When gravity hits: projecting Ireland's migration

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Working Paper No. 11

December 2019

Irish Fiscal
Advisory Council

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December, 2019

Abstract

What is the future of Ireland's migration? This is the first paper to project Ireland's migration flows through a gravity model. We use granular data—for 232 countries since 1960—and novel econometric techniques to explain bilateral world migration with fundamentals like economic growth, demographics, and other relevant variables. The results are broadly consistent with the international literature, suggesting that our model can be an important tool for forecasting Ireland's migration. Unlike other papers, we find that economic growth in home countries does not help explain migration flows. What matters is the destination country's growth. When gravity "hits" the model, the projections may differ substantially from other official forecasts. We project that net migration flows to Ireland will be positive overall in the coming decades, largely reflecting favourable productivity growth. We show that shocks to Irish growth—which could impact future productivity and the public finances—would also have significant impacts on Ireland's migration inflows.

Keywords: Migration, Projection, Gravity Model, PPML
JEL No. F22, J11, J18, J61, O15

Peer reviewed by: Dr. Íde Kearney (De Nederlandsche Bank) and Gonzalo López-Molina (Universidad Complutense de Madrid)

This report can be downloaded at www.FiscalCouncil.ie

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1. Introduction

Understanding migration flows is important for well-founded fiscal policy, given its potential links to revenue growth and expenditure plans. A number of economic conditions and other characteristics like distance and language can influence where individuals ultimately decide to migrate to. Recognising this, there is a rich literature that applies gravity model approaches to migration flows.

This is the first paper to model and project Irish migration flows through a gravity model. We use granular world migration data to explain migration with fundamentals like economic growth, demographics, distance, and other relevant features. Our model gauges migration flows between 232 countries since 1960. We also apply the Poisson Pseudo Maximum Likelihood (PPML) estimation method, a novel econometric technique in the context of gravity models of migration that allows us to overcome potential biases that Ordinary Least Squares (OLS) might entail when applied to this type of data.

The highly volatile nature of migration flows is especially notable in small open economies like Ireland, where migration has proven to follow very marked procyclical trends over the last number of years. Its incidence in population growth is paramount.

More broadly, migration is typically the most challenging demographic component to forecast and the main source of error in population projections. This is largely due to the volatility and institutional dependency of migration flows. However, improvements in microdata availability and econometric modelling have contributed to a better understanding of migration flows. Gravity models are the most commonly used paradigm to explain bilateral migration flows. These models are often compared to Newton's gravitational law: in their simplest form, they assume that flows between two countries are positively correlated with the stock of co-nationals already residing in the country, and inversely related to distance. These models are widely applied due to their consistency with migration theories, their ease of estimation in their simplest form, and their goodness of fit in most applications (Poot *et al.*, 2016).

The majority of the migration literature in Ireland has focused on explaining past trends. For example, past research (Kearney, 1998) explored the relation between Irish and UK migration by considering relative lagged wages as the explanatory variable. This type of linear model (estimated through OLS) worked well between the 1950s and the 1990s, but weakened in the 2000s when migration from elsewhere became significant in Ireland following accession to the EU of central and eastern European countries, as well as a bubbling Irish economy in terms of property and credit. As a result of globalisation, and given the strong degree of migration openness existing in Ireland, it is now necessary to consider a wider range of countries, which the proposed model attempts to capture.

On the estimation side, our findings are broadly in line with international literature, suggesting that our model can be an important tool for forecasting future migration in Ireland. Unlike other papers, we find that economic growth in home countries does not help explain migration flows. What matters is the destination country's growth. In terms of the projection exercise, our model projects that the long-term migration dynamics of Ireland will be positive over almost the whole projection horizon largely on the basis of a relatively favourable productivity growth. The projections suggest that net inflows will amount to 14,000 by 2030, and will then slightly trend down to 12,500 by 2040, before being close to zero by 2050. More broadly, annual net migration flows will average to over 9,000 over the medium to long term, close to the observed long-term average.

This paper also shows that shocks to Irish growth can have significant impacts on the inflow of net migration in Ireland. This is especially the case for inflows of foreign migrants in Ireland, for whom the destination country's growth is crucial and represents an average elasticity of 0.17. Assuming a positive shock that places Ireland's convergence growth at 4.0 per cent, the projected migration flows would average over 11,000 per annum. This is in contrast to a negative shock to growth that converges to 1.5 per cent, which would place the projected flows to an annual average of roughly 7,000. As a share of total population, the baseline scenario suggests that foreign immigrants will account for 18.8 per cent of the total population in Ireland by 2050. This compares to a projected share of 19.7 per cent under the optimistic growth scenario (of 4.0 per cent); and 18.2 per cent under the pessimistic scenario (of 1.5 per cent).

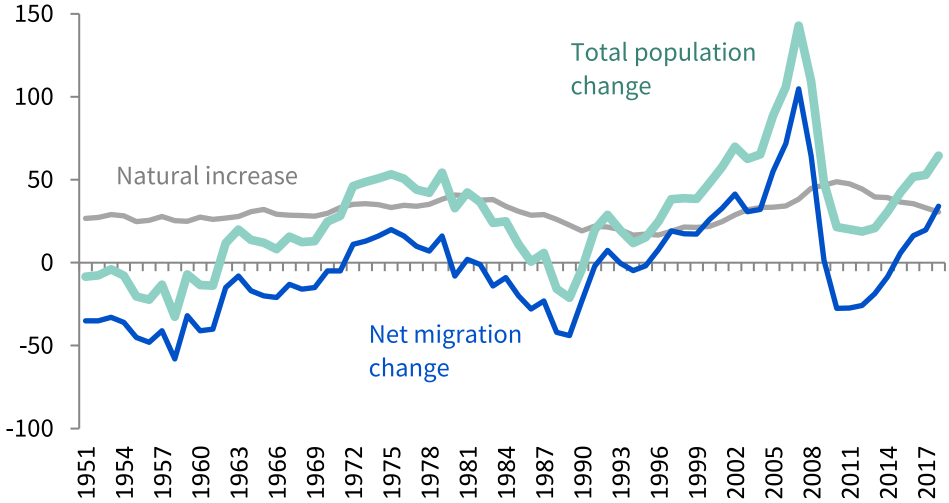
2. Context and Relevant Literature

Context

Ireland's demographic evolution since the middle of the last century has been somewhat unique compared to international trends. Population growth in the 1950s was negative (Figure 1). This reflected negative net migration flows, which were not offset by natural increases of population (the difference between births and deaths). This pattern reversed between the 1960s and the 1990s, when slightly negative average migration flows were fully offset by a relative strong natural increase of population. From the mid-1990s up until the pre-crisis peak (2007), Ireland's population grew strongly, fully driven by very positive net inward migration as a result of a booming economy. The opposite effect took place with the onset of the Great Recession, though the recovery of the economy has brought about positive contributions of net migration to total population growth since 2015.

Figure 1: Net migration in Ireland is a key contributor to population growth (1951–2017)

Thousands, year-on-year growth



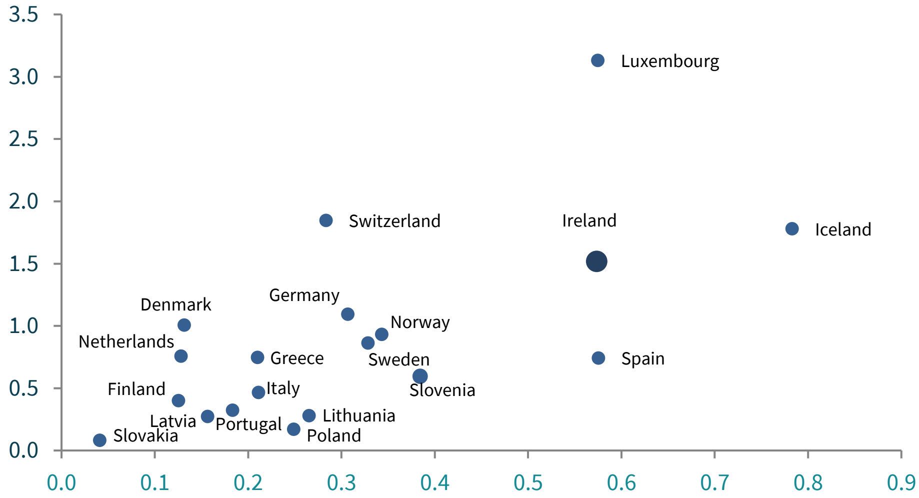
Sources: CSO.

Note: The natural increase refers to the difference between births and deaths.

One of the key challenges in terms of modelling Irish migration is the volatility of flows and their relative importance to the overall population. Figure 2 shows that (1) the volatility of immigration as a share of total population in Ireland is one of the highest in Europe, and (2) immigration as a share of total population in Ireland is one of the highest in Europe. Relatedly, Figure 3 shows the close correlation between net migration flows and the Irish cycle.[2] The fact that Irish migration is so volatile implies that the overall Irish population structure is also subject to significant risks in the event of potential shocks. With this in mind, well-founded migration projections are paramount: their dynamics impact on population projections, which are a key pillar in the evolution of the public finances. In order for sound long-term policies to be possible, and admitting the underlying uncertainty of such projections, a solid methodological basis is necessary.

Figure 2: Scale and volatility of immigration in Europe (1990–2016)

Horizontal axis= Volatility, vertical axis= Share of Total Population (%)

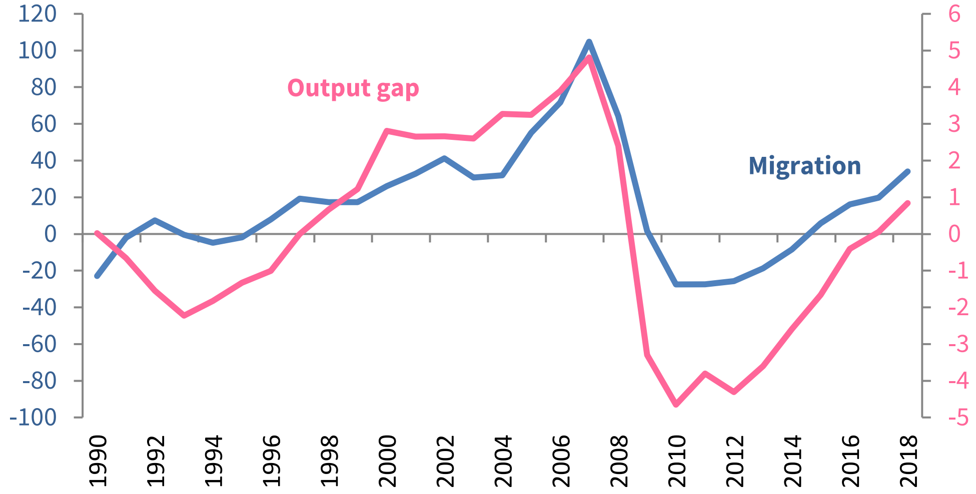


Sources: Eurostat; and author's own calculations.
Note: Volatility is measured as the standard deviation of the mean share of immigration over total population for the period 1990–2016. The share of immigration over the total population comprises the average attained over the period 1990–2016.

[2] The Irish cycle is reflected here through the "output gap", a measure that aims to reflect the cyclical position of the economy. This is calculated as the difference between the actual output and the estimated potential output at any particular point in time. The potential output is the maximum level of economic output that is sustainable in the medium to long run, where "sustainable" implies that output, when at its potential, is not unduly influenced in any particular direction by imbalances in the economy, be they external, internal or financial. The output gap estimates shown in this paper are based on Casey (2018).

Figure 3: Net migration and the cyclical position in Ireland

Migration in thousands (LHS); Output gap, % of potential output (RHS)



Sources: CSO; Casey (2018); and author's own calculations.
Note: Output gap estimates are based on Casey (2018).

Literature on Irish Migration Modelling

The migration literature for Ireland to date has focused on explaining past trends, with projection exercises being scarce. Kearney (1998) found that Irish migration over 1951–1995 could be explained through relative wages and relative employment between Ireland and the UK in the previous period. Based on this specification, FitzGerald and Kearney (1999) showed that migration has made the supply of labour in Ireland significantly more elastic than it would be in a closed economy. They found that migration has helped to relax capacity constraints when the economy is growing rapidly, allowing for even stronger growth than would otherwise be the case.

The increased elasticity of labour supply via migration was also found to serve as a so-called "safety valve" in Ireland. This suggests that migration can be a means of insulating the economy from potential shocks (FitzGerald and Kearney, 1999).[3] In downturns, for instance, an increase in migration outflows can lead to less expenditure on unemployment benefits than if individuals were to remain in Ireland. This can entail more scope for discretionary fiscal policy to support the economy and, hence, a less disruptive shock.

[3] For instance, when the economy was performing poorly, many Irish people chose emigration instead of unemployment, reducing the purely domestic impact of shocks.

