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Abstract

This paper explores the complex interplay between technology adoption, specifically robotisation and digitalisation, and international migration within the EU and other advanced economies, including Australia, the UK, Japan, Norway and the US, over the period 2001-2019. Utilising a gravity model approach grounded in neoclassical migration theory, the study analyses how technological advancements influence migration flows. It examines two key technological variables: the extent of digitalisation, represented by ICT capital per person employed, and the adoption of industrial robots, measured by the stock of robots per thousand workers. The research uniquely integrates these technological factors into migration analysis, considering both push and pull effects. Additionally, it accounts for various other migration determinants such as macroeconomic conditions, demography and policy factors. The findings reveal insightful dynamics about the relationships between technological progress, labour market conditions and migration patterns, contributing significantly to the current literature and informing future migration policies and the impact of technology adoption.

Keywords: Robot adoption, digitalisation, novel technologies, migrant workers

JEL classification: O33, F22, D24

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1. Introduction

Recent decades have been marked by continuous technological advancements, including robotisation and digitalisation, which have brought about significant transformations across many industries. These developments have impacted the dynamics of the labour market, and this has been extensively explored in the literature (e.g. Arntz, Gregory and Zierahn, 2019; Acemoglu and Restrepo, 2017; Goos, Manning and Salomons, 2014). Historically, such transformations have also influenced migration patterns by altering labour demand (see Autor, 2015), including easing cross-border mobility by reducing barriers including transportation and information costs. Apart from recent technological advancements, other factors have also led to an increase in global mobility of workers, leading to a rise in migrant employment across various countries and sectors, with the majority of these workers being employed in high-income economies, which account for approximately 67% of international migrant workers (ILO, 2021). The broader effects of recent technological advancements on domestic labour markets, including their impact on migration patterns, are becoming areas of interest for policymakers and businesses both in origin and destination countries of migrants (IOM, 2021).

In the context of ongoing routine-biased technological change (Goos and Manning, 2007; Autor, Levy and Murnane, 2003), technology may serve as a substitute for lower- and middle-skilled immigrants, especially in the manufacturing sector, as suggested by Borjas and Freeman (2019). However, technological advancements extend beyond robotisation, especially with the widespread adoption of digital technologies (and, in the future, of artificial intelligence (AI) – see IMF, 2024). These advancements may also significantly impact labour markets by creating skills shortages that attract migrants with specific skills (Beerli, Indergand and Kunz, 2023), which might lead to complementarity between technology and migrant flows. Additionally, the income elasticity effect suggests that rising incomes may bolster the demand for low-skilled, manual service jobs, further attracting immigrants who often take on these occupations (Mandelman and Zlate, 2022; Basso, Peri and Rahman, 2020).

Hence, understanding the relationship between migration and the adoption of these recent technologies is essential for comprehending their implications for trends in migration and labour markets. This is particularly relevant for the European Union (EU) and other advanced economies grappling with the problems arising from decreasing working-age populations and ageing societies. Such demographic trends lead to labour market shortages and can constitute an impediment to economic growth (Grieveson, Leitner and Stehrer, 2019). Accordingly. the focus of this paper is to investigate the relationship between flows of migrants and of technology adoption (robotisation and the use of digital technologies) across countries of the EU together with those of some other advanced economies, namely Australia, the UK, Japan, Norway and the US, over the period 2001-2019 in a gravity model setting.

Extensive research has been conducted on the determinants of migration, especially encompassing its economic aspects (e.g. Adovor et al., 2021; Ramos and Suriñach, 2017; Czaika and Parsons, 2017; Ortega and Peri, 2013; Mayda, 2010; Kahanec, Zaiceva and Zimmermann, 2009), but few studies have thoroughly investigated the technological factors that influence it. Although the role of technology in migration remains underexplored in most of these analyses, recent research does emphasise the importance of studying migration within the broader context of economic, political, cultural, technological and demographic changes (de Haas, 2021). Existing studies predominantly focus on how technology facilitates migration by reducing barriers such as transport and information costs (Pesando et al., 2021; Collin and Karsenti, 2012). There is still a gap in the literature on the broader impact of robotisation and digitalisation on migration patterns, with only limited research addressing this interplay (Liu and Portes, 2021; Borjas and Freeman, 2019).

