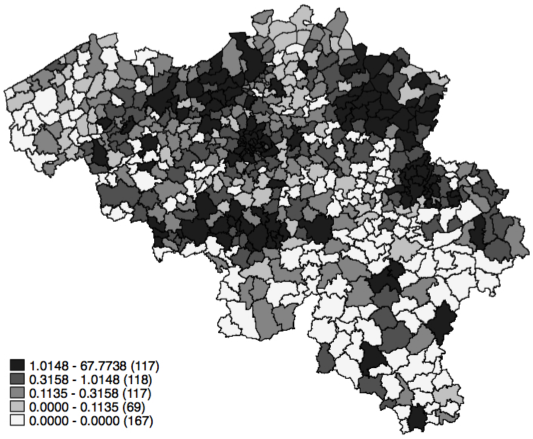
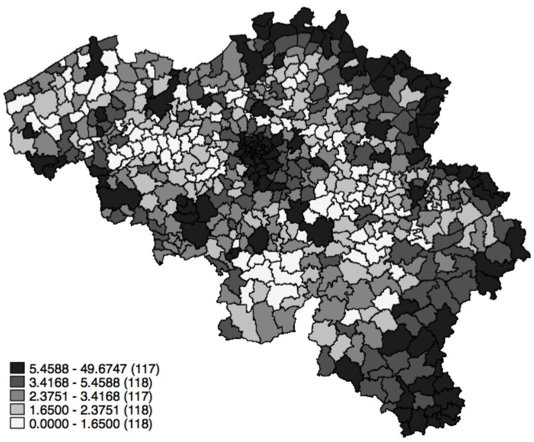
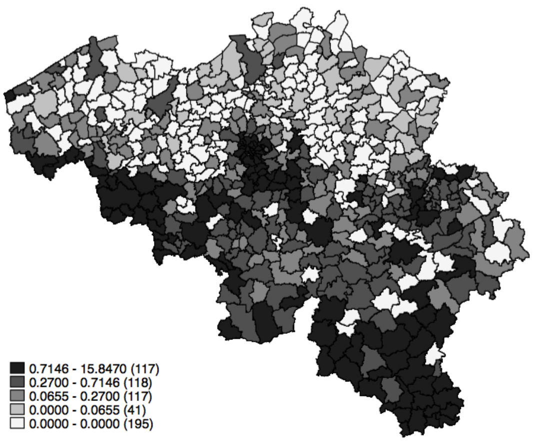


Turkey

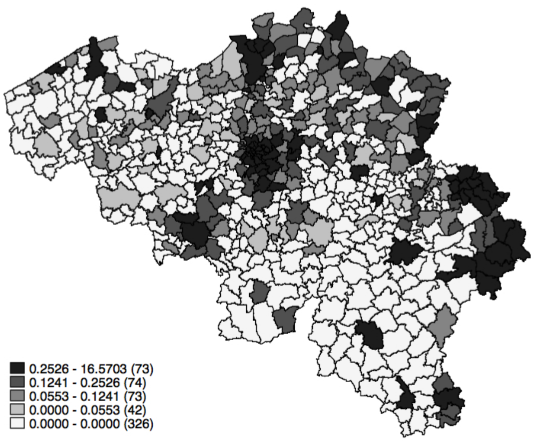
Figure A-2: Working age immigrant flows in thousands of the population by municipality and origin, 2007