On the other hand, more recent literature (Lozej, 2018) found that migration can amplify business cycles due to country-specific shocks. Positive shocks to the economy may increase migration and, initially, unemployment. This lowers the scope for wage negotiation, making firms become more profitable and more likely to post more job vacancies. Because there are simultaneously more vacancies and more searching workers, the matching process on the labour market is less congested, and employment and output increase more quickly and by more. The model by Lozej (2018) was calibrated with Irish data.

In terms of wages, Barrett *et al.* (2011) found that the impact of immigration on the wages of natives in Ireland is dependent on whether the cells are analysed by education/experience or by occupation/experience. Barrett *et al.* (2012) showed that the wage penalty for migrants is particularly significant for workers arriving from countries that joined the EU in 2004. Along these lines, Walsh (2013) found that there are substantial wage penalties for migrants across different groups, except for migrants who enter regulated sectors, where the penalisation is found to disappear.

Official Migration Projections for Ireland

Turning to the projection side of migration flows, official projections for Ireland undertaken by domestic and international institutions are generally based on expert judgement. For example, Ireland's Central Statistics Office (CSO, 2018) offers a set of three migration scenarios over the long run, where net migration flows are assumed to remain flat at 10,000, 20,000 and 30,000, respectively, over the projection horizon 2019–2051.[4] These figures are said to be based on recent migration trends, and other economic and demographic factors. The projections are based on judgement and do not explicitly have a link to economic conditions. The methodological note cites the challenges faced: "…given the difficulties associated in predicting future economic conditions, not alone in Ireland but in the wider global economy, the Expert Group considered it unwise to explicitly factor economic growth into the assumptions on migration".

The United Nations (2019b) long-term migration projections for Ireland also point at relatively constant flows of 50,000 over the whole projection horizon 2020–2100 in

[4] While the CSO is not a forecasting agency, their population projections for Ireland are widely used by researchers and policymakers.

the "medium" scenario. The baseline migration assumptions for the 235 analysed countries generally depend on: (1) information on net international migration or its components (immigration and emigration) as recorded by countries; (2) data on labour migration flows; (3) estimates of undocumented or irregular migration; and (4) data on refugee movements over recent years (United Nations, 2017). The 2019 revision (United Nations, 2019) assumes that international migration from 2050 to the end of the 21st century would remain constant at the level projected in 2045–2050.[5]

Eurostat (2018) offers a more refined methodology for its long-term migration projections. Using migration data since 1960, migration trends are extrapolated by applying ARIMA models which are selected by an automated model specification procedure. These values progressively fade within values derived from an assumed convergence component of the model, a transition that is set to be completed by 2050 for most countries.[6] In the short term, the convergence component is country-driven and forces the series to converge in 2022, which is linearly interpolated from the value of 2017. The 2022 point is calculated as the average of the net migration over the last 20 years (1998–2017, in this case). The latest Eurostat (2018) projections for Ireland point to net migration flows of 10,125 in 2020, slightly increasing to around 15,880 in 2050. From 2050 onwards, the projected flows trend down to around 8,400 by 2100.

International Literature on Migration Projections through Gravity Models

In projecting migration, gravity models are increasingly employed, especially as data availability increases. However, as previously outlined, official projections are not—as yet—based on such models. Hanson and McIntosh (2016) provide a pioneering application of gravity models of migration into a world-projection model over the long run. Drawing on extensive literature on the theoretical framework around gravity models of migration (see, for example, Beine *et al.,* 2011 or Bertoli *et al.,* 2013), their findings point that, because the Americas are entering a period of

[5] Except for the countries where migration fluctuated significantly, or whether there existed refugee flows or temporary labour flows, migration levels were kept constant over the projection horizon.

[6] This is applied to all countries except for those whose working-age populations are projected to shrink, for whom convergence is set to be completed by 2030.

low population growth, flows across Rio Grande will slow markedly. Europe is projected to face substantial demographically-driven migration pressures from across the Mediterranean. However, the dataset employed in their paper covers the period 2000–2010 for OECD countries, a particularly critical period for Ireland following the pre-crisis migration boom and the early crisis migration decline. This is overcome in this paper by including a larger timeframe, which covers the period 1960–2019.

A more recent paper also offers a world-prediction approach through gravity models, focusing on the particular case of Spain (Fernández-Huertas and López-Molina, 2018). The paper finds that migration flows depend more heavily on the span of the dataset used to estimate the model than on the specific variables chosen for the model prediction, though demographic factors are found to be significant. It shows that fixed effects absorb the largest part of the historical variation of migration flows across origins, destinations and time, implying that economic and demographic variables, as well as network effects (the stock of co-nationals already living in a given country), do not play such a meaningful role in explaining the variation of migration flows. The models proposed in Fernández-Huertas and López-Molina (2018) are estimated through OLS, which can be problematic in the presence of zeros in the data. To deal with this, our paper is based on the PPML estimation method, which offers robust estimates to heteroscedasticity patterns and provides a natural way to deal with the presence of zeros in the data.

Based on the gravity model research on migration flows available to date, the aim of this paper is to build a world-projection model for migration, with a focus on the specific case of Ireland.

3. Data and Methodology

This section describes the data and methodology followed in the paper, including ways to deal with potential endogeneity of the variables in the model.

Data

In order to study bilateral migration flows, we employ a wide range of migratory, demographic, economic and time-invariant information.

Migration data

Migration data is retrieved from Özden *et al.* (2011)—published in the World Bank's Global Bilateral Migration Database—for the decadal period 1960–2000, and from the United Nations (2017 and 2019b) for the years 2010 and 2019.[7] The migration estimates for 2019 are used as a proxy to the decade of 2020. Counting on this additional decade is important to the model given the relatively limited data frequency of the database. Both the World bank and the United Nations provide information of bilateral migration in stock terms for a number of country pairs. Hence, the data is provided in net migration terms, meaning that changes in migration stocks are influenced by return migration, migration to third countries, deaths, naturalisations (when migrants are categorised by citizenship) or births (when the country of destination adopts the *ius sanguinis*), as pointed out in Bertoli and Fernández-Huertas (2015).

In terms of the categorisation of migrants, the World Bank's Global Bilateral Migration Database provides migration data primarily based on the "foreign-born" concept. This means that, where possible, migrants are categorised by country of birth rather than by nationality. From the point of view of this analysis, the country of birth criterion is most adequate, since it avoids potential inconsistencies in the quantification of migrants and it offers a number of additional advantages (Özden *et al.,* 2011; United Nations, 2017). For example, while nationality can change, place of birth cannot. In addition, it is a more appropriate criterion in analysing physical movements and dealing with the cases of former colonies and dependencies (e.g.,

[7] For the data on Irish-born migrants living abroad, the World Bank data for 2000 is substituted by the United Nations data in cases where strong discrepancies pointed at the latter proving more sensible in terms of migration estimates. This was the case in few countries of destination of Irish migrants in that year; for example, France.

residents of Martinique, a French dependency, are automatically granted French citizenship).[8] The World Bank's Global Bilateral Migration Database is the pioneering source to enable this type of detailed analysis, with over one thousand census and population register records combined to construct decennial matrices corresponding to the last five completed census rounds.

In parallel, the United Nations database compiles estimates of the international migrants stock for the five-year period 1990–2015, and for the years 2017 and 2019.[9] As in Özden *et al.* (2011), migrants are primarily identified by country of birth. This is the case in the majority of countries or areas. Yet, whenever this data is missing, information on country of citizenship is used instead.

Given the 10-year frequency of the data in Özden *et al.* (2011), the last observed period considered in this exercise is 2020, using the latest United Nations (2019b) data for 2019 as a proxy of this decade. With this in mind, the combination of both databases gives rise to a 232×232×7 matrix, showing the corresponding countries of origin and countries of destination, for each of the 7 time periods considered. An important amendment was done to the original data on Irish-born people living in the UK in 1960. While the World Bank data pointed to a figure of 892, the UK censuses provided a figure that totalled 737,192.[10]

Figure 4 shows the evolution of foreign migrant stocks in Ireland and those of Irish nationals abroad for the top 5 countries in 2019. In terms of immigration, the UK is significantly ahead of the rest of the countries, with close to 300,000 migrants in Ireland. This is followed by Poland, for whom Ireland became a popular country following its accession to the European Union and a booming economy—particularly in the construction sector—in Ireland. Regarding the stock of Irish

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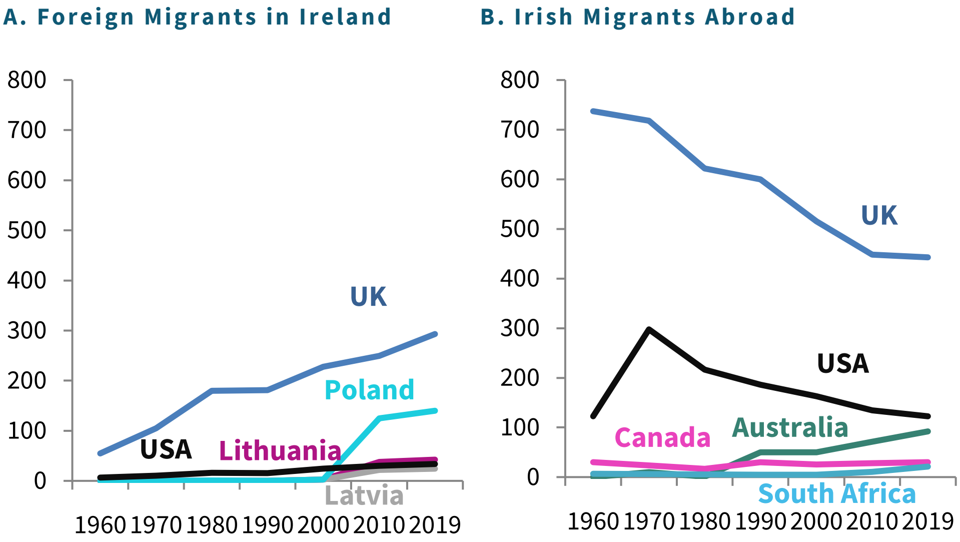
[8] For example, if the country of citizenship is based on *jus sanguinis*, people born in the country of residence may be included in the number of migrants, while they may have never lived abroad (United Nations, 2017).

[9] While most of the data is obtained from population censuses, additional sources like population registers or nationally representative surveys provided information on the number and composition of the migrants (United Nations, 2017).

[10] This data refers to the Northern Irish, English and Welsh, and Scottish 1961 censuses on Irish-born individuals registered in the corresponding censuses. The disaggregated figure is: 644,398 in England and Wales; 53,124 in Northern Ireland; and 39,670 in Scotland.

people abroad, the UK is again the most popular destination, though the trend of stocks in the country has declined in recent decades.

Figure 4: Migrant stocks, top 5 countries in 2019
Thousands



Sources: World Bank (Özden *et al.,* 2011); and United Nations.
Note: The number of Irish migrants in the UK in 1960 is not based on the World Bank data, but on data provided by the Scottish, Northern Irish, English and Wales Central Statistics Offices.

Demographic data

In terms of the demographic factors included in the model, we use United Nations data for the non-Irish population, and CSO data for the Irish population. For the projections, we use the United Nations' "medium" population variant, and the CSO's projections for the Irish population.[11] Both databases provide age breakdowns, which are included in the model. In particular, we provide a population breakdown by three broad age-groups (as in Fernández-Huertas and López-Molina, 2018) for each country of destination and country of origin: below-15, between 15 and 64, and over 65. This allows us to incorporate cross-elasticities across cohort-cells, following Bertoli (2017). This contrasts with the approach undertaken by Hanson and McIntosh (2016), where the elasticity assumed for both origin and destination countries is the same.

[11] The CSO's population projections use their F1 scenario, which assumes that Total Fertility Rates remains at its 2016 level of 1.8 for the lifetime of the projections. As outlined in the methodological section, the population projections are updated to incorporate the migration projections shown in this paper.

Economic data

The economic conditions at origin and destination are captured through a measure of real GDP per capita from Feenstra *et al.* (2015) available at the Penn World Tables.[12] This is done for all the countries except for Ireland, where the activity of multinational companies in the country heavily distorts the GDP figure. In order to provide a measure that better reflects the underlying Irish economy, we use the real GNP series for 1960–2011 and grow them by real Domestic GVA thereafter.[13]

For the projection part of the exercise, Irish Domestic GVA per capita growth is based on the Irish Department of Finance's (2018) forecasts as per *Budget 2019* out to 2020, followed by assumptions on long-term growth projections thereafter. These assume that real Domestic GVA growth converges to 2.5 per cent in the medium to long run, close to the upper end of potential growth forecasts for advanced economies. It is also close to the ESRI's recovery scenario of the Medium-Term Review (ESRI, 2013), and slightly below the ESRI's baseline scenario in the 2016 Economic Outlook (ESRI, 2016), which places potential growth at 3 per cent by 2025.