Our study is informed by a body of research examining the impact of emerging technologies on labour market outcomes. Studies by Acemoglu and Restrepo (2017) and Autor (2015) provide crucial insights into how automation and digitalisation are transforming job markets, affecting employment rates and wage structures. These technological shifts in the labour market are especially pivotal in understanding migration trends, as their impact on job availability and skill demand can alter the attractiveness of destinations for potential migrants. Our research bridges these two areas of study by exploring how the labour market changes arising from technological advancements intersect with migration patterns. We argue that the dynamics of technology adoption in labour markets not only influence the local employment situation but also can impact on international migration flows. This linkage provides a novel perspective to the existing literature, highlighting the interconnected nature of technological progress, labour market changes and migration patterns.

The exploration by Borjas and Freeman (2019) of labour market conditions in the face of technological change provides a basis for our investigation into whether technology acts as a substitute or complement to migrant workers. Furthermore, our analysis extends to the concept of the ‘automation gap’ – the disparity in technology adoption between migrants’ origin and destination countries – and its subsequent effect on migration.

Methodologically, this paper employs a gravity model approach, a method grounded in neoclassical migration theory as conceptualised by Tinbergen (1962) and discussed by Anderson and van Wincoop (2003). This approach allows us to quantify the relationship between migrant flows and technology adoption, utilising comprehensive data across countries in the EU and selected advanced economies from 2001 to 2019. The analysis looks at both migration flows and migration flows relative to the population in the origin country within the context of a gravity model (see Beine, Bertoli and Fernández-Huertas Moraga, 2016; Ramos, 2016; Anderson, 2016; Bertoli and Fernández-Huertas Moraga, 2015). Furthermore, this methodology enables us to control for other push and pull factors of migration, both separately (in terms of country of origin and country of destination) and comparatively between the two countries. The estimated model incorporates traditional gravity variables such as geographical distance, common language, population size, development level, existing migrant network from the same country of origin, and human capital index. Additionally, it includes as a policy variable preferential trade agreements with labour provisions. The main variables of interest in the analysis are two technological variables: one proxies the extent of digitalisation in a country, calculated as the ICT capital in constant 2015 USD per person employed in the countries of destination and origin; the other measures the adoption of industrial robots, quantified as the stock robots in thousands per person employed in the countries of destination and origin. All these measures for countries of destination and origin will be used both as separate push and pull factors in the estimations of migration flows, or in terms of relative values of these measures (country of destination to country of origin).

The structure of the rest of the paper is as follows: in the next section, we provide an extensive survey of the existing literature. Section 3 presents the methodology and the sources of data. Section 4 presents and discusses the estimation results. Section 5 provides our concluding remarks.

2. Literature review

Exploring the determinants and effects of international migration, and developing appropriate migration policies, have been central topics of contemporary economic debates on international migration. Although at present international migrants account for only about 3.6% of the world's total population (IOM, 2021) and migration intensity has changed little since the 1960s (see de Haas et al., 2019), the spatial patterns of international migration have undergone significant changes associated with geopolitical shifts and phases of economic liberalisation, and along with technological advancements and structural change that have been transforming economies. The wide income gaps across the world economy led to an increasing concentration of immigrants in a small set of advanced economies, and 'push and pull' factors altered the composition of their immigrant populations (see Czaika and de Haas, 2014). Europe has shifted from a prominent source of international migrants in the 19th and early 20th centuries to an important destination region, with Northern, Southern and Western Europe hosting nearly 25% of total global migrant workers (ILO, 2021). Consequently, a growing interest in understanding the underlying factors and effects of migratory movements led to migration theories and empirical analyses across various disciplines, which employ distinct perspectives in their attempts to explain international migration (see Massey et al., 1993; Kurekova, 2011; Abreu, 2012). So far, no comprehensive general theory of international migration has been developed, owing to the multifaceted nature of the migration process that can hardly be adequately explained by a single theory (Arango, 2000).