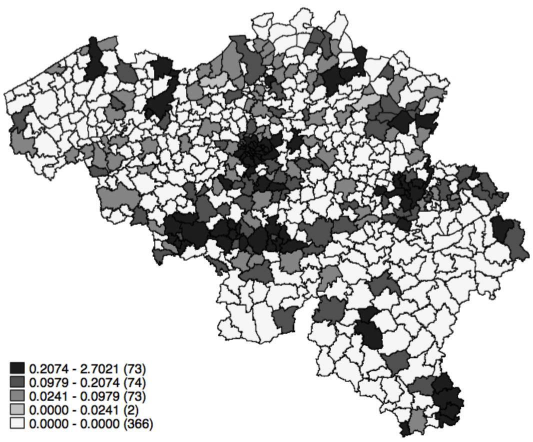
All origins



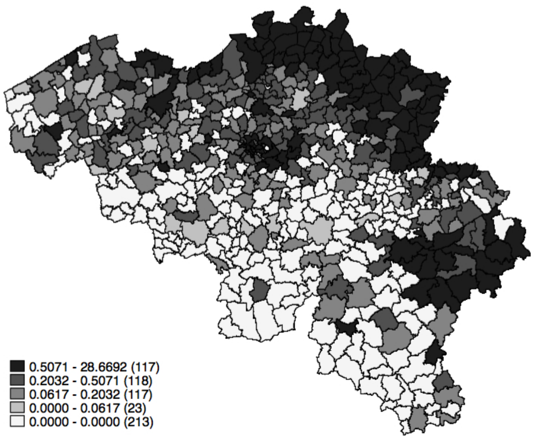
France



Germany



Italy



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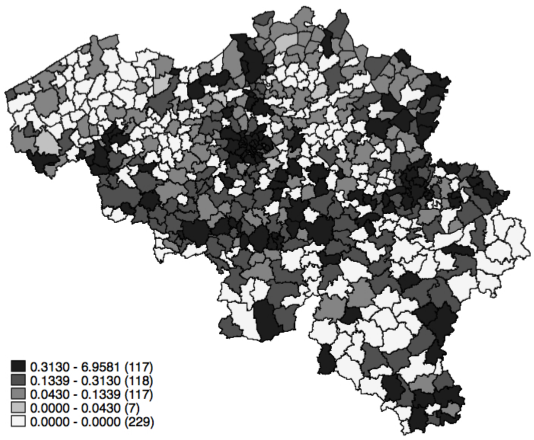
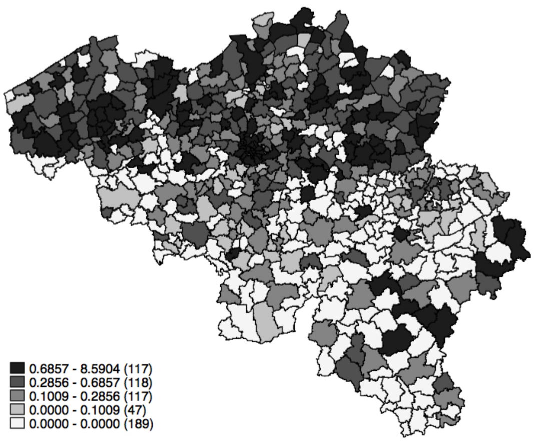
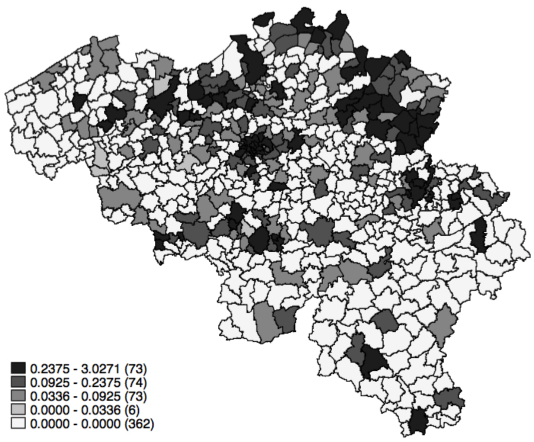


Morocco



Poland



Turkey

Appendix B Tables

Table A-1: Total (working age and retired) migrant stocks by country of origin 1993-2006

	TOT	DE	FR	IT	MA	NL	PL	TR	Sum	Share
1993	649961	29327	95229	217596	144993	69730	4817	88269	862964	75.32
1994	654711	30250	97199	216079	145363	72610	4908	88302	871514	75.12
1995	653654	31046	98804	213590	143969	75047	5217	85981	885970	73.78
1996	647310	31823	100168	210720	140304	77175	5376	81744	872676	74.18
1997	645928	32706	101825	208275	138253	80615	5722	78532	866959	74.51
1998	637828	33326	103638	205851	132838	82320	6037	73818	859782	74.18
1999	628300	34051	105185	202717	125087	84234	6322	70704	859227	73.12
2000	625718	34328	107322	200354	121991	85783	6755	69185	862773	72.52
2001	598412	34587	109398	195658	106828	88831	6936	56174	829170	72.17
2002	574744	34668	111225	190866	90646	92582	8891	45866	811484	70.83
2003	568523	35096	113120	187092	83633	96663	10357	42562	812752	69.95
2004	569050	35540	115025	183091	81766	100718	11574	41336	819683	69.42
2005	573013	36334	117431	179080	81285	104997	14000	39886	826917	69.30
2006	582096	37014	120698	175561	80613	110513	18032	39665	863222	67.43
93-'06	8609248	470096	1496267	2786530	1617569	1221818	114944	902024	11905093	
Growth	-10.61	28.78	27.83	-17.44	-47.52	67.36	280.34	-61.17	0.03	

Notes: Authors' calculations based on data from the Belgian Directorate for General Statistics and Economic Information. *TOT* reflects the sum of migrant stocks from the origin countries in our sample whereas *Sum* denotes the total immigrant stock in Belgium, regardless of the country of origin. *Share* then captures the share of immigrant stocks from our sample of origin countries in the total immigrant stock, or the percentage of the total immigrant stock that is represented in our sample. *Growth* denotes the percentage change in migrant stocks between 1993 and 2006.