For the rest of the countries, we resort to a number of different sources and assumptions. In particular, projections for the UK are taken from the Office for Budgetary Responsibility's (OBR) forecasts of real GDP per capita contained in their Fiscal Sustainability Report (2018), as they provide up-to-date estimates that reflect potential risks like Brexit, and they also include well-founded long-run estimates of GDP. With the exception of the UK, the rest of the countries' real GDP is grown by the IMF's World Economic Outlook projections (2018) out to 2023. From then onwards, we employ Oxford Economics forecasts or trend-analyses to grow real GDP and to stabilise its growth over the long run.

Additionally, two alternative GVA scenarios are presented for Ireland, with the aim of analysing the responsiveness of migration flows to changes in the Irish economy. The optimistic growth scenario assumes a convergence growth of 4 per cent,

[12] The specific indicator we use is the expenditure-side real GDP at chained PPPs (in mil. 2011 US dollars).

[13] FitzGerald (2015) outlines a number of problems in interpreting the Irish national accounts as a result of the impact of the globalisation process in the Irish economy.

whereas the pessimistic one assumes a growth of 1.5 per cent, close to the ESRI's stagnation scenario of the Medium-Term Review (ESRI, 2013).

Time-invariant data

Time-invariant variables are taken from the CEPII's Gravity and GeoDist databases, a well-known resource to capture both unilateral and bilateral features of countries (such as geographical distance between two countries, whether they share a common language, or the specific area of the countries). An important consideration, further developed in the methodological section, is that these do not allow us to explicitly incorporate the relative attractiveness of country-pairs, both among themselves and relative to a third country. To account for this, country-pair fixed effects will be included in order to gauge all the time-invariant features.

Methodology and endogeneity issues

The specification of the gravity equation is broadly comparable to that in Fernández-Huertas and López-Molina (2018), where migration depends on the lagged migration stocks, population structures by broad age groups at origin and destination, GDP per capita at origin and destination, and other time invariant features. However, an important difference arises in the estimation method. While their equations are estimated through OLS, this paper proposes a non-linear (exponential) equation, which is estimated through PPML (Santos and Tenreyro, 2006).

In general, the log-linearisation of the models and their estimation via OLS has been common practice in the literature. However, the interpretation of these parameters can be misleading in the presence of heteroscedasticity.[14] Testing the gravity equations both in their traditional form (Tinbergen, 1962) and more recent ones that take into account multilateral resistance terms or fixed effects (as suggested by Anderson and van Wincoop, 2003), the research by Santos and Tenreyro (2006) find that heteroscedasticity is indeed a severe problem.

[14] This is known as the Jensen's inequality, which implies that $E(\ln y) \neq \ln E(y)$, i.e., the expected value of the logarithm of a random variable is different from the logarithm of its expected value (Santos and Tenreyro, 2006).

In order to overcome this potential source of bias, Santos and Tenreyro (2006) argue that the gravity equation and, more broadly, constant-elasticity models, should be estimated in their multiplicative form. They propose a PML estimation technique that, besides being consistent in the presence of heteroscedasticity, provides a natural way to deal with the problem of zeros in the dependent variable. This is an important matter given the common presence of zeros in this type of data. Based on the statistical robustness of this estimation method, the equations in this paper will be estimated through PPML.

The model is based on the so-called random utility maximisation model (RUM) (McFadden, 1974), which assumes that the decision to migrate depends on the destinations chosen by utility-maximising individuals. Beine *et al.* (2016) provide a detailed exposition of the model, as well as its advantages and drawbacks. The probability of individuals migrating from country of origin o to country of destination d ($odds_{od}$) is expressed as the share of the total population at the country of origin (Pop_o, lagged) who actually migrate to the country of destination ($mg_{o,d}$):

$$odds_{o,d,t} = \frac{mg_{o,d,t}}{Pop_{o,t-1}}$$

Where $odds = [0,1]$. In terms of the numerator, a wide range of definitions of migration have been used in the literature. For example, Mayda (2010), Ortega and Peri (2013), Bertoli and Fernández-Huertas (2013), McKenzie *et al.* (2014) and Bertoli *et al.* (2013) use gross flows; conversely, some other papers use variations in migration stocks (for example, Bertoli and Fernández-Huertas, 2015), which can be problematic due to the presence of negative values; and others used stocks for the numerator (for example, Llul, 2011), which can be in conflict with the micro-foundation of the gravity equation (Bertoli and Fernández-Huertas, 2016). In this paper, our preferred numerator comprises migration stocks, given the nature of our data. This is in contrast with choosing variation in migration stocks (i.e., flows), which can prove extremely problematic in an exponential model, given the necessary condition of PPML models of a positive conditional mean.

Equations 1 and 2 show that the odds of migrating from origin o to destination d are expressed as an exponential function of the lagged logarithms of migration stocks; the population structures at origin and destination disaggregated by age groups, denoted with an i; the real GDP per capita ($GDPc$) at both origin and destination (Domestic GVA for Ireland); and time-invariant features (language, distance, and area—$lang$, $dist$, and $area$ respectively in equation 1—and Multilateral Resistance to Migration, MRM, in equation 2). The rationale for the specification of equations 1 and 2 is explained in the reminder of the section, as well as how potential endogeneity bias is dealt with in the paper.

Equation 1: Model with Time-Invariant Explicit Variables

$$odds_{o,d,t} = exp\Big(\beta_0 * lnM_{o,d,t-1} + \sum_i \beta_{1,i} * lnPop_{i,o,t-1} + \sum_i \beta_{2,i} * lnPop_{i,d,t-1} + \beta_3 * lnGDPc_{o,t-1} + \beta_4 * lnGDPc_{d,t-1} + \beta_5 * Lang_{o,d} + \beta_6 * lnDist_{o,d} + \beta_7 * lnArea_o + \beta_8 * lnArea_d\Big) + \alpha_{o,d,t}$$

$$\forall \mathrm{o} \neq \mathrm{d}, \text{where } \mathrm{o} = 1, \dots, 232; \mathrm{d} = 1, \dots, 232; \mathrm{t} = 1970, \dots, 2020; \mathrm{i} = [15^-, 15-64, 64^+]$$

Equation 2: Model with Country-Pair Fixed Effects (Projection Model)

$$odds_{o,d,t} = exp\Big(\delta_0 * lnM_{o,d,t-1} + \sum_i \delta_{1,i} * lnPop_{i,o,t-1} + \sum_i \delta_{2,i} * lnPop_{i,d,t-1} + \delta_3 * lnGDPc_{o,t-1} + \delta_4 * lnGDPc_{d,t-1} + \delta_{5,\mathrm{o,d}} * MRM_{o,d,t}\Big) + \alpha_{o,d,t}$$

$$\forall \mathrm{o} \neq \mathrm{d}, \text{where } \mathrm{o} = 1, \dots, 232; \mathrm{d} = 1, \dots, 232; \mathrm{t} = 1970, \dots, 2020; \mathrm{i} = [15^-, 15-64, 64^+]$$

A number of explanatory variables are included in the model. Firstly, a wide range of literature has found that migration flows are generally positively correlated with the stock of co-nationals (or "diasporas") already living in a given country. As noted in Fernández-Huertas and López-Molina (2018), this pull-effect may arise due to the possibility of reducing migration costs (Mckenzie and Rapaport, 2007) and the possibility of increasing the earnings of potential immigrants at the destination country (Munshi, 2003).[15] This concept is often referred to as the "network effect". The inclusion of this variable in our model—in logarithmic terms—introduces dynamism to the projections, where the lagged migration stocks in the model are based on our own estimates over the projection horizon.

[15] For example, Beine *et al.* (2011) analyse a bilateral dataset of international migration by educational attainment from 195 countries to 30 developed countries in 1990 and 2000 and find that diasporas increase migration flows and even explain the majority of the variability of migration flows. They also find that diasporas lower the average educational level and lead to higher concentration of low-skill migrants.

The construction of equations 1 and 2 attempts to alleviate potential endogeneity issues by lagging the explanatory variables. However, there might be reasons to argue that this might be problematic for the projection part of the exercise. Most of the projected variables are exogenously taken from other institutions—which might implicitly be reflecting their own migration assumptions—and are not updated based on the migration projections calculated in this paper. In terms of the dependent variable (migration odds), however, the denominator is updated in the projection exercise such that the Irish population takes account of the migration projections calculated for each projection year. While this might not have a significant impact on the projections, it ensures full consistency with the demographic projections.

Population structures can also be potential determinants of migration flows, yet the impact of the origin and destination cohorts is somewhat mixed. These variables are incorporated into the model in their logarithmic form. While it could be argued that the inclusion of demographic variables can bias the true elasticities given the possible existence of endogeneity, the paper takes them as exogenous. The rationale for this is that Ireland is a comparatively small enough country as to not influence significantly on the (log) structure of the world population, as also argued in Fernández-Huertas and López-Molina (2018) for the case of Spain. In particular, the Irish population represented less than 1 per cent of the total population in Europe in 2018, and less than 0.1 per cent of the total world population (United Nations, 2019a).

Economic conditions at origin and destination are included in logarithmic terms and lagged to the previous decade. Concerns on potential endogeneity issues seem apparent if migration was to exert a significant impact on the economic conditions of a given country. Kangasniemi *et al.* (2012) showed that the impact of foreign labour on performance depends on the skills set of the migrants. For example, they found that immigration during 1996–2005 has barely contributed to total factor productivity in the UK, while it has negatively impacted productivity in Spain.[16,17]

[16] Their findings broadly hold across all sectors, but they note considerable variation in terms of magnitudes of the impact.

[17] They suggest that immigrants can play an important role in spreading the use of technology and innovation. However, they also point to the fact that immigration can influence the way in which firms carry out business and the development of industrial structure as “they affect the relative price of inputs, (making capital relatively more expensive) and therefore the choice of production

Conversely, González and Ortega (2011) found that the large inflow of immigration between 2001 and 2006 in Spain did not affect the wages or employment rates of unskilled workers in the destination regions.[18] In terms of the impact of migration policies, Ortega and Peri (2014) found that openness to immigration has a positive effect on long-run income per capita.[19] A recent paper (Tombe and Zhu, 2019) found that reductions in trade and migration costs in China accounted for 27 per cent of China's aggregate labour productivity growth from 2000 to 2005.

In our model, we take the lagged real GDP (real Domestic GVA in the Irish case) as exogenous, admitting that this can be problematic for a number of countries, including Ireland, where the share of migration can be large enough as to expect endogeneity bias to become an issue. However, endogenising our economic variable would introduce huge complexities to the model, as it would potentially require establishing a country-pair relationship on the impact of migration on economic growth/productivity. As previously explained, this might require counting on data in terms of the specific skills of the migrants, which we lack. Also, the aggregate nature of the model (which does not identify individual migrants) would limit the scope to introduce this to the exercise. An alternative option would be to find an instrument that is correlated with GDP but does not directly impact migration flows. This might be challenging, and given the large number of countries, it might seem unlikely to find an instrument that covers the information for all of them (or, at least, for as many countries as we have GDP data for).

The inclusion of time-invariant features is paramount, and their omission can lead to biased estimates of the true elasticities. These are included in different forms in equations 1 and 2, respectively. Equation 1 aims to identify the impact of the language, distance between two countries, and the area of the origin and destination countries on migration flows. The way these are included in the model is as follows: common language ($lang$) is a dummy variable that takes value one if the

technology". Dustmann *et al.* (2008) showed that an increase in low-skilled labour supply can increase capital accumulation and shift the output mix towards the production of goods used by unskilled workers more intensively. This is known as the "Rybczynski effect".

[18] In particular, they noted that the observed growth of unskilled workers was mostly absorbed through increases in total employment.

[19] In particular, Ortega and Peri (2014) show that "the effect of migration operates through an increase in total factor productivity, which appears to reflect increased diversity in productive skills and, to some extent, a higher rate of innovation".

country-pair share a common official language; distance ($dist$) measures the geodesic distance following the great circle formula, which uses latitudes and longitudes of the most important cities/agglomerations (in terms of population); and area ($area$) measures the area of the country of origin and destination, respectively, in km^2 (Mayer and Zignago, 2011).[20] This equation intends to gauge the incidence of those specific time-invariant factors in explaining migration flows.

Instead of using specific time-invariant features, equation 2 incorporates country-pair fixed effects, which aim to capture all the time-invariant country-pair specific features. This refers to an extremely important concept in the migration literature within this type of models: the Multilateral Resistance to Migration (MRM) (Bertoli and Fernández-Huertas, 2013). The concept is based on the premise that the rate of migration observed between two countries is not only dependent upon their relative attractiveness, but also on the attractiveness of alternative destinations. As outlined above, equation 2 will mainly be used for the implementation of migration projections.[21]

After projecting the odds of migrating, and the migration stocks (M_t) for a given decade, we then calculate the implied migration flows. Because our data is provided in net terms—as opposed to gross—migration flows are calculated as the change in stocks of foreigners (from country o) in the country of study w, minus the change in the stocks of natives of that country w who migrated to another country of destination (d). As previously noted, using the change of stocks as a proxy of the flows can be problematic, given the possible incidence of deaths, naturalisations and other factors that might interfere in the change of stocks.

$$mg_{w,t} \equiv \sum \left(M_{o,w,t} - M_{o,w,t-1}\right) - \sum \left(M_{w,d,t} - M_{w,d,t-1}\right) \equiv \sum mg_{o,w,t} - \sum mg_{w,d,t}$$

$$\forall \mathrm{o} \neq \mathrm{w}, \text{and } \forall \mathrm{d} \neq \mathrm{w}$$

[20] This is reflected in the CEPII’s bilateral file dist._cepii.xls, under the variable “comlang_off”. The data on bilateral distance (denoted as “dist” in the CEPII database) and to the area of each country (“area”) are both included in the geo_cepii.xls file.