Empirical studies of migration determinants have been growing, in the EU especially in the context of Eastern enlargements (e.g. Ramos and Suriñach, 2017; Kahanec, Zaiceva and Zimmermann, 2009). This topic has gained importance in the EU, owing to its rising demographic challenges of ageing societies and shrinking working-age populations, and – more recently – labour shortages (Grieveson, Leitner and Stehrer, 2019; Leitner and Stehrer, 2019a). Advanced economies have also been experiencing a wave of new technologies adoption, with a consequent transformative impact on employment conditions (e.g. Goos, Manning and Salomons, 2014; Arntz, Gregory and Zierahn, 2019). Historically, technological advancements played an important role in shaping migration, both through effects of structural changes on labour market demand and as facilitator of the process of migration by reducing the barriers to migration including transport and information costs (Ghodsi, Mara and Barišić, in progress). Thus, the adoption of novel technologies can be expected to impact the intensity and composition of migrant flows. An important question that arises from the ongoing trajectories of technological change is whether new technologies serve as a substitute for migrant workers or as a complement to them. As Borjas and Freeman (2019) highlight, the decision to buy robots or employ an immigrant in developed economies will depend on labour market conditions in host and origin countries and on the impact on costs of adopting new technologies in different sectors of the economy. However, technological change (robotisation, digitisation) does not only occur in destination countries, but also in migrants' origin countries. Therefore, the automation gap defined by the difference in the stock of robots and digital technologies per employee between the destination and origin countries is expected to have important implications for international migration. And, of course, so will other factors that affect international migration flows.

2.1. PUSH AND PULL FACTORS OF INTERNATIONAL MIGRATION

Labour markets have usually been considered to be at the centre of the migration decision. Nearly 70% of today's international migrants are classified as labour migrants, and they account for an average of nearly 20% of the labour force in high-income economies (ILO, 2021). In recent decades, a large body of economic studies has empirically explored the determinants of international migration from the perspective of the oldest theory of migration – neoclassical migration theory. From the macro-level perspective, neoclassical theory emphasises labour market differentials (i.e. wage and employment rate disparities), resulting from the uneven geographical distribution of capital and differences in technological (total factor productivity, TFP) levels, as the primary determinant of international migration (Todaro, 1969; Fei and Ranis, 1961; Lewis, 1954). Its micro-level setting (Sjaastad, 1962) places rational decision-making by individuals at the centre of analysis, as migrants aim to improve their income prospects by migrating to countries with higher wages or better job opportunities. The factors determining micro-level individual decisions, are of course influenced by macro-level determinants of income and welfare disparities between countries.

Neoclassical theory has most often been specified through the 'push and pull' migration framework (Lee, 1966) which goes back to the 'laws of migration' outlined by the Anglo-German geographer Ravenstein, who in the 1880s sought to explain the complex forces driving the first wave of mass migration during the First Industrial Revolution (Grigg, 1977). Following Ravenstein's doctrine, the 'push and pull' migration model (Lee, 1966) outlines four crucial sets of factors influencing migration decisions: (1) factors associated with the area of origin; (2) factors associated with the area of destination; (3) intervening obstacles; and (4) personal factors (Greenwood, 2019; Greenwood and Hunt, 2003; Lee, 1966). Among the key factors shaping migration obstacles are geographical distance indicating the cost of migration; cultural distance, including language and religion proximity; the existing stock of migrants, reflecting benefits from the support of existing networks (Ferrie and Hatton, 2013); and the legal/policy environment, primarily in relation to migration policies (Borjas, 1989). Additional contributions to this model, emphasising the complexity of the migration process, were proposed by Van Hear, Bakewell and Long (2018), who introduced the 'push-pull plus' model, which distinguishes between predisposing, proximate, precipitating and mediating drivers of migration.[1]