Table A-2: Total (working age and retired) migrant flows by country of origin 1994-2007

	TOT	DE	FR	IT	MA	NL	PL	TR	Sum	Share
1994	27578	3063	6150	2754	4768	6477	793	3573	66147	41.69
1995	25327	3132	6236	2557	3596	6486	800	2520	62950	40.23
1996	27777	3189	6579	2731	4007	7834	946	2491	61521	45.15
1997	25569	3114	7022	2767	3880	6287	1063	1436	58849	43.45
1998	27229	3206	7386	2503	4327	6242	1118	2447	61266	44.44
1999	28020	3070	7933	2603	4936	6201	1151	2126	68466	40.93
2000	30536	3037	8108	2600	5667	7178	1134	2812	68616	44.50
2001	34512	2884	8040	2439	7072	8167	2928	2982	77584	44.48
2002	36609	2966	8135	2310	8495	8404	2427	3872	82654	44.29
2003	36331	2942	8191	2293	8444	8547	2086	3828	81913	44.35
2004	38648	3308	9521	2301	8014	8789	3481	3234	85378	45.27
2005	41510	3250	10378	2464	7106	10109	4816	3387	90364	45.94
2006	46142	3290	11570	2613	7488	11488	6694	2999	96290	47.92
2007	50136	3385	12269	2708	7831	11370	9393	3180	106576	47.04
'94-'07	475924	43836	117518	35643	85631	113579	38830	40887	1068574	

Note: see A-1. *Growth* denotes the percentage change in migrant stocks between 1994 and 2007.

Table A-3: Working age migrant flows by country of origin 1994-2007

	TOT	DE	FR	IT	MA	NL	PL	TR	Sum	Share
1994	20253	2249	4356	1860	3617	4784	621	2248	45228	44.78
1995	18678	2272	4420	1814	2715	4924	620	1545	43111	43.33
1996	20383	2322	4630	1952	3039	5875	720	1502	42686	47.75
1997	19448	2313	5129	2032	3088	4699	845	893	41977	46.33
1998	20473	2329	5359	1860	3351	4678	907	1525	43431	47.14
1999	21641	2277	5810	1948	3934	4703	918	1379	48335	44.77
2000	23253	2236	6086	1919	4289	5317	888	1765	48983	47.47
2001	26948	2136	5993	1836	5694	6121	2109	1962	55813	48.28
2002	28423	2218	6128	1805	6433	6287	1898	2559	59603	47.69
2003	27753	2194	6154	1774	5987	6267	1699	2500	58387	47.53
2004	30505	2502	7037	1828	5981	6404	2826	2232	61393	49.69
2005	36348	2636	8585	1999	5963	7686	4017	2783	64963	55.95
2006	40600	2611	9559	2138	6253	8500	5690	2606	70080	57.93
2007	44668	2532	9100	2131	6065	7922	7930	2494	78655	56.79
'94-'07	379374	32827	88346	26896	66409	84167	31688	27993	762645	

Note: see A-1. *Growth* denotes the percentage change in migrant stocks between 1994 and 2007.

Table A-4: Descriptive statistics: district and municipality level

	District level				Municipality level			
Variable	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Flows								
TOT	1141.00	2613.00	14.00	26806.00	83.00	294.00	0.00	7718.00
DE	53.00	143.00	0.00	908.00	4.00	17.00	0.00	301.00
FR	136.00	416.00	0.00	4479.00	10.00	43.00	0.00	1168.00
IT	44.00	114.00	0.00	934.00	3.00	13.00	0.00	218.00
MA	98.00	353.00	0.00	3349.00	7.00	42.00	0.00	909.00
NL	133.00	291.00	0.00	2154.00	10.00	41.00	0.00	1466.00
PL	44.00	190.00	0.00	2768.00	3.00	22.00	0.00	1149.00
TR	44.00	96.00	0.00	748.00	3.00	17.00	0.00	362.00
Ln $s_{i,t-1}$								
TOT	8.79	1.48	4.98	12.50	5.80	1.56	0.69	10.94
DE	5.09	1.63	1.61	9.49	2.29	1.59	0.00	8.43
FR	6.74	1.44	3.76	10.64	3.54	1.75	0.00	8.88
IT	6.41	2.27	0.00	10.96	3.30	2.18	0.00	10.06
MA	5.99	1.80	3.14	10.03	2.12	2.15	0.00	9.98
NL	5.61	2.25	0.00	11.27	3.30	1.79	0.00	9.05
PL	3.92	1.50	0.00	9.19	1.26	1.30	0.00	7.56
TR	5.13	2.48	0.00	9.99	1.53	2.08	0.00	9.20

Note: Number of observations at district level: 774 (N=43 ant T=18); number of observations at municipality level: 10584 (N=588 ant T=18).