[21] The estimation of Equation 2 is attained using the -xtpqml- command in Stata (Simcoe, 2007), with country-pair fixed effects and robust standard errors. Conversely, Equation 1 is estimated using the command -ppml- in Stata, with robust standard errors.

Another challenge relates to the limited frequency of the data. Since our migration data is on a 10-year basis, there is no accurate way to know the exact annual flows; rather, this is an indication of where the country stands by the end of the decade.[22] Once the decadal stocks are projected, these are then annualised through a cubic spline interpolation to later construct annual migration flows.

Given the nature of the historical data, the primary migration projections are shown in aggregate terms (i.e., without an age breakdown). However, it is important to analyse the expected age distribution of the migrants, as this can help evaluate the impact of migration on the overall population structure and can give an indication of its impact on the labour market structure. Appendix A outlines how these disaggregated migration figures can be incorporated into the cohort-component model, a method to project population widely used by national and international institutions.[23] Appendix B details the underlying age and gender assumptions made in this paper for the projected migration flows in Ireland. Those are based on Vector of AutoRegression (VAR) models which are estimated for the series of immigrants and emigrants—by sex—available since 1987. The immigrants' age and gender distributions are applied to the foreign population migration into Ireland, while the emigrants' distributions are applied to the Irish migrants abroad. This assumption is needed given the nature of the data, where migrants are shown in net terms. However, we would not expect this to be a major problem given the relatively similar age and gender profiles projected for both immigrants and emigrants, as well as the strong concentration of working-age migrants projected in both cases.

[22] If flows are, for example, positive, that does not necessarily imply that flows were consistently positive in every year of the decade. Another consideration to take into account is that part of the changes in migration stocks can be down to mortality. However, we expect this not to significantly impact on the observed changes in stocks, especially given the age profile of the migrants. In other words, improvements in survival rates over the past decades in most countries have been especially strong in very early ages (i.e., newborns) or in later ages, with most of migrants lying outside these age ranges.

[23] Matrix A shows how migration, by age and gender, feeds into the current year's population base. Since the population base is used for the calculation of newborns and "survivors" (i.e., those who survived from one year to the other), this means that the migration structure will also play a role in the calculation of these.

4. Results

4.1 Estimation results

The estimated coefficients are plausible in size and are broadly consistent with international literature on migration explained through gravity models. Tables 1 and 2 show the estimated coefficients from equations 1 and 2 above respectively, as well as some variations of these equations. Table 1 relates the odds of migration to population structures, GDP per capita, and time-invariant features. Table 2 relates the odds of migration to population structures, GDP per capita, and country-pair fixed effects (Multilateral Resistance to Migration).

Table 1 shows that language tends to play a significant and positive role in explaining migration odds, as one would expect. In terms of distance, its effect is consistently negative and significant across all four models. This is in line with the premises of gravity models. The area of the destination country is found to positively help explain the probability of migrating, whereas the impact of the area of origin is much less clear.

A potential shortcoming of Table 1 is that the omission of Multilateral Resistance to Migration can bias the estimates of the true elasticities. As previously outlined, this concept gauges the relative attractiveness of country pairs, as well as the attractiveness of a country relative to alternative destinations. To include the principles of Multilateral Resistance to Migration, Table 2 includes country-pair fixed effects, with the first model (2.a) being the preferred one for its completeness, overall consistency with international research, and goodness of fit. This model contains 57,497 observations.

As an exception, however, Irish emigration to the UK and the US will be projected through model 1.a (which includes the network variable, as well as demographic, economic and specific time-invariant features). This is due to the unique past relationship of Irish emigrants with those two countries, where the strong historical links—especially in the initial years of the sample, with substantial declines as the in recent decades—leads to implausibly high migration projections when using model 2.a. For example, the odds of Irish migration to the UK in the 1970s amounted to 25 per cent. Only in 0.04 per cent of the sample can we find examples where the migration odds are that high. The implication for those two countries is that the country-pair fixed effects become extremely high as the model pulls these high odds into the migration projections.[24,25]

Consistent with international literature, the network effect is positive and significant across all six models (Tables 1 and 2), confirming the relevance of the diaspora effect as analysed in Beine *et al.* (2011). Taking the preferred model (2.a), the network impact is 0.20, significantly lower than the typically-reported estimates of close to the unity (Beine *et al.,* 2011), but above the 0.08 reported in Fernández-Huertas and López-Molina (2018). However, when analysing the network effect reported in Table 1, the most complete model (1.a) shows a coefficient of 0.75, more in line with previous research. However, the omission of Multilateral Resistance to Migration might pose concerns in terms of bias of this estimate.

In terms of the incidence of economic conditions in explaining migration flows, GDP per capita at destination is found to be highly significant and positive across all six models where it is included (1.a, 1.b, 1.d; and 2.a, 2.b, 2.d), in line with previous literature. As regards the origin GDP per capita, this is found to be negative, as one would expect. While highly significant in the models where country-pair features are specifically included (Table 1), it is found not be significant in the models where fixed effects are included (and, in particular, in the preferred model 2.a). Focusing on Table 2, both findings on origin and destination GDP per capita are in line with the principles of micro-founded gravity models, which state that the elasticity of economic conditions at destination over migration should be larger (in absolute terms) than the elasticity of the economic conditions at the origin country.

[24] This may be for a number of reasons, including time-varying effects that the model appears unable to gauge. If the dependent variable were defined as the migration flows, the declining trend of the odds might be more accurately reflected in the country-pair fixed effects. However, this is not appropriate given the functional form of our equation.

[25] An alternative approach would be to include a country-pair linear trend.

Table 1: Odds of migrating: PPML estimations with time-invariant characteristics (1970–2020)

		(1.a)	(1.b)	(1.c)	(1.d)
Network		0.75***		0.69***	0.48***
		(0.02)		(0.06)	(0.04)
GDP per capita	origin	-0.14***	-0.54***		-0.60***
		(0.04)	(0.05)		(0.03)
	destination	0.08*	0.37***		0.18***
		(0.04)	(0.05)		(0.04)
Population >65	origin	-0.08	0.42 ***	0.25*	
		(0.05)	(0.10)	(0.24)	
	destination	0.08**	0.45 ***	-0.17***	
		(0.04)	(0.12)	(0.25)	
Population 15-64	origin	-0.65 ***	-0.45**	-1.59***	
		(0.13)	(0.20)	(0.50)	
	destination	0.28**	0.55***	0.93*	
		(0.12)	(0.25)	(0.50)	
Population <15	origin	-0.19*	-0.37***	0.57*	
		(0.10)	(0.13)	(0.34)	
	destination	-0.32***	-0.65***	-0.63***	
		(0.09)	(0.15)	(0.18)	
Common language		0.21***	1.58***	0.33***	0.28***
		(0.05)	(0.07)	(0.08)	(0.05)
Distance		-0.12***	-1.05***	-0.28***	-0.48***
		(0.03)	(0.03)	(0.10)	(0.04)
Area	origin	0.05*	-0.01	-0.07	-0.49***
		(0.03)	(0.03)	(0.07)	(0.02)
	destination	0.07***	0.30***	0.02	0.18***
		(0.02)	(0.03)	(0.06)	(0.04)
Country-pair fixed effects		No	No	No	No
R^2		0.52	0.23	0.03	0.08
Observations		59,191	97,651	81,971	59,191
Number of country-pairs		16,830	26,896	20,959	16,830

Sources: United Nations, World Bank, CSO, Penn World Tables, CEPII, and author's own calculations.

Note: ***p<0.01; ** p<0.05; * p<0.1. Robust standard errors in brackets. The equation is shown in exponential terms, with migration odds as the dependent variable. All variables are shown in logarithmic terms (except for the dependent variable and the dummy variable on language) and are lagged to the previous decade (except for the time-invariant variables).

Table 2: Odds of migrating: PPML estimations with country-pair fixed effects (1970–2020)

		(2.a)	(2.b)	(2.c)	(2.d)
Network		0.20***		0.15***	0.18***
		(0.03)		(0.06)	(0.03)
GDP per capita	origin	-0.05	-0.07		-0.04
		(0.08)	(0.07)		(0.06)
	destination	0.17***	0.19***		0.20***
		(0.06)	(0.07)		(0.06)
Population >65	origin	0.27**	0.42 **	1.33**	
		(0.13)	(0.18)	(0.59)	
	destination	-0.07	-0.02	-0.36	
		(0.16)	(0.29)	(0.76)	
Population 15-64	origin	-0.52 ***	-0.24	-1.40***	
		(0.18)	(0.22)	(0.42)	
	destination	0.40*	0.36	2.07**	
		(0.24)	(0.31)	(1.03)	
Population <15	origin	-0.01	-0.12	0.22	
		(0.16)	(0.17)	(0.19)	
	destination	-0.54***	-0.53**	-0.74***	
		(0.15)	(0.23)	(0.27)	
Country-pair fixed effects		Yes	Yes	Yes	Yes
R^2		0.85	0.79	0.56	0.84
Observations		57,497	73,553	83,146	57,497
Number of country-pairs		13,976	16,750	19,238	13,976

Sources: United Nations, World Bank, CSO, Penn World Tables, and author's own calculations. Note: ***p<0.01; ** p<0.05; * p<0.1. Robust standard errors in brackets. Model 2.a is the baseline model used for the projections. The equation is shown in exponential terms, with migration odds as the dependent variable. All variables are shown in logarithmic terms (except for the dependent variable) and are lagged to the previous decade.

The impact of the demographic structures is slightly more complex to verify in that the literature is not conclusive on the direction of their impact. When specifically including time-invariant country-pair features (Table 1), one can see that the demographic structures explain a great deal of the variation of migration odds: for example, the R^2 in model 1.a is a lot higher than in model 1.d, where population structures are excluded as explanatory variables. This is in line with Hanson and McIntosh (2016). However, this variation disappears when instead including country-pair fixed effects, more in line with Fernández-Huertas and López-Molina (2018). Looking at Table 2, the working-age population at origin is found to negatively impact the odds of migrating. Conversely, the working-age population at destination is associated with increased migration odds, in line with Fernández-Huertas and López-Molina (2018). Also in line with their paper, our results suggest that an increase in older cohorts in the origin country help positively explain the odds of migrating. Lastly, the younger cohorts at destination in the previous decade are found to negatively impact on migration.

As a robustness check to these results, Appendix C shows the coefficients estimated through OLS, with the log odds of migrating as the dependent variable. The network effect is found to be positive and highly significant in all the models, and their magnitude is close to the corresponding coefficients estimated through PPML. Consistent with the PPML estimates—and with the theoretical micro-foundations of gravity models—the models estimated through OLS also show positive and significant effects of per capita GDP at destination. The impact of origin GDP is much weaker than in the PPML models, and its effect is broadly insignificant (as was the case in all PPML models in Table 2). In most of the OLS models, the sign of the origin GDP per capita coefficient does not go in line with what one could expect, whereas it is always consistent (i.e., negative) in all the PPML models. As regards population structures, the signs of nearly all the coefficients in the OLS models coincide with those in the PPML models, although their significance sometimes differs.[26]

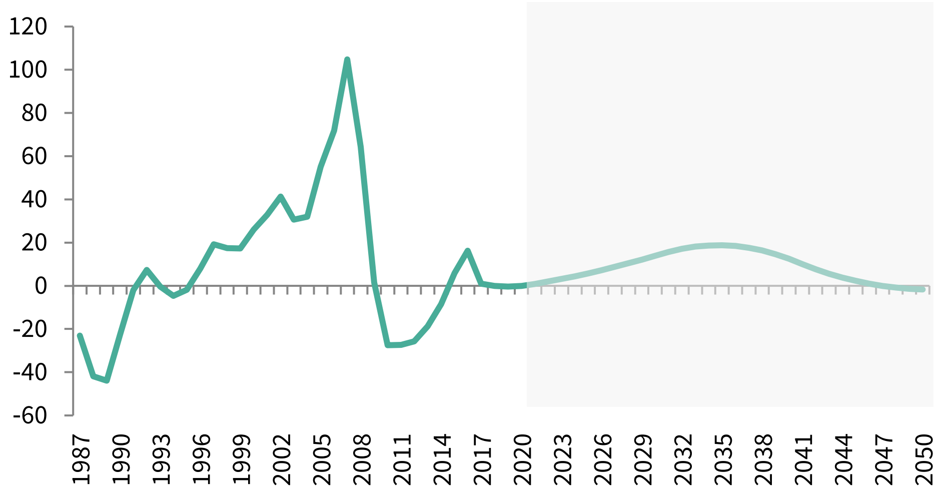
4.2 Projection results

This section explores the projection of migration flows with a focus on Ireland. The projections suggest that net flows will amount to 14,000 by 2030, and then slightly trend down to 12,500 by 2040, before being close to zero by 2050. The projected flows average to 9,000 per annum over the projection horizon, as shown in Figure 5, largely reflecting relatively favourable productivity growth in Ireland. These positive flows are the result of (1) foreign migration flows to Ireland projected to be consistently positive over nearly the whole projection horizon, broadly in line with their long-term average (Figure 6A); and (2) Irish emigration being comparatively lower nearly over the whole projection horizon (Figure 6B).