Some of the often-explored economic push/pull factors include GDP per capita, wage levels, taxes, unemployment rates, welfare benefits and cost of living, while non-economic ones frequently include institutional quality factors such as corruption, war, crime, discrimination, rights, freedom, law and migration policies (e.g. Arif, 2020; Czaika and Parsons, 2017; Ortega and Peri, 2013; Mayda, 2010; Warin and Swaton, 2008). Demographic factors also have often been included in gravity models, in view of their expected importance for migration (e.g. Kim and Cohen, 2010; Mayda, 2010). Furthermore, some recent analysis has put the main focus on exploring non-economic aspects such as linguistic variables (e.g. Adserà and Pytliková, 2015), climate-related variables (e.g. Wesselbaum and Aburn,

[1] *Predisposing* drivers are those that contribute to the creation of a context in which migration is more likely. They can be seen through structural disparities between migrants' origin and destination countries, including economic, political and environmental disparities and geographical factors. *Proximate* drivers emanate from deep-seated structural disparities and exert a more direct bearing on migration (e.g. economic upturn in country of destination, which yields new employment opportunities). *Precipitating* drivers are tied to events or developments that usually occur in economic, political or security spheres of the countries of origin, and that trigger departure (e.g. hurricane, surge in unemployment, escalation of conflict). *Mediating* drivers are those factors that enable, facilitate, constrain, accelerate, consolidate or diminish migration.

2019; Beine and Parsons, 2015; Cattaneo and Peri, 2016) and institutional factors such as corruption and education (e.g. Poprawe, 2015).

Additionally, some of the studies specifically focus on the migration of workers towards certain job categories characterised by global shortages, such as health workers (e.g. Adovor et al., 2021; Botezat and Ramos, 2020), which are especially important given the rising demand of ageing populations in developed nations. Others focus on specific income groups, such as Czaika and Parsons (2017), who explore the role of income taxation for high-income employees.

To the authors' knowledge, migration push-pull models have not yet incorporated any variables relating to gaps in automation and digitalisation. Extensive research has, however, been conducted on the effects of automation on labour markets. Advancements of novel technologies, digitalisation and robotisation have been reshaping the dynamics of often tight labour markets across developed economies, leading to changes in the demand for different types of labour. A widespread concern about the future of work brought the issue of 'technological unemployement' into the centre of labour market debates (Frey and Osborne, 2013; Baldwin, 2019). Although earlier changes in labour demand indicated skill-biased technological change (SBTC) (Katz and Murphy, 1992), more recent research argued that routine-biased technological change (RBTC) has been taking place, given not only the rising demand for high-skilled workers, but also for low-skilled manual workers who provide income-elastic services (Goos and Manning, 2007; Autor, Levy and Murnane, 2003).

Although there is vast empirical evidence on the effects of this technological change on the labour market, exploring migration in this context has received much less attention. Some important implications of technological changes, differentiating their effects on migrant and native workers, have been noted in previous studies. Basso, Peri and Rahman (2020) have shown that computerisation resulted in increasing immigration of workers in low-skilled manual service occupations in 1980-2010 across US commuting zones. Consequently, RBTC did not exist among the native workers, as immigrants tend to work in manual service occupations (Mandelman and Zlate, 2022; Basso, Peri and Rahman, 2020). Wages of low-skilled immigrant workers often do not rise in line with the wages of the highly skilled, and remain stagnant (Mandelman and Zlate, 2022). Furthermore, availability of low-skilled immigrant workers in some cases might decrease the incentives to automate production (Liu and Portes, 2021). On the other hand, anti-immigrant sentiment can affect future migrant flows through its influence on immigration policies, as some people are keener to blame immigrants than robots and other technologies for their economic struggles (Wu, 2022).

Rising demand for highly skilled workers may be at least partly filled by natives' upskilling, and immigrants with skills in high demand have been targeted through selective immigration policies by several developed economies including Australia, Canada, the UK and the US (Fasani, Llull and Tealdi, 2020). Additionally, it is important to consider the potential effects of automation-induced reshoring from developing to developed economies on their labour markets (Krenz, Prettner and Strulik, 2021), including its impact on eroding the labour cost advantage of less developed economies (Carbonero, Ernst and Weber, 2020) that are potential origin countries of migrants.