Table A-5: Correlation coefficients - Time varying explanatory variables

	$\ln sn_{i,t-1,NAT}$	$\ln e_{k,t}$	$\ln ph_{i,t}$	$\ln pa_{i,t}$	$\ln th_{i,t}$	$\ln ta_{i,t}$
$\ln s_{i,t-1,TOT}$	0.523***	−0.096***	0.016	0.010	−0.113***	0.144***
$\ln s_{i,t-1,IT}$	0.198***	−0.097***	−0.009	−0.016	−0.020	−0.006
$\ln s_{i,t-1,NL}$	0.348***	0.428***	0.015	−0.004	−0.11***	0.151***
$\ln s_{i,t-1,PL}$	0.399***	0.028*	0.09***	−0.071***	−0.066***	0.115***
$\ln s_{i,t-1,FR}$	0.171***	−0.327***	0.013	0.014	−0.056***	0.097***
$\ln s_{i,t-1,MA}$	0.253***	−0.0142	−0.024**	0.016	0.023**	−0.061***
$\ln s_{i,t-1,TR}$	0.214***	−0.0061	−0.02*	0.011	0.038***	−0.065***
$\ln s_{i,t-1,DE}$	0.036***	0.107***	0.025**	−0.02*	−0.012	0.029***
$\ln sn_{i,t-1,TOT}$	1.000	−0.042***	−0.010	0.031***	−0.052***	0.077***
$\ln sn_{i,t-1,IT}$	1.000	−0.058***	0.009	0.002	0.044***	−0.003
$\ln sn_{i,t-1,NL}$	1.000	0.460***	−0.002	−0.036***	−0.166***	0.216***
$\ln sn_{i,t-1,PL}$	1.000	0.110***	0.083***	−0.107***	−0.112***	0.19***
$\ln sn_{i,t-1,FR}$	1.000	−0.270***	0.021*	−0.026*	−0.106***	0.135***
$\ln sn_{i,t-1,MA}$	1.000	0.059***	−0.039***	0.071***	0.107***	−0.14***
$\ln sn_{i,t-1,TR}$	1.000	0.045***	0.003	0.056***	0.106***	−0.163***
$\ln sn_{i,t-1,DE}$	1.000	0.168***	0.043***	−0.013	−0.006	0.084***
$\ln e_{k,t,TOT}$		1.000	0.370***	0.369***	−0.307***	0.326***
$\ln e_{k,t,IT}$		1.000	0.025*	0.242***	−0.068***	0.077***
$\ln e_{k,t,NL}$		1.000	0.551***	0.382***	−0.342***	0.388***
$\ln e_{k,t,PL}$		1.000	0.378***	0.267***	−0.344***	0.399***
$\ln e_{k,t,FR}$		1.000	0.551***	0.382***	−0.342***	0.388***
$\ln e_{k,t,MA}$		1.000	0.340***	0.321***	−0.323***	0.324***
$\ln e_{k,t,TR}$		1.000	0.089***	0.216***	−0.184***	0.094***
$\ln e_{k,t,DE}$		1.000	0.551***	0.387***	−0.342***	0.388***
$\ln ph_{i,t}$			1.000	−0.001	0.097***	−0.003
$\ln pa_{i,t}$				1.000	0.047***	0.505***
$\ln th_{i,t}$					1.000	−0.047***
$\ln ta_{i,t}$						1.000

Note: Pairwise within correlations. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively, and $NAT = (TOT, IT, NL, PL, FR, MA, TR, DE)$.

Table A-6: Correlation coefficients - Time invariant explanatory variables

	$\ln sf_i$	$\ln pd_i$	$\ln dbo_i$	$\ln dbr_i$	$\ln ho_i$	$\ln sc_i$	$\ln sp_i$	$\ln mw_i$	$\ln to_i$
$\ln sf_i$	1.000								
$\ln pd_i$	-0.685^{***}	1.000							
$\ln dbo_i$	-0.317^{***}	0.283^{***}	1.000						
$\ln dbr_i$	0.491^{***}	-0.623^{***}	-0.368^{***}	1.000					
$\ln ho_i$	0.050	-0.642^{***}	-0.092^{*}	0.326^{***}	1.000				
$\ln sc_i$	0.178^{***}	-0.288^{***}	-0.143^{***}	0.219^{***}	0.395^{***}	1.000			
$\ln sp_i$	0.057	-0.239^{***}	-0.167^{***}	0.110^{***}	0.327^{***}	0.150^{***}	1.000		
$\ln mw_i$	0.077^{**}	0.169^{***}	0.082^{*}	-0.057	-0.279^{***}	-0.141^{***}	-0.072^{**}	1.000	
$\ln to_i$	0.418^{***}	-0.244^{***}	-0.207^{***}	0.182^{***}	0.040	0.264^{***}	0.069^{**}	-0.001	1.000
$cl_{i,Dutch}$	-0.140^{***}	0.274^{***}	0.187^{***}	-0.195^{***}	-0.289^{***}	-0.114^{***}	-0.971^{***}	0.020	-0.049
$cl_{i,French}$	0.298^{***}	-0.461^{***}	-0.235^{***}	0.418^{***}	0.361^{***}	0.140^{***}	0.849^{***}	0.000	0.056
$cl_{i,German}$	-0.435^{***}	0.511^{***}	0.128^{***}	-0.610^{***}	-0.192^{***}	-0.069^{**}	0.369^{***}	-0.057	-0.018