[26] For example, comparing the preferred models that incorporate country-pair fixed effects (model 2.a in Table 2 and model 4.a in Table C.2), the OLS equation shows that the negative coefficient of old-age population at destination is actually significant.

Figure 5: Net migration flows, projections for Ireland

Thousands (decade average for the projection period)

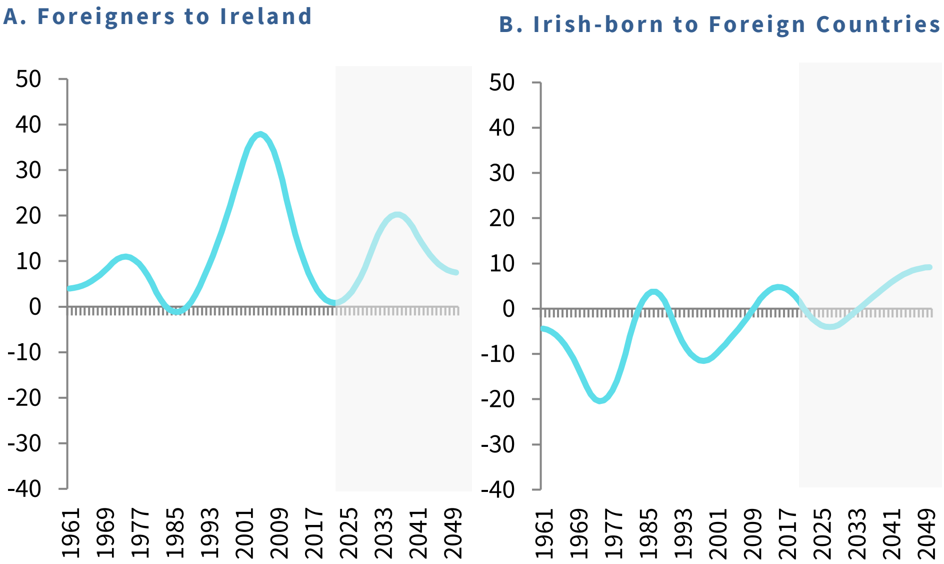


Sources: CSO; and author's own projections.

Note: Net migration flows are projected on decadal terms, and are annualised through a cubic spline interpolation. Historical data until 2016 (census year) is based on the CSO's estimates; from then onwards, projections are shown.

Figure 6: Projected net migration inflows and outflows in Ireland

Thousands (decade average)



Sources: World Bank (Özden *et al.*, 2011); United Nations (historical data); and author's own projections.

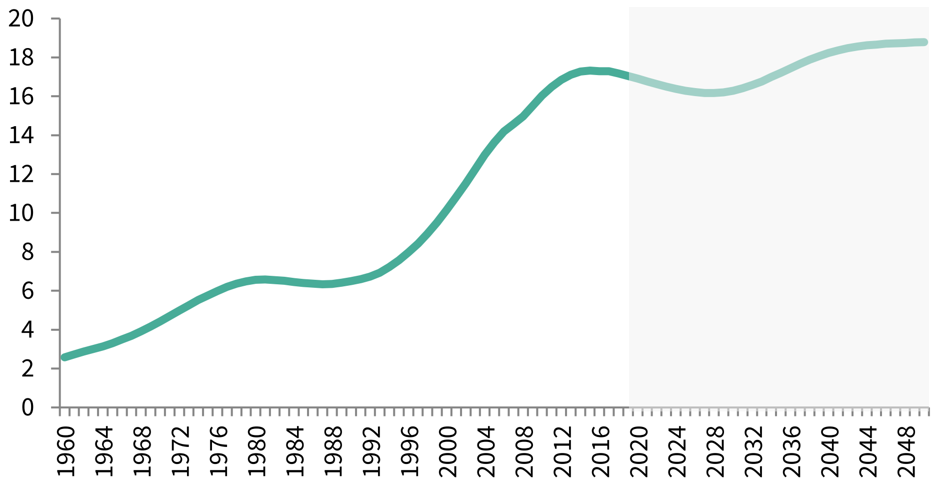
Note: Migration flows are shown on decadal terms, and are annualised through a cubic spline interpolation. This implies that the annual (non-multiple of 10) years are not showing the actual flows, but the interpolated flows between decades.

When thinking of the results in stock terms, the projections show that the stock of foreign migrants in Ireland will increase consistently over time, mirroring the expected positive flows for almost all the projection horizon. As shown in Figure 7, the stock of foreign migrants in Ireland is projected to account for an increasing share of the total population Ireland, reaching a share of close to 20 per cent by

2050. However, for the last 10 years of the forecast period, the overall population of sending countries is expected to grow at a slower pace than the odds of migrating. This implies that migration stocks will grow but not as strongly as in the previous decade, triggering a slight slowdown in the migration flows.[27] The broadly increasing trend for Irish emigration mirrors the opposite effect, with a strongly-growing population in Ireland expected to foster Irish emigration over the coming decades.

Figure 7: Foreign migrants in Ireland projected to account for an increasing share of total population

% of total population in Ireland



Sources: United Nations, World Bank, CSO, and author's own projections.
Note: The total population projections for Ireland, taken from the CSO, are updated to take account of the migration projections calculated in this paper.

In terms of stocks, the UK, Poland, the US, Lithuania or Nigeria are still expected to be one of the most prominent birth-nationalities of foreign migrants in Ireland. In terms of Irish migrants abroad, countries like the UK, the US, Australia, Canada, Germany, South Africa or Spain are expected to still be amongst the most popular over the studied projection horizon. Taking a more granular look into the projections, Figure 8 shows the projections for the Ireland-UK and Ireland-Poland bilateral migration flows.

[27] Since migration stocks are derived from the product of the estimated odds of migrating and the lagged population at origin, the growth in stocks (i.e., the flows) is given by the difference between the growth of the odds and the growth of population.

Figure 8: Projected net migration flows: Ireland–UK and Ireland–Poland

Thousands

Sources: World Bank (Özden *et al.*, 2011); United Nations (historical data); and author's own projections.

Note: The 1960 migration stock data of Irish-born population in the UK was modified as per information provided by the UK population censuses.

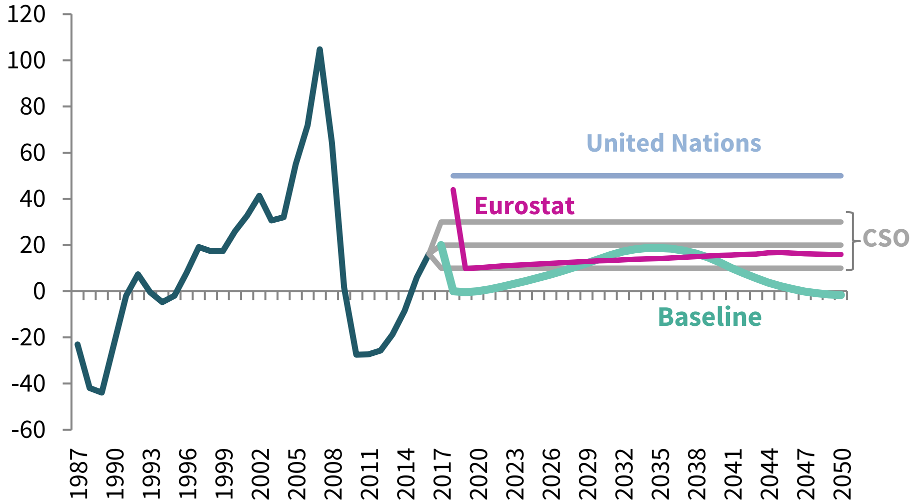
While the amount of UK-born citizens in Ireland is expected to increase over the coming years, the opposite is projected to happen with Irish-born people in the UK—partly mirroring past trends—where the negative growth approaches to zero over the medium to long term. The decadal nature of the data limits the scope for short-run shocks or structural breaks to be reflected in the annual migration flows. For instance, the model offers limited scope for assuming how a shock like Brexit can impact on migration flows in the very short term, although it can reflect it in the long-term dynamics, as shown in the following section.

In terms of net inward Polish migration in Ireland, panel C shows that migration flows will weaken over the projection horizon, partly reflecting the declining trend that followed in the crisis period in Ireland.

Figure 9 compares the baseline projections with those undertaken by other institutions, whose projection methodology is outlined in section 2. Our baseline projections show that, on average, we are close to the CSO's first migration scenario of average net migration flows of 9,000 over the whole projection horizon. For the 2030s part of our projections coincide with those of the CSO's second scenario, as well as with Eurostat. For the last decade, our baseline scenario is lower than those proposed by the institutions shown in Figure 9. In particular, our projections are significantly lower than those of the United Nations, which point at strong net migration flows of 50,000 over the whole projection horizon.

Figure 9: Migration flows projections, comparison with other institutions

Thousands (baseline projections are annualised)



Sources: CSO; Eurostat (2018; United Nations; and author's own projections ("Baseline").
Note: Data shown in terms of net migration flows.

While the majority of the estimated coefficients are broadly in line with previous research, the projections need to be taken with caution. In particular, the projections exclude potential policy changes that might importantly impact on migration flows; for example, possible visa restrictions in a given country that might limit future flows. In other words, given that the country-pair fixed effects included are time-invariant by definition, these cannot be projected into the future.

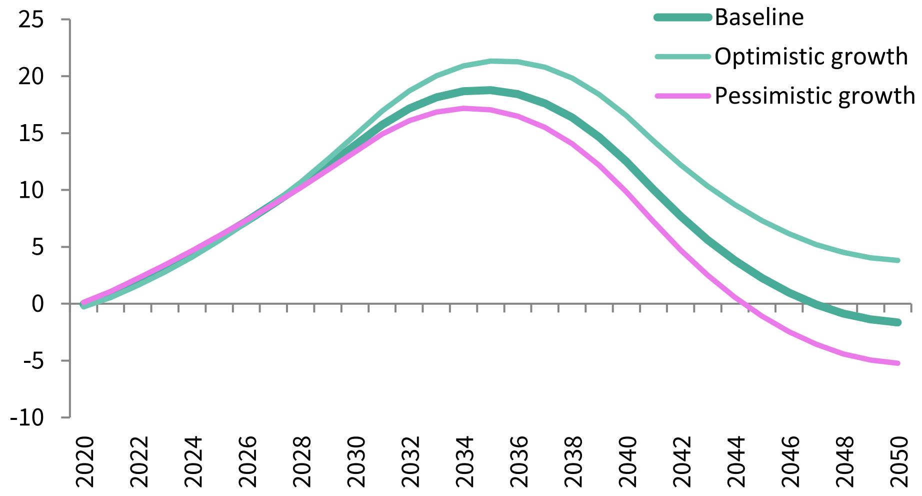
4.3 Shock scenarios

Two alternative scenarios show how shocks to Irish Domestic GVA can impact migration over the long run. The shocks are applied to annual figures over the projection horizon. However, given that the model follows a 10-year frequency, the responses of migration flows to such shocks are slower than would be desired. Still, the exercise allows us to analyse the long-run impact of such shocks over the long-run stock of migrants.

Figures 10 and 11 show that a long-term shock to Irish growth—holding growth elsewhere constant—can have a significant impact on net migration. A positive shock (where Irish growth is assumed to converge to 4.0 per cent over the long run, as opposed to 2.5 per cent assumed under the baseline scenario) would imply an overall change in net migrant stocks of 340,000 persons between 2020 and 2050. This is substantially higher than the implied impact of an increase of 263,000 migrants under the baseline. The pessimistic scenario of long-term growth converging to 1.5 per cent would increase stocks between 2020 and 2050 by just 212,000.