When considering technological advancements, studies have also pointed to their importance in telecommunications and transportation as a facilitator for migration, as they support information flows on opportunities in destination countries, make migration itself easier and less costly, facilitate the recruitment of workers, and strengthen the connection of migrants to their families and countries of origin (Czaika and de Haas, 2015; Xiang and Lindquist, 2014). The internet acts as a ‘supportive agent’ (in both the pre-migration phase and the post-migration phase), as it can increase aspirations to migrate and facilitate migration, while decreasing its costs (Pesando et al., 2021; Collin and Karsenti, 2012). On the other hand, ICT advancements have enabled remote work across a range of occupations that do not require physical presence, thus enabling ‘telemigration’, which refers to foreign-based online service workers (Baldwin and Forslid, 2020). This could be especially important in the case of high-skilled potential migrants, as it allows them to work from their countries of origin while being employed in prospective destination countries. Thus, the relationship of novel technologies can be positively or negatively related to migration, depending on the effects that prevail.

Criticisms of ‘push-pull’ models have highlighted their tendency to oversimplify the migration process, and their theoretically weak foundations, which overlook non-economic variables, as well as failing to explain emigration resulting from development-induced factors such as decreased constraints to mobility, rising aspirations and occupational specialisation (de Haas, 2010, 2011; Arango, 2000). To address some of these limitations, the ‘new economics of labour migration’ (NELM) theory emphasised the significance of relative deprivation of the potential migrant in their origin country as a key determinant of migration and shifted the point of reference from individual to family income maximisation (Stark and Bloom, 1985). However, NELM is also sometimes seen as a revised version of the neoclassical theoretical framework, and one that fails adequately to address its weaknesses, particularly those relating to oversimplification of the migration process (Abreu, 2012). Additionally, de Haas (2011) proposes to include indicators that capture key structural features of economies, such as inequality (e.g. Gini index), social security (e.g. governments’ welfare spending) and structural features of economies (e.g. sectoral composition). Thus, with some additions and alterations, ‘push-pull’ models have continued to be central in empirical studies exploring the determinants of international migration, given the micro-decision theoretical foundation of the model and increasing availability of bilateral data across economies.

2.2. ESTIMATING MIGRATION DETERMINANTS USING THE GRAVITY MODEL

Gravity models have been used as a tool to analyse different push-pull factors in a range of studies. Although the pioneering use of gravity models in explaining migration is often attributed to Ravenstein, its widespread acceptance is linked to international trade studies (Tinbergen, 1962) and the more recent development of theoretical micro-foundations for the gravity equation in trade (Anderson, 1979, 2011), which enabled its application to various types of bilateral flows, including international flows of labour and capital (see Head and Mayer, 2021; Anderson, 2016; Lewer and Van den Berg, 2008). The Random Utility Maximisation (RUM) model provided a theoretical justification of the intuition behind the gravity model in migration studies, as it describes the utility that individuals receive from living in their country of origin compared with the expected utility if they emigrate to an alternative destination (Ramos, 2016). Similarly to international trade, international migration is driven by the attractive force between origin and destination countries, while being impeded by the costs associated with moving between them (Lewer and Van den Berg, 2008). Therefore, once the migration gravity equations are specified, they are usually amenable to testing using the same techniques as the ones for trade flows (Head and Mayer, 2014).

Recent important improvements in availability of bilateral (origin-destination) migration data – including OECD’s International Migration database, the United Nations Global Migration Database and the World

Bank's Global Bilateral Migration DataBank – led to a more frequent use of gravity models in estimations of migration determinants (Ramos, 2016). The dependent variable in the model in a certain period refers to bilateral migration flows, and is usually the ratio between the gross flows of migrants from the origin to the destination country divided by the number of individuals who remain in the origin country; the latter can be expressed by size of population or, in some cases, restricted to certain age cohorts (see Beine, Bertoli and Fernández-Huertas Moraga, 2016).