Note: P-values between brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table A-7: Time varying determinants of immigrants' location choice - conditional logit

Variable	TOT	DE	FR	IT	MA	NL	PL	TR
$\ln s_{i,t-1}$	-0.129^{***}	0.056	0.280^{***}	0.153^{**}	0.16^{***}	0.287^{***}	0.131^{***}	0.291^{***}
	(0.000)	(0.20)	(0.000)	(0.025)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln sn_{i,t-1}$	-0.089^{***}	0.283^{***}	0.364^{***}	0.804^{***}	0.055	-0.390^{***}	0.203^{***}	0.121^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.138)	(0.000)	(0.000)	(0.000)
$\ln ph_{i,t}$	0.235^{***}	0.76^{***}	0.074	0.243^{***}	-0.534^{***}	0.810^{***}	-0.549^{***}	0.308^{***}
	(0.000)	(0.000)	(0.123)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln pa_{i,t}$	-0.035^{***}	-0.135^{***}	-0.035^{**}	0.050	-0.057^{*}	-0.004	-0.141^{***}	-0.188^{***}
	(0.000)	(0.000)	(0.039)	(0.204)	(0.077)	(0.819)	(0.000)	(0.000)
$\ln th_{i,t}$	-0.003	-0.099^{***}	0.016	-0.091^{**}	0.119^{***}	0.090^{***}	-0.109^{***}	-0.126^{***}
	(0.661)	(0.000)	(0.383)	(0.012)	(0.000)	(0.000)	(0.001)	(0.001)
$\ln ta_{i,t}$	0.036^{***}	0.059^{***}	0.007	-0.020	0.030	0.047^{***}	0.142^{***}	0.033
	(0.000)	(0.004)	(0.594)	(0.458)	(0.159)	(0.000)	(0.000)	(0.183)
$\ln e_{k,t}$	1.114^{***}	2.549^{***}	2.257^{***}	-0.383	0.562^{***}	-0.218	2.954^{***}	-0.006
	(0.000)	(0.000)	(0.000)	(0.522)	(0.000)	(0.592)	(0.000)	(0.949)
LL	-3679587	-141360	-385596	-115998	-252952	-379675	-141195	-112302

Note: P-values between brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Table A-8: Determinants of time-invariant local effects - OLS