Figure 10: A shock to Irish growth could have a substantial impact on net migration flows to Ireland

Net inward migration, thousands

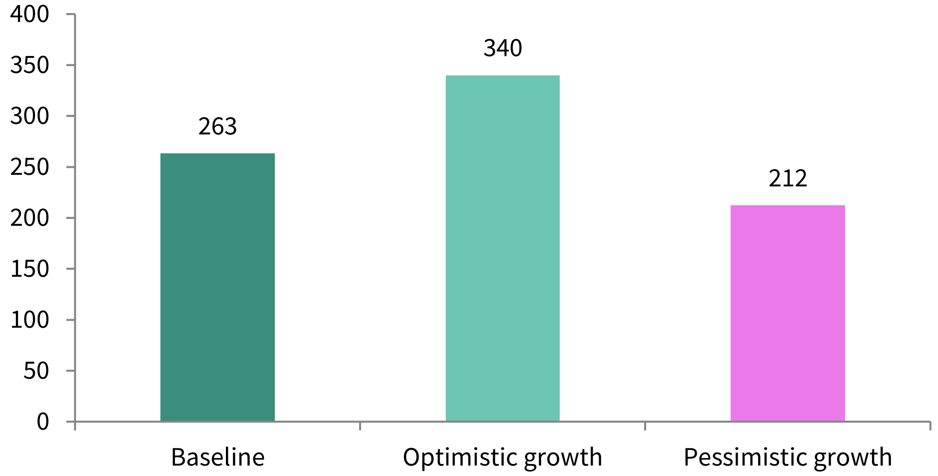


Sources: author's own projections.
Note: Net migration flows are projected on decadal terms, and are annualised through a cubic spline interpolation. The baseline scenario assumes that Irish economic growth will converge to 2.5 per cent; this compares to 4.0 per cent assumed in the optimistic growth scenario, and 1.5 per cent in the pessimistic growth scenario. Since the assumed shocks are not symmetric, and because the growth of the baseline scenario is closer to the pessimistic growth than to the optimistic one, the projected migration flows under the baseline scenario are closer to the pessimistic growth projections than to the optimistic growth ones.

In terms of flows, a positive shock to growth would imply consistently positive shocks over the whole projection horizon—averaging almost 11,000 per annum, compared to roughly 9,000 under the baseline scenario—whereas a negative shock would imply substantially lower flows (close to 7,000 per annum, on average). As a share of total population, the baseline scenario suggests that foreign immigrants will account for 18.8 per cent of the total population in Ireland by 2050. This compares to a projected share of 19.7 per cent under the optimistic growth scenario; and 18.2 per cent under the pessimistic growth one.

Figure 11: Change in net migration stocks in Ireland (2020–2050)

Thousands, change in stocks between 2020 and 2050



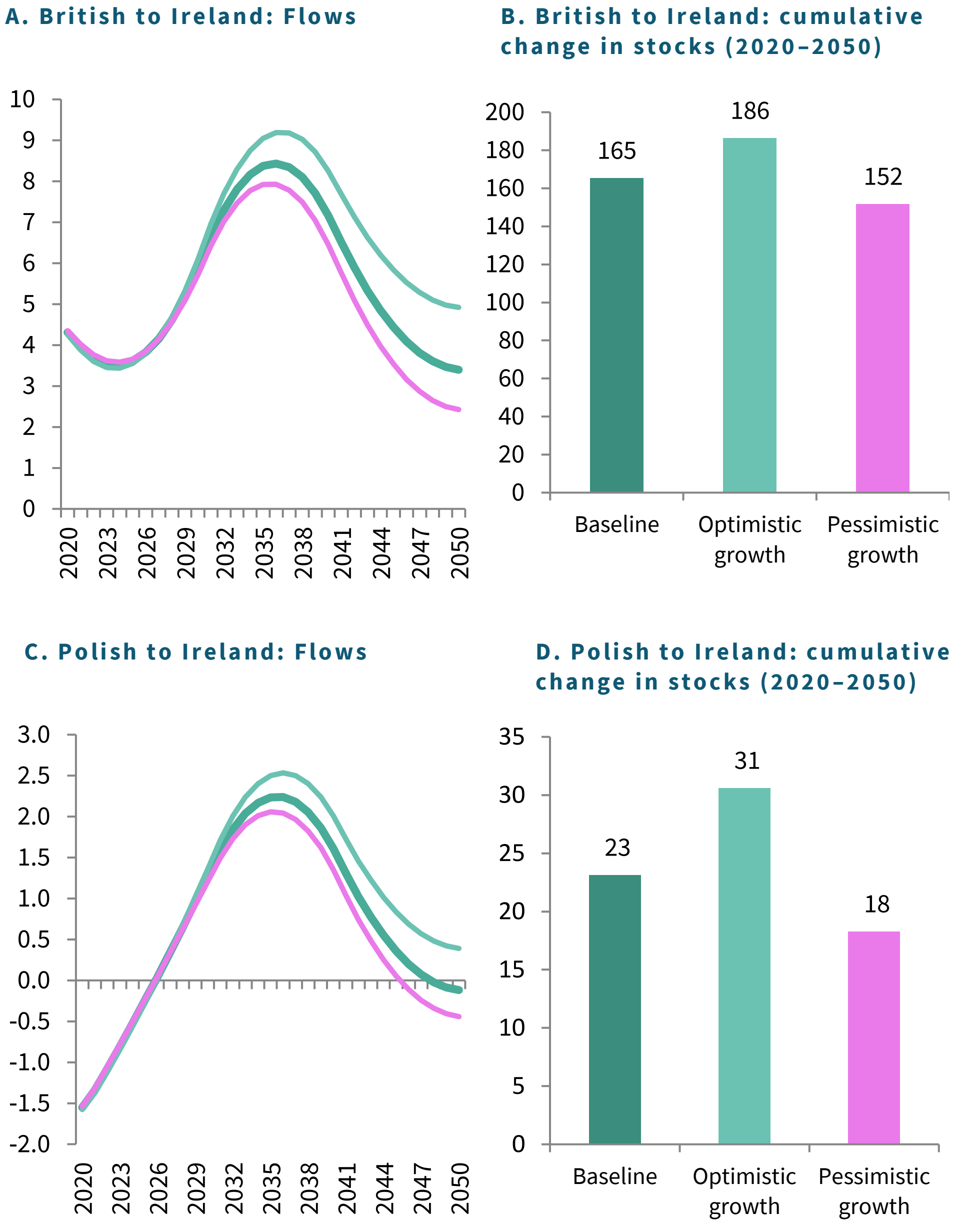
Sources: author's own projections.

Figure 12 shows how shocks to the domestic economy can influence two major migration partners for Ireland: the UK and Poland. Migration flows from the UK to Ireland are projected to average 5,500 flows per annum. However, taking the pessimistic and optimistic scenarios for Irish growth, this could range from around 5,000 to 6,200, respectively. In cumulative terms, this implies a change in stocks between 2020 and 2050 of 186,000 in the optimistic growth scenario and 152,000 in the pessimistic growth one. This compares to a baseline projected change of 165,000.

In terms of Poland, where the baseline flows for 2020–2050 average 700 migrants, the pessimistic and optimistic growth scenarios imply net migration flows that amount to 540 and 940 under each scenario respectively. In cumulative terms, this implies a change of stocks between 2020–2050 of 31,000 in the optimistic scenario and 18,000 in the pessimistic one, as compared to the baseline change of 23,000.

Figure 12: Impact of a shock to Irish growth on long-term UK and Polish migrants in Ireland

Thousands



Sources: author's own projections.

Note: Panels B and D show the change in the stocks of UK/Polish migrants in Ireland between 2020 and 2050.

5. Conclusions

This is the first paper that explores the dynamics of the bilateral world migration flows specifically focusing on Ireland. Drawing on relatively new panel data on bilateral migration, as well as developments in estimation techniques, a gravity-model approach is used to project bilateral world migration up to 2050.

Migration is modelled as a function of demographic, economic and time-invariant features like distance, language, or relative attractiveness. The model has a non-linear functional form, estimated through Poisson Pseudo-Maximum Likelihood (PPML), a relatively novel technique in the context of migration projections that is robust to heteroscedasticity patterns and that provides a natural way to deal with zeros in the data.

On the estimation side, our findings are broadly in line with the international literature. In terms of the projection exercise, we find that the long-term migration dynamics of Ireland will be positive over almost the whole projection horizon—largely as a result of a relatively favourable productivity growth in Ireland—averaging to over 9,000 net migration flows per annum over the medium to long term, close to the observed long-term average.

The paper also shows that shocks to Irish growth can have a significant impact on the flow of net migration to Ireland. A positive shock is projected to increase the long-run migration flows to an average of over 11,000 per annum, in contrast to a negative shock where the flows would average roughly 7,000. As a share of total population, the baseline scenario suggests that foreign immigrants will account for 18.8 per cent of the total population in Ireland by 2050. This compares to a projected share of 19.7 per cent under the optimistic growth scenario; and 18.2 per cent under the pessimistic growth scenario.

Future research could look at ways to endogenise economic growth into the model, which appears critical, especially in an Irish context. Higher frequency data, if available, could help with estimation in future by increasing the accuracy of annual projections over the long run, better tracking movements in the economic cycle, and allowing for migration flows to react to shocks faster.

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Appendix A: Cohort Component Method for Population Projections

The cohort-component model is a well-known method for population projections widely used by both national and international institutions. It allows one to project population levels with an age and sex breakdown. This is done by following the evolution of each of the cohorts (by sex) over time, and adding the births (by sex) and net migration (by cohort and sex). Matrix A shows the functioning of the cohort-component model, which is represented in matrix form through a time-dependent first-order Markov chain (Luenberger 1979; Girosi and King 2008).

Matrix A: Cohort-Component Model for Population Projections

$$\begin{bmatrix} N_{1,1,t} \\ \vdots \\ \vdots \\ N_{X,1,t} \\ N_{1,2,t} \\ \vdots \\ \vdots \\ N_{X,2,t} \end{bmatrix} = \begin{bmatrix} 0 & \cdots & \cdots & 0 & \mathrm{F}_{1,2,t-1} & \cdots & \cdots & \mathrm{F}_{X,2,t-1} \\ \mathrm{S}_{2,1,t-1} & & & \vdots & 0 & 0 & & 0 \\ \vdots & \ddots & & \vdots & \vdots & & \ddots & \vdots \\ 0 & \cdots & \mathrm{S}_{X,1,t-1} & 0 & 0 & 0 & \cdots & 0 \\ 0 & \cdots & \cdots & 0 & \mathrm{F}_{1,2,t-1} & \cdots & \cdots & \mathrm{F}_{X,2,t-1} \\ \vdots & & & \vdots & \mathrm{S}_{2,2,t-1} & 0 & 0 & \vdots \\ \vdots & & & \vdots & \vdots & \ddots & 0 & \vdots \\ 0 & \cdots & \cdots & 0 & 0 & \cdots & \mathrm{S}_{X,2,t-1} & 0 \end{bmatrix} \times \begin{bmatrix} N_{1,1,t-1} \\ \vdots \\ \vdots \\ N_{X,1,t-1} \\ N_{1,2,t-1} \\ \vdots \\ \vdots \\ N_{X,2,t-1} \end{bmatrix} + \begin{bmatrix} M_{1,1,t} \\ \vdots \\ \vdots \\ M_{X,1,t} \\ M_{1,2,t} \\ \vdots \\ \vdots \\ M_{X,2,t} \end{bmatrix} - \begin{bmatrix} E_{1,1,t} \\ \vdots \\ \vdots \\ E_{X,1,t} \\ E_{1,2,t} \\ \vdots \\ \vdots \\ E_{X,2,t} \end{bmatrix}$$

Source: Osés-Arranz and Quilis (2018).
Note: N refers to the population; S, to the survival probabilities; F, to the fertility rates; M, not the immigration flows; and E, to the emigration flows. The first sub-index denotes the age group of the cohort, where $age = [1, X]$. Fertility rates are non-zero only for the fertile age of the mothers, often assumed to be between 15 and 49. The second sub-index refers to the gender, where $gender = [1,2]$ refers to male and female, respectively. The last sub-index refers to the current period t, and to the previous period t-1.

As a first step, the portion of the population that survived from period t-1 to period t is calculated—which is the product of the survival rates, or one minus the mortality rates, and the population in the previous period—and the projected net migration flows for the period are added. This part of the process excludes the newborns of the period, which are calculated by applying the age-specific fertility rates to the surviving woman (including migrants), and adjusting for the probability of the newborn’s gender.

The vectors contain as many rows as age groups (in the range of 1 to X) per gender, the first half corresponding to men G=1, and the second half to women G=2.