However, measurement challenges of bilateral migration still exist. Some of the data limitations are pointed out by Ramos (2016). First, if data by place of birth[2] are used, they can be misleading as in some instances they do not truly reflect a migrant's origin country, although they can be useful in the case of some determinants, such as language or more generally cultural proximity. Second, changes in stocks are often used as proxies for net flows, but these do not account explicitly for return migration or migration to third countries. Third, although census data provide a more comprehensive view, censuses are mostly conducted only every 10 years and so can provide insights only in the medium and long term; they are therefore not especially useful to estimate a RUM model.

An analytical challenge to gravity equations estimation is to take account of 'multilateral resistance' to migration, i.e. the influence that the attractiveness of alternative destinations exerts on the bilateral migration data (Bertoli and Fernández-Huertas Moraga, 2013). If ignored, this can generate biases in estimations of coefficients of migration determinants, and especially of the impact of migration policies. Several approaches can be used to account for it. Bertoli and Fernández-Huertas Moraga (2013) suggest using the Common Correlated Effects (CCE) estimator (Pesaran, 2006) which requires a sufficiently large panel and length of the time dimension. In case of less data availability, alternatives for controlling for differentiated preferences for migration are origin-year dummies (Ortega and Peri, 2013) or destination-year dummies (Beine and Parsons, 2015). The choice of gravity model estimation technique determines the variety of estimators that can be used to address the issue, as linear models can adopt a set of estimators, while Poisson pseudo-maximum likelihood (PPML) requires the use of origin-time dummies (Beine, Bertoli and Fernández-Huertas Moraga, 2016).

To sum up, the impact of technology on changes in labour demand, resulting in the substitution of routine jobs and a simultaneous rise in demand for other types of work, is likely to further alter the composition and intensity of migrant flows. Consequently, it is important to thoroughly comprehend the effects of the technological changes – particularly the more recent developments in robot adoption and digitalisation – on international migration, in order to understand the important aspects of migration flows and draw conclusions for migration policies. Our research aims to contribute to this literature by utilising a gravity model to explore the technological push and pull factors influencing migrant flows. As these factors cannot be the sole determinants of workers' migration, we also include other variables suggested in the literature. The empirical model specification is presented in the following section, together with the sources of data used in the analysis. The authors believe that this study represents a pioneering effort to empirically explore the relationship between technology adoption, specifically robot adoption and the use of digital technology, and migrant flows using a properly specified gravity model.

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[2] The alternative is to identify migrants by nationality, but this creates problems of cross-country comparability as the naturalisation process (the length of time needed to acquire the host country's nationality) differs greatly between host countries.

3. Methodology and data sources

In this paper, we analyse the push-pull factors of bilateral migration among 31 OECD and EU countries over the period 2001-2019 in a gravity setting. The dataset includes all EU27 member states with the exception of Romania,[3] plus some of the OECD countries, i.e. Australia, the UK, Japan, Norway and the US. The main dependent variable is M_{dot}, representing the inflow of the foreign population in destination country d from origin country o in year t, as collected by the OECD. As suggested by Beine, Bertoli and Fernández-Huertas Moraga (2016), we employ migrant flows data in our analysis as they are not influenced by return migration, migration to third countries, deaths and naturalisation – factors that can impact migration stock data. Following the literature (Head and Mayer, 2021; Beine, Bertoli and Fernández-Huertas Moraga, 2016; Bertoli and Fernández-Huertas Moraga, 2015), we normalise migration flows by the population of the country of origin, P_{ot}, and calculate the ratio of the migrant inflow into the country of destination divided by size of the population in the country of origin: $m_{dot}^{ot} = \frac{M_{dot}}{P_{ot}}$. In the benchmark specification, this relative value of migrant inflow is used as the dependent variable. As an alternative, the absolute number of migrant flows will be used as a dependent variable in robustness checks. The gravity equation is estimated as follows:

$$y_{dot} = exp^{\begin{Bmatrix} \alpha_0+\alpha_1 m_{do,t-1}^{dt}+\alpha_2 X_{dt}+\alpha_3 X_{ot}+\alpha_4 ICT_{dt}+\alpha_5 ICT_{ot}+\alpha_6 R_{dt}+\alpha_7 R_{ot} \\ +\alpha_8 PTA_{dot}+\alpha_9 Lang_{do}+\alpha_{10} Dist_{do}+\delta_t+\delta_{do}+\delta_{ot}+\delta_{dt}+\varepsilon_{dot} \end{Bmatrix}} \quad (1)$$

y_{dot} is either of the dependent variables mentioned above; $m_{do,t-1}^{dt}$ controls for the existing network of migrants from the same country of origin o, relative to the population in the destination country d in the previous year $(t-1)$; X_{dt} and X_{ot} control for country-level variables in the destination and origin countries, respectively. These include GDP per capita in constant 2015 USD, the unemployment rate, the share of the population aged between 15 and 64 years, and a human capital index based on years of schooling and rates of returns to education. Furthermore, when the dependent variable is the absolute level of migration flow, the populations of the country of origin and of destination are also included as additional explanatory variables to control for the size of each country. ICT_{dt} and ICT_{ot} represent ICT capital in constant 2015 USD per person employed in the countries of destination and origin, respectively. R_{dt} and R_{ot} measure the intensity of stock robots in thousands of persons employed in the countries of destination and origin, respectively. PTA_{dot} is a dummy variable indicating whether the two countries have a joint preferential trade agreement (PTA) with labour provisions legally enforced at time t. $Lang_{do}$ is a dummy variable indicating whether the two countries have a common language spoken by at least 9% of their populations. $Dist_{do}$ is the geographical distance between the most populated cities in the two countries. δ_t, δ_{do}, δ_{ot}, δ_{dt} are, respectively, time-, bilateral, origin-time and destination-time fixed effects that are used selectively in separate estimations to infer conclusions on the impact of variables on the dependent variable. ϵ_{dot} is the robust standard error.

3 The Romanian data could not be merged, owing to a lack of some of the data required.

In a robustness specification, we will change the country-level independent variables into bilateral independent variables. The equation for this specification is as follows:

$$y_{dot} = exp\left\{ \begin{matrix} \beta_0 + \beta_1 m_{od,t-1}^{dt} + \beta_2 GDPpc_{dot} + \beta_3 U_{dot} + \beta_4 HC_{dot} + \beta_5 ICT_{dot} + \beta_6 R_{dot} \\ + \beta_7 PTA_{odt} + \beta_8 Lang_{od} + \beta_9 Dist_{od} + \mu_{do} + \mu_{ot} + \mu_{dt} + \epsilon_{dot} \end{matrix} \right\} \quad (2)$$

$GDPpc_{dot}$ is the absolute gap in GDP per capita between the destination and origin countries. U_{dot} represents the ratio of unemployment rates between the destination and origin countries. HC_{dot} is the absolute difference in the human capital index between both countries. ICT_{dot} denotes the ratio of ICT capital in constant 2015 USD per person employed between the destination and origin countries. R_{dot} is the ratio of the intensity of stock robots in thousands of persons employed between the destination and origin countries. μ_{do}, μ_{ot}, μ_{dt} are, respectively, bilateral, origin-time and destination-time fixed effects. ϵ_{dot} is the robust standard error.

The estimation of the models takes into account the possibility that the dependent variables may include zero values and that the distribution of the share of migrant workers is skewed around zero. To address this, the PPML estimation technique is employed, following the gravity literature (Santos Silva and Tenreyro, 2006; and Correia, Guimarães and Zylkin, 2019a, 2019b). This technique is also robust against heteroscedasticity in the error term. Moreover, for continuous variables, the arcsine or the inverse hyperbolic sine transformation of variables is calculated, providing asymptotically similar marginal effects to those of the natural logarithm (Bellemare and Wichman