	TOT	DE	FR	IT	MA	NL	PL	TR
Intercept	2.708^{***}	-1.056^{**}	1.600^{***}	-3.070^{***}	0.346	-2.708^{***}	1.003^{*}	-1.396^{***}
	(0.000)	(0.041)	(0.001)	(0.000)	(0.375)	(0.003)	(0.054)	(0.003)
$\ln sf_i$	0.125^{*}	0.650^{***}	0.301^{***}	0.941^{***}	0.473^{***}	0.386^{***}	0.446^{***}	0.631^{***}
	(0.055)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln pd_i$	0.476^{***}	0.634^{***}	0.510^{***}	0.981^{***}	0.744^{***}	0.457^{***}	0.545^{***}	0.769^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln dbo_i$	-0.050^{***}	-0.016^{***}	-0.040^{***}	-0.033^{***}	-0.011^{**}	-0.071^{***}	0.003	-0.012^{**}
	(0.000)	(0.007)	(0.000)	(0.000)	(0.014)	(0.000)	(0.585)	(0.020)
$\ln dbr_i$	-0.3^{***}	-0.023	-0.204^{***}	0.087^{*}	-0.119^{***}	-0.081^{*}	-0.195^{***}	-0.028
	(0.000)	(0.414)	(0.000)	(0.054)	(0.000)	(0.080)	(0.000)	(0.272)
$\ln ho_i$	-0.083	0.171^{***}	0.167^{***}	0.357^{***}	0.030	-0.095	0.105^{*}	0.134^{***}
	(0.238)	(0.002)	(0.002)	(0.000)	(0.458)	(0.296)	(0.058)	(0.007)
$\ln sc_i$	0.044^{***}	0.003	0.047^{***}	-0.001	0.045^{***}	0.068^{***}	-0.014^{**}	0.011^{**}
	(0.000)	(0.604)	(0.000)	(0.908)	(0.000)	(0.007)	(0.010)	(0.031)
$\ln sp_i$	-0.097^{**}	-0.037	-0.268^{***}	-0.002	-0.057^{*}	0.168^{**}	-0.061	0.035
	(0.058)	(0.368)	(0.000)	(0.979)	(0.073)	(0.011)	(0.139)	(0.354)
$\ln mw_i$	0.023^{**}	-0.001	0.014^{**}	0.001	0.001	0.015	-0.003	0.005
	(0.015)	(0.921)	(0.045)	(0.898)	(0.878)	(0.210)	(0.691)	(0.458)
$\ln to_i$	0.013^{**}	0.024^{***}	0.011^{***}	0.032^{***}	0.014^{***}	0.053^{***}	0.007	0.013^{***}
	(0.013)	(0.000)	(0.009)	(0.000)	(0.000)	(0.000)	(0.100)	(0.000)
cl_i		0.889^{***}	0.835^{***}		0.155^{***}	1.548^{***}		
		(0.000)	(0.000)		(0.007)	(0.000)		
Adj R^2	0.572	0.562	0.689	0.498	0.792	0.534	0.629	0.659
LM spatial lag	32469.000^{***}	111.601^{***}	1864.500^{***}	210.775^{***}	172.788^{***}	938.109^{***}	1020.900^{***}	59.269^{***}
Prob > $\chi(1)$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LM spatial lag (robust)	181.794^{***}	37.425^{***}	183.644^{***}	89.487^{***}	87.150^{***}	275.112^{***}	100.627^{***}	50.129^{***}
Prob > $\chi(1)$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LM spatial error	14610.000^{***}	108.022^{***}	1703.000^{***}	142.48^{***}	163.845^{***}	832.861^{***}	988.156^{***}	68.586^{***}
Prob > $\chi(1)$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LM spatial error	213.398^{***}	28.094^{***}	192.979^{***}	110.491^{***}	64.993^{***}	226.772^{***}	81.322^{***}	34.058^{***}
Prob > $\chi(1)$	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LM spatial lag and error	1067.557^{***}	10.029^{***}	194.236^{***}	195.897^{***}	14.219^{***}	500.960^{***}	72.435^{***}	0.354
Prob > $\chi(2)$	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.552)
Wald SDM vs SAR	49.573^{***}	0.505	8.542^{***}	52.726^{***}	4.561^{***}	48.678^{***}	6.181^{**}	4.543^{**}
Prob > $\chi(7)$	(0.000)	(0.477)	(0.003)	(0.000)	(0.033)	(0.000)	(0.013)	(0.033)
LR SDM vs SAR	1795.135^{***}	40.826^{***}	491.274^{***}	201.950^{***}	128.038^{***}	2031.477^{***}	321.881^{***}	40.416^{***}
Prob > $\chi(7)$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wald SDM vs SEM	777.150^{***}	31.302^{***}	305.580^{***}	58.780^{***}	118.380^{***}	1579.194^{***}	255.627^{***}	44.605^{***}
Prob > $\chi(7)$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LR SDM vs SEM	1844.708^{***}	41.331^{***}	499.816^{***}	254.676^{***}	132.599^{***}	2080.154^{***}	328.061^{***}	44.959^{***}
Prob > $\chi(7)$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: P-values between brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Table A-9: Determinants of time-invariant local effects - Direct effects

	TOT	DE	FR	IT	MA	NL	PL	TR
$\ln sf_i$	0.551^{***}	0.676^{***}	0.367^{***}	0.742^{***}	0.545^{***}	0.608^{***}	0.656^{***}	0.504^{***}
	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln pd_i$	0.997^{***}	0.661^{***}	0.582^{***}	1.038^{***}	0.767^{***}	0.566^{***}	0.838^{***}	0.563^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln dbo_i$	-0.091^{***}	-0.008	-0.046^{***}	-0.036^{***}	-0.004	-0.057^{***}	-0.003	0.006
	(0.000)	(0.233)	(0.000)	(0.000)	(0.442)	(0.000)	(0.609)	(0.265)
$\ln dbr_i$	-0.059	-0.026	0.06	-0.041	-0.015	-0.05	-0.038	0.056
	(0.364)	(0.641)	(0.186)	(0.585)	(0.703)	(0.434)	(0.425)	(0.306)
$\ln ho_i$	0.304	0.16^{***}	0.541^{***}	0.133	0.058	0.066	0.149^{***}	0.217^{***}
	(0.124)	(0.003)	(0.000)	(0.104)	(0.159)	(0.355)	(0.002)	(0.000)
$\ln sc_i$	0.024^{***}	0.001	0.005	0.037^{***}	0.014^{*}	-0.005	-0.004	0.003
	(0.009)	(0.897)	(0.77)	(0.008)	(0.081)	(0.803)	(0.665)	(0.742)
$\ln sp_i$	0.102	-0.012	-0.289^{***}	0.035	-0.026	0.136^{***}	0.066^{**}	-0.065
	(0.192)	(0.78)	(0.000)	(0.622)	(0.405)	(0.005)	(0.067)	(0.109)
$\ln mw_i$	0.197^{***}	-0.002	0.055^{***}	0.008	-0.002	0.01	0.003	-0.001
	(0.000)	(0.82)	(0.001)	(0.43)	(0.706)	(0.292)	(0.608)	(0.942)
$\ln to_i$	0.04^{***}	0.015^{***}	0.011^{**}	0.02^{***}	0.008	0.032^{***}	0.005	0.003
	(0.000)	(0.001)	(0.022)	(0.002)	(0.015)	(0.000)	(0.204)	(0.394)
cl_i		0.598^{***}	0.952^{***}		0.222^{***}	0.789^{***}		
		(0.005)	(0.000)		(0.002)	(0.000)		