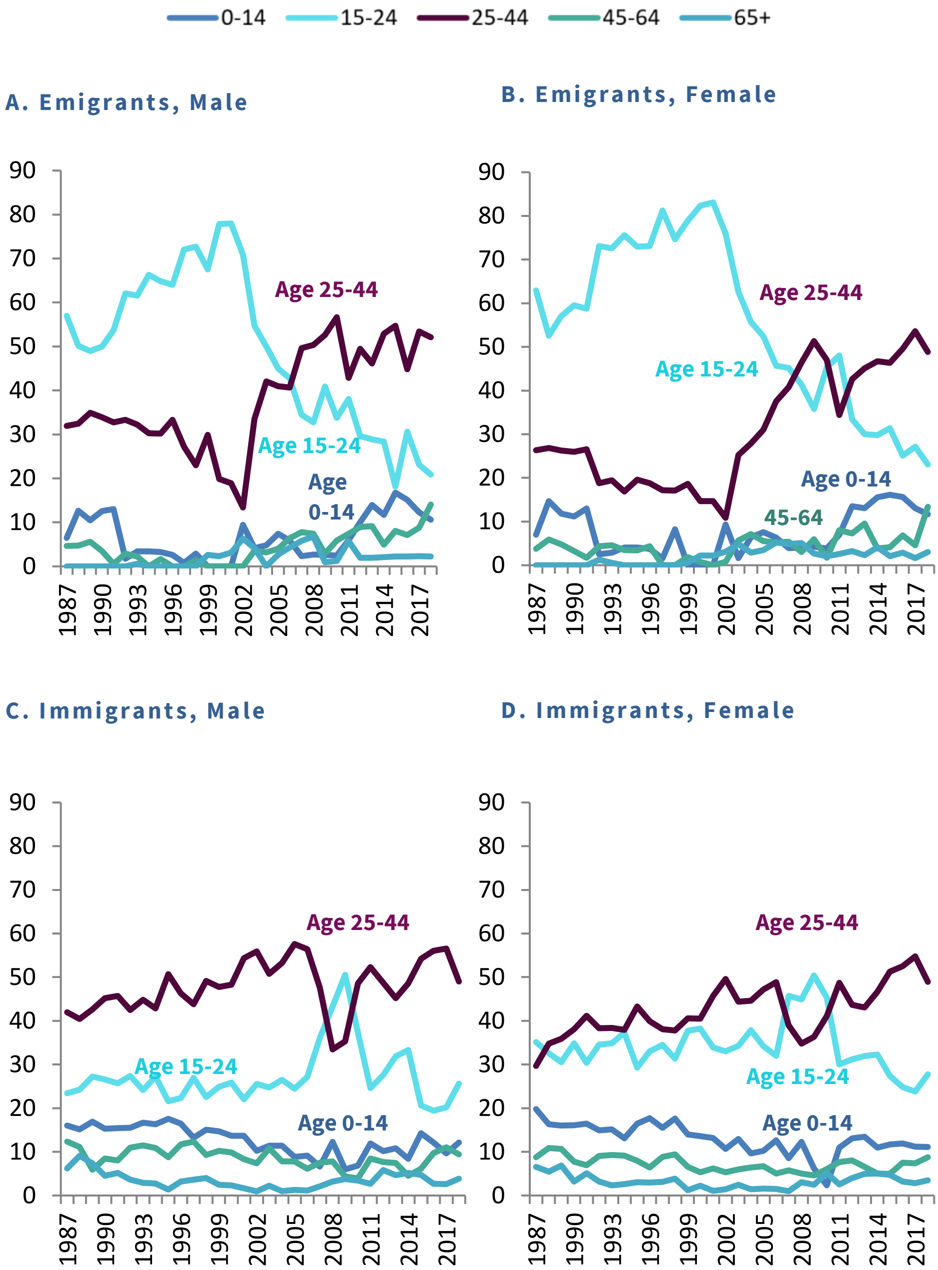
Appendix B: Age and Gender Distribution of Migrants in Ireland

The migration projections presented in this paper refer to the total migration flows expected between two countries. An age and gender breakdown is not provided given the nature of the historical data provided by the World Bank and the United Nations. This Appendix B proposes a framework to disaggregate the projections by age and gender based on past trends, as shown in the following graphs. The second part of the Appendix deals with the methodology proposed in this paper in order to disaggregate the total figures by age and gender.

Historical Data

Figure B.1: Age distribution of migrants in Ireland

% of total emigration (Panels A and B); % of total immigration (C and D)

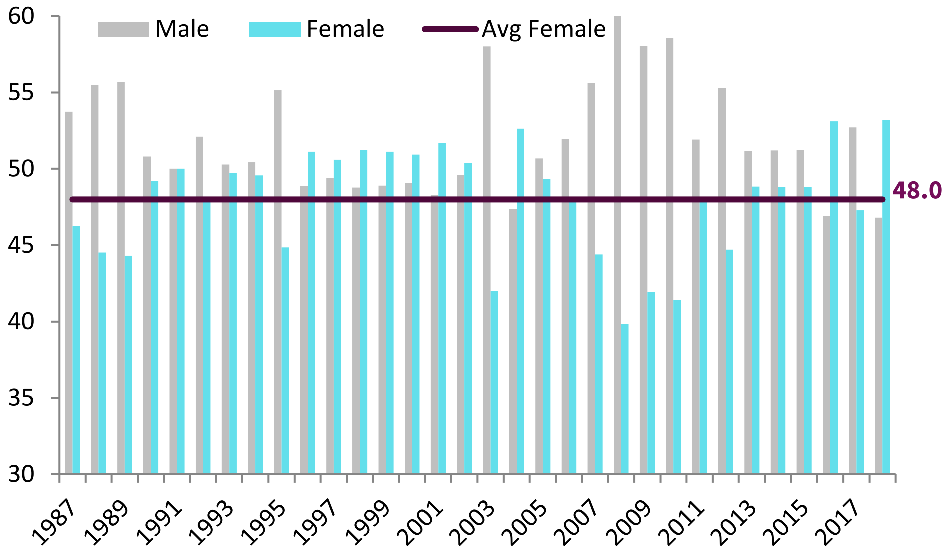


Sources: CSO; and author's own calculations.

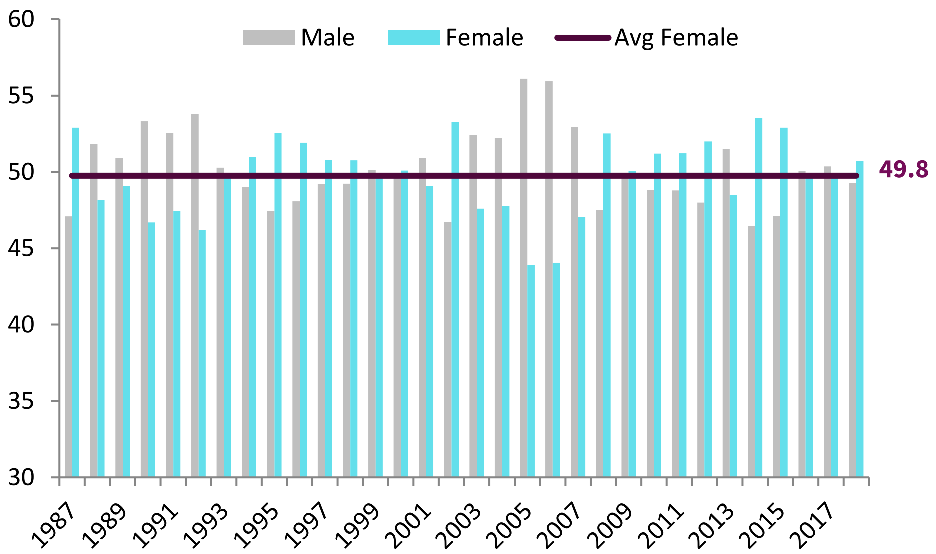
Figure B.2: Gender distribution of migrants in Ireland

% of total emigration (Panel A); % of total immigration (Panel B)

Panel A. Emigrants by Gender



Panel B. Immigrants by Gender



Sources: CSO; and author's own calculations.

Assumptions on Age and Gender Distributions

The cohort-component method as applied in Matrix A requires gender disaggregation, as well as an age breakdown of certain cohorts (with broad, as opposed to single, age groups provided). The aggregate nature of our data requires making certain assumptions on the projected evolution of the age and gender distribution of migrants. Approaches used by the CSO and other international institutions are to keep these constant or relatively constant based on recently observed trends.

The CSO's (2018) migration projections assume a constant age distribution over the whole projection horizon based on the average observed in the period 2011–2016. In terms of the gender distribution, this is derived from the observed migration flows over the period 1997–2016.

Eurostat's (2018) criterion for age and sex disaggregation of migration flows is based on linearly interpolating between initial values (corresponding to a 3-years average, i.e., 2015–2017) and common age profiles derived for the longer term.

The United Nations distribution of net migrants by age and gender is kept constant throughout the projection horizon. However, for countries which are known to attract temporary labour migrants, the United Nations attempt to incorporate these impacts by modelling the return flow of those labour migrants accounting for the ageing of migrants involved.

The approach taken in this paper departs from the abovementioned ones in that we explicitly model the age distributions of migrants and forecast them forward using VAR models. For each panel shown in Figure B.1, a VAR model attempts to gauge the historical dynamics and project them up until 2050. This is done for ages 0–14, 15–44, 45–64, and over 65. Given that the models aim to estimate the weight of each age group in the overall migration flows, the over-65 group is calculated as the residual for collinearity reasons. Equation B.1 shows the general specification of the equation, where A is a vector of the x age-groups abovementioned for each sex and migration category (immigration or emigration).[28]

Equation B.1: General VAR models of age distribution for each sex and migration inflows and outflows

$$A_X = \alpha_0 + \beta_X A_{X,t-1} + \omega_X A_{X,t-2} + \delta_X A_{X,t-3}$$

$$where\ X = [0-14, 15-44, 45-64, 65+], and\ t = 1987, \ldots, 2018$$

The estimations of the coefficients are shown in the following tables:

Table B.1: Estimation of Age Coefficients

Panel A. Emigration (Male)

	0-14	15-24	25-44	45-64
0-14 (-1)	0.84	0.35	-0.50	-0.18
	-0.47	-0.86	-0.70	-0.29
	[1.79]	[0.41]	[-0.72]	[-0.61]
0-14 (-2)	-0.01	1.16	-1.14	-0.04
	-0.47	-0.86	-0.70	-0.29
	[-0.02]	[1.35]	[-1.64]	[-0.14]
15-24 (-1)	0.33	1.30	-0.76	-0.37
	-0.44	-0.80	-0.65	-0.27
	[0.76]	[1.62]	[-1.17496]	[-1.33]
15-24 (-2)	0.05	1.40	-1.43	-0.13
	-0.46	-0.85	-0.69	-0.29
	[0.10]	[1.65]	[-2.08]	[-0.44]
25-44 (-1)	0.32	0.81	-0.44	-0.24
	-0.41	-0.75	-0.61	-0.26
	[0.78]	[1.08]	[-0.72]	[-0.94]
25-44 (-2)	-0.03	1.18	-1.19	-0.07
	-0.42	-0.76	-0.62	-0.26
	[-0.07]	[1.55]	[-1.94]	[-0.26]
45-64 (-1)	0.96	0.13	-0.61	-0.09
	-0.77	-1.41	-1.14	-0.48
	[1.25]	[0.09325]	[-0.53]	[-0.19]
45-64 (-2)	0.40	1.10	-0.97	-0.41
	-0.76	-1.40	-1.13	-0.48
	[0.52]	[0.78]	[-0.86]	[-0.85]
C	-34.11	-176.06	226.36	44.03
	-45.62	-83.68	-67.74	-28.64
	[-0.75]	[-2.10]	[3.34]	[1.54]

[28] The selected order of the specific dynamic VAR models is as follows: 2 for emigration, male; 1 for emigration, female; and 3 for male and female immigration.

Source: author's own calculations.
Note: for each age group (and lag), the rows show, in order: the estimated coefficient, the standard errors, and the t-statistics.

Panel B. Emigration (Female)

	0-14	15-24	25-44	45-64
0-14 (-1)	0.83	1.82	-1.71	-0.13
	-0.47	-0.73	-0.42	-0.31
	[1.78]	[2.49]	[-4.07]	[-0.41]
15-24 (-1)	0.37	2.93	-2.19	-0.27
	-0.50	-0.79	-0.45	-0.33
	[0.73]	[3.71]	[-4.82]	[-0.81]
25-44 (-1)	0.46	2.13	-1.53	-0.20
	-0.55	-0.86	-0.50	-0.36
	[0.84]	[2.47]	[-3.09]	[-0.56]
45-64 (-1)	0.84	1.73	-1.56	-0.16
	-0.65	-1.02	-0.59	-0.43
	[1.30]	[1.69]	[-2.66]	[-0.37]
C	-36.78	-194.94	219.63	27.19
	-50.35	-79.11	-45.44	-33.12
	[-0.73]	[-2.46]	[4.83]	[0.82]

Source: author's own calculations.
Note: for each age group (and lag), the rows show, in order: the estimated coefficient, the standard errors, and the t-statistics.