Note: P-values between brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Table A-10: Determinants of time-invariant local effects - Indirect effects

	TOT	DE	FR	IT	MA	NL	PL	TR
$\ln sf_i$	97.542	-34.238	-35.936	-121.207	-15.095	16.073	-13.63	-71.346
	(0.28)	(0.464)	(0.399)	(0.318)	(0.573)	(0.81)	(0.676)	(0.153)
$\ln pd_i$	249.604^{***}	-27.346	34.135	-115.66	2.974	98.169	-29.621	15.158
	(0.005)	(0.435)	(0.298)	(0.295)	(0.846)	(0.147)	(0.484)	(0.625)
$\ln dbo_i$	-33.654^{***}	-7.694	-20.709^{**}	-7.486	-2.931	-17.418^{*}	-7.979	-0.955
	(0.000)	(0.284)	(0.036)	(0.382)	(0.44)	(0.076)	(0.404)	(0.837)
$\ln dbr_i$	-45.636^{**}	-8.233	2.419	-71.047	-4.459	-20.45	-24.157	39.549^{*}
	(0.018)	(0.575)	(0.795)	(0.296)	(0.541)	(0.235)	(0.407)	(0.071)
$\ln ho_i$	115.738	56.201	277.231^{**}	-41.577	11.176	60.412	46.393	165.39^{**}
	(0.175)	(0.32)	(0.028)	(0.556)	(0.646)	(0.399)	(0.426)	(0.03)
$\ln sc_i$	12.947^{***}	-3.341	-26.786^{*}	-5.813	6.886	-20.002	0.142	0.404
	(0.000)	(0.343)	(0.057)	(0.34)	(0.426)	(0.387)	(0.928)	(0.86)
$\ln sp_i$	79.021^{**}	-27.922	-133.628^{**}	57.952	-2.247	105.158	-6.213	-77.678^{**}
	(0.029)	(0.389)	(0.028)	(0.411)	(0.846)	(0.048)	(0.786)	(0.049)
$\ln mw_i$	90.745^{***}	5.328	27.065^{*}	1.725	-0.178	43.387^{**}	5.349	13.366
	(0.000)	(0.587)	(0.054)	(0.864)	(0.965)	(0.042)	(0.538)	(0.174)
$\ln to_i$	18.782^{***}	1.773	3.678	7.494	0.972	21.027^{**}	2.364	4.077
	(0.000)	(0.571)	(0.218)	(0.33)	(0.589)	(0.034)	(0.485)	(0.223)
cl_i		150.338	236.625^{*}		-45.962	-143.919		
		(0.427)	(0.05)		(0.455)	(0.432)		

Note: P-values between brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Table A-11: Determinants of time-invariant local effects using conditional logit estimates - SDM