Panel C. Immigration (Male)

	0-14	15-24	25-44	45-64
0-14 (-1)	-0.43	1.13	-0.59	0.25
	-0.56	-1.10	-1.29	-0.39
	[-0.76592]	[1.02861]	[-0.45835]	[0.63564]
0-14 (-2)	0.36	-0.32	-0.13	0.35
	-0.54	-1.06	-1.25	-0.37
	[0.66858]	[-0.30499]	[-0.10323]	[0.93580]
0-14 (-3)	-0.35	-0.49	0.28	0.58
	-0.56	-1.09	-1.29	-0.39
	[-0.63550]	[-0.44541]	[0.21746]	[1.50706]
15-24 (-1)	-0.40	1.18	-0.55	0.03
	-0.54	-1.07	-1.26	-0.38
	[-0.74267]	[1.09715]	[-0.43407]	[0.07997]
15-24 (-2)	0.35	0.36	-0.46	0.03
	-0.49	-0.96	-1.13	-0.34
	[0.70719]	[0.37115]	[-0.40912]	[0.09436]
15-24 (-3)	-0.64	-0.42	0.79	0.27
	-0.45	-0.88	-1.04	-0.31
	[-1.43612]	[-0.47178]	[0.75619]	[0.86869]
25-44 (-1)	-0.38	-0.08	0.65	0.14
	-0.48	-0.94	-1.11	-0.33
	[-0.79710]	[-0.08045]	[0.58929]	[0.41943]
25-44 (-2)	0.28	1.24	-1.41	0.07

	0-14	15-24	25-44	45-64
	-0.46	-0.90	-1.06	-0.32
	[0.61181]	[1.37243]	[-1.32871]	[0.23115]
25-44 (-3)	-0.74	-0.47	1.14	0.15
	-0.47	-0.91	-1.08	-0.32
	[-1.59489]	[-0.51573]	[1.05576]	[0.47301]
45-64 (-1)	0.00	-0.07	0.28	0.01
	-0.55	-1.09	-1.28	-0.38
	[-0.00686]	[-0.06408]	[0.21990]	[0.01775]
45-64 (-2)	0.49	0.80	-0.85	-0.19
	-0.56	-1.10	-1.30	-0.39
	[0.86974]	[0.72716]	[-0.65289]	[-0.47751]
45-64 (-3)	-0.47	-0.35	1.03	-0.09
	-0.44	-0.87	-1.03	-0.31
	[-1.05767]	[-0.40260]	[0.99365]	[-0.29504]
C	77.07	-43.30	38.28	-30.73
	-38.11	-74.91	-88.48	-26.44
	[2.02214]	[-0.57794]	[0.43266]	[-1.16218]

Source: author's own calculations.

Note: for each age group (and lag), the rows show, in order: the estimated coefficient, the standard errors, and the t-statistics.

Panel D. Immigration (Female)

	0-14	15-24	25-44	45-64
0-14 (-1)	0.03	1.49	-1.33	0.13
	-0.43	-0.86	-0.84	-0.29
	[0.08176]	[1.73711]	[-1.58843]	[0.45275]
0-14 (-2)	0.08	0.27	-0.12	0.01
	-0.43	-0.85	-0.83	-0.29
	[0.18274]	[0.31453]	[-0.14266]	[0.04660]
0-14 (-3)	0.32	0.07	0.27	-0.33
	-0.44	-0.89	-0.87	-0.30
	[0.72501]	[0.08152]	[0.31507]	[-1.08656]
15-24 (-1)	0.07	0.85	-0.77	0.08
	-0.38	-0.76	-0.74	-0.26
	[0.17788]	[1.12260]	[-1.03427]	[0.32368]
15-24 (-2)	0.21	0.48	-0.32	-0.03
	-0.34	-0.69	-0.67	-0.23
	[0.61854]	[0.69619]	[-0.48212]	[-0.13409]
15-24 (-3)	0.21	0.04	0.12	-0.31
	-0.40	-0.80	-0.78	-0.27
	[0.52607]	[0.05239]	[0.15156]	[-1.12681]
25-44 (-1)	0.24	-0.23	0.13	0.12
	-0.37	-0.74	-0.72	-0.25
	[0.64493]	[-0.31237]	[0.17297]	[0.46401]
25-44 (-2)	0.38	0.72	-0.63	-0.05
	-0.34	-0.67	-0.66	-0.23
	[1.12705]	[1.06815]	[-0.95537]	[-0.23925]
25-44 (-3)	0.08	-0.05	0.31	-0.35
	-0.39	-0.79	-0.77	-0.27
	[0.19869]	[-0.06969]	[0.40810]	[-1.30195]
45-64 (-1)	1.62	-1.70	-0.42	0.73
	-0.55	-1.10	-1.08	-0.37
	[2.94917]	[-1.54254]	[-0.39034]	[1.95782]

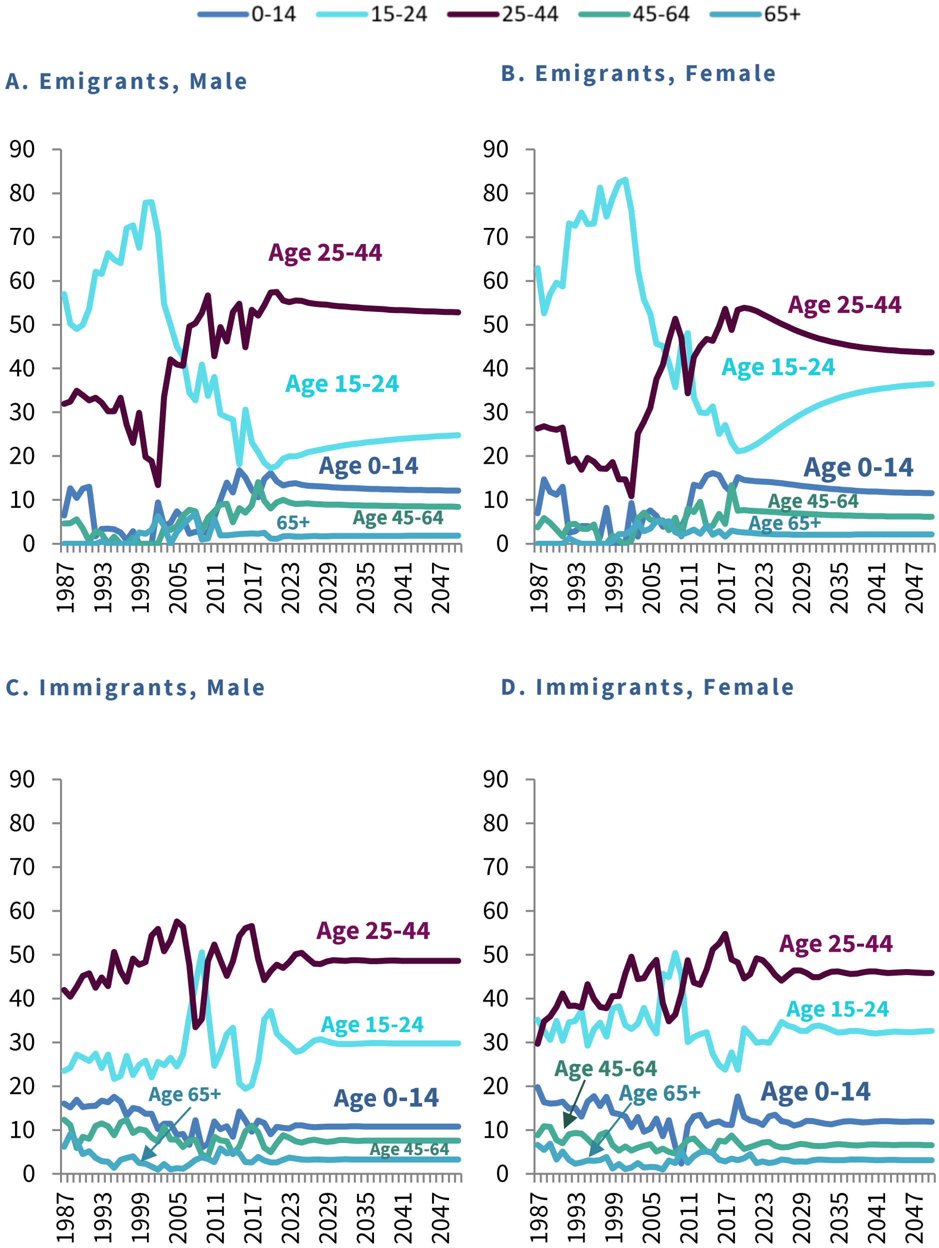
	0-14	15-24	25-44	45-64
45-64 (-2)	-0.03	1.87	-0.98	-0.59
	-0.52	-1.05	-1.02	-0.36
	[-0.05064]	[1.79176]	[-0.96108]	[-1.65656]
45-64 (-3)	1.65	-2.11	0.51	-0.19
	-0.66	-1.32	-1.29	-0.45
	[2.50477]	[-1.60227]	[0.39248]	[-0.42798]
C	-62.47	-40.96	106.02	30.54
	-39.62	-79.37	-77.55	-27.00
	[-1.57679]	[-0.51609]	[1.36720]	[1.13075]

Source: author's own calculations.
Note: for each age group (and lag), the rows show, in order: the estimated coefficient, the standard errors, and the t-statistics.

Based on these estimations, the underlying projections are shown in Figure B.3. In terms of the gender distribution of our total migration projections, we assume that the gender weights remain unchanged according to the average of the last 42 years as shown in Figure B.2.

Figure B.3: Projected age distribution of migrants in Ireland

% of total emigration (Panels A and B); % of total immigration (C and D)



Sources: CSO; and author's own projections.

Appendix C: Robustness Checks, OLS Estimation

As a robustness check to the estimated Equations 1 and 2, this Appendix shows the estimated coefficients when these models are estimated through OLS with the log odds of migrating as the dependent variable.

Table C.1: Log odds of migrating: OLS Estimations with time-invariant characteristics (1970–2020)

		(3.a)	(3.b)	(3.c)	(3.d)
Network		0.81***		0.85***	0.52***
		(0.00)		(0.00)	(0.00)
GDP per capita	origin	0.01	0.04***		-0.03***
		(0.01)	(0.01)		(0.01)
	destination	0.25***	0.45***		0.37***
		(0.01)	(0.01)		(0.01)
Population >65	origin	-0.03*	0.23***	-0.07***	
		(0.01)	(0.03)	(0.01)	
	destination	0.03**	0.18***	-0.02	
		(0.01)	(0.03)	(0.01)	
Population 15–64	origin	-0.68***	-0.20***	-0.63***	
		(0.03)	(0.06)	(0.02)	
	destination	0.08**	0.87***	0.63***	
		(0.03)	(0.07)	(0.03)	
Population <15	origin	-0.18***	-0.32***	-0.20***	
		(0.02)	(0.04)	(0.02)	
	destination	-0.01	-0.77***	-0.59***	
		(0.02)	(0.04)	(0.02)	
Common language		0.28***	1.71***	0.27***	0.83***
		(0.01)	(0.04)	(0.01)	(0.03)
Distance		-0.23***	-1.39***	-0.17***	-0.72***
		(0.01)	(0.02)	(0.01)	(0.01)
Area	origin	-0.01	-0.09***	-0.01*	-0.43***
		(0.00)	(0.01)	(0.00)	(0.01)
	destination	0.02***	0.24***	0.038***	0.21***
		(0.00)	(0.01)	(0.00)	(0.01)
Country-pair fixed effects		No	No	No	No
R^2		0.20	0.12	0.22	0.21
Observations		56,542	63,386	77,770	56,542
Number of country-pair		15,990	17,646	19,948	15,990

Sources: United Nations, World Bank, CSO, Penn World Tables, CEPII, author's own calculations. Note: ***p<0.01; ** p<0.05; * p<0.1. Robust standard errors in brackets. The equation is shown in linear terms, with the logarithm of the migration odds as the dependent variable. All variables are shown in logarithmic terms (except for the dummy variable on language) and are lagged to the previous decade (except for the time-invariant variables).

Table C.2: Log odds of migrating: OLS estimations with country-pair fixed effects (1970–2020)

		(4.a)	(4.b)	(4.c)	(4.d)
Network		0.30***		0.35***	0.31***
		(0.00)		(0.00)	(0.00)
GDP per capita	origin	-0.01	0.02		0.07***
		(0.02)	(0.02)		(0.01)
	destination	0.20***	0.23***		0.30***
		(0.02)	(0.02)		(0.02)
Population >65	origin	0.33***	0.51 ***	0.34***	
		(0.05)	(0.05)	(0.04)	
	destination	-0.10 *	-0.07	-0.14***	
		(0.05)	(0.06)	(0.04)	
Population 15-64	origin	-0.21 ***	-0.01	-0.31***	
		(0.06)	(0.07)	(0.05)	
	destination	0.58***	0.90***	0.90***	
		(0.07)	(0.08)	(0.05)	
Population <15	origin	-0.20***	-0.17 ***	-0.18***	
		(0.04)	(0.05)	(0.03)	
	destination	-0.75***	-1.10***	-1.00***	
		(0.04)	(0.05)	(0.03)	
Country-pair fixed effects		Yes	Yes	Yes	Yes
R^2		0.24	0.14	0.23	0.21
Observations		58,304	65,490	81,817	58,304
Number of country-pairs		16,595	18,289	21,216	16,595

Sources: United Nations, World Bank, CSO, Penn World Tables, author's own calculations.
Note: ***p<0.01; ** p<0.05; * p<0.1. Robust standard errors in brackets. The equation is shown in linear terms, with the logarithm of the migration odds as the dependent variable. All variables are shown in logarithmic terms and are lagged to the previous decade.