	TOT	DE	FR	IT	MA	NL	PL	TR
Intercept	29.433^{***}	-9.540^{***}	-8.009	9.769^{***}	-3.538	-18.392^{***}	-15.807^{***}	-4.288^{**}
	(0.001)	(0.001)	(0.150)	(0.001)	(0.346)	(0.000)	(0.000)	(0.048)
$\ln sf_i$	1.223^{***}	1.201^{***}	0.622^{***}	0.972^{***}	1.321^{***}	1.620^{***}	1.525^{***}	1.454^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln pd_i$	1.433^{***}	1.258^{***}	1.199^{***}	1.503^{***}	1.761^{***}	1.209^{***}	1.262^{***}	1.797^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln dbo_i$	-0.053^{***}	-0.027^{**}	-0.101^{***}	-0.080^{***}	-0.002	-0.026^{*}	0.025^{*}	0.002
	(0.000)	(0.041)	(0.000)	(0.000)	(0.828)	(0.059)	(0.054)	(0.868)
$\ln dbr_i$	-0.004	-0.023	0.153^{*}	0.039	-0.068	-0.181	0.041	-0.128
	(0.957)	(0.826)	(0.086)	(0.725)	(0.457)	(0.108)	(0.703)	(0.196)
$\ln ho_i$	0.132^{*}	0.276^{***}	0.231^{***}	0.224^{**}	0.160^{*}	0.153	0.279^{***}	0.304^{***}
	(0.052)	(0.005)	(0.005)	(0.039)	(0.063)	(0.158)	(0.006)	(0.002)
$\ln sc_i$	0.041^{***}	-0.028	0.064^{***}	0.060^{***}	0.009	0.000	0.001	-0.005
	(0.001)	(0.202)	(0.001)	(0.003)	(0.650)	(0.996)	(0.953)	(0.805)
$\ln sp_i$	-0.042	0.009	-0.075	-0.086	-0.010	0.132	0.001	0.147^{*}
	(0.409)	(0.914)	(0.244)	(0.402)	(0.895)	(0.111)	(0.99)	(0.068)
$\ln mw_i$	0.000	-0.006	0.007	0.008	0.001	-0.008	-0.019	0.002
	(0.996)	(0.655)	(0.528)	(0.566)	(0.920)	(0.579)	(0.163)	(0.859)
$\ln to_i$	0.023^{***}	0.029^{***}	0.025^{***}	0.020^{**}	0.024^{***}	0.039^{***}	0.009	0.008
	(0.000)	(0.001)	(0.000)	(0.036)	(0.001)	(0.000)	(0.308)	(0.333)
cl_i		1.584^{***}	0.854^{***}		0.541^{***}	1.443^{***}		
		(0.000)	(0.000)		(0.003)	(0.000)		
Spatial lags								
$W \ln sf_i$	-4.224^{***}	0.068	2.353	-6.876^{***}	-3.749^{**}	-4.644^{**}	-4.293^{***}	-2.705
	(0.002)	(0.968)	(0.118)	(0.000)	(0.011)	(0.027)	(0.007)	(0.132)
$W \ln pd_i$	-3.398^{***}	0.054	1.002	-6.826^{***}	-2.924^{***}	-0.194	-2.077^{*}	-4.807^{***}
	(0.008)	(0.964)	(0.373)	(0.000)	(0.004)	(0.906)	(0.078)	(0.003)
$W \ln dbo_i$	-0.835^{***}	-0.505^{***}	-0.528^{***}	-0.432^{**}	-0.255^{*}	-0.452^{**}	0.043	-0.697^{***}
	(0.000)	(0.007)	(0.000)	(0.029)	(0.098)	(0.037)	(0.812)	(0.002)
$W \ln dbr_i$	-1.332^{***}	-0.220	-0.691^{*}	-4.192^{***}	-0.414	0.263	1.229^{**}	-1.715^{***}
	(0.000)	(0.700)	(0.050)	(0.000)	(0.328)	(0.580)	(0.025)	(0.008)
$W \ln ho_i$	-0.617	5.307^{***}	10.609^{***}	-1.800	2.119	-0.208	6.710^{***}	3.466^{**}
	(0.648)	(0.000)	(0.000)	(0.403)	(0.146)	(0.919)	(0.000)	(0.019)
$W \ln sc_i$	0.072	0.047	-1.062^{***}	-0.628^{***}	0.276	-0.394	-0.156^{*}	-0.015
	(0.206)	(0.657)	(0.000)	(0.000)	(0.371)	(0.549)	(0.090)	(0.885)
$W \ln sp_i$	-1.407^{**}	-2.285^{**}	-4.581^{***}	3.980^{**}	-1.202	2.878^{***}	-4.296^{***}	-1.166
	(0.011)	(0.031)	(0.000)	(0.020)	(0.148)	(0.002)	(0.000)	(0.325)
$W \ln mw_i$	0.936^{***}	0.941^{**}	0.916^{***}	0.868^{**}	-0.113	0.938^{***}	0.380	0.341
	(0.000)	(0.012)	(0.000)	(0.022)	(0.689)	(0.007)	(0.222)	(0.360)
$W \ln to_i$	0.246^{***}	-0.053	0.135	0.513^{***}	0.104	0.540^{***}	0.110	0.033
	(0.000)	(0.670)	(0.167)	(0.000)	(0.354)	(0.000)	(0.321)	(0.801)
$W cl_i$		19.412^{***}	6.836^{***}		-2.662	-4.650		
		(0.004)	(0.005)		(0.290)	(0.375)		
$W \hat{\alpha}_i$	0.984^{***}	0.994^{***}	0.844^{***}	1.000^{***}	0.880^{***}	1.000^{***}	0.898^{***}	0.803^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)
Adj R^2	0.838	0.667	0.736	0.693	0.791	0.754	0.666	0.672
LL	-276.762	-427.445	-381.789	-439.441	-387.561	-487.466	-481.226	-350.965

Note: P-values between brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Institut de Recherches Économiques et Sociales
Université catholique de Louvain

Place Montesquieu, 3
1348 Louvain-la-Neuve, Belgique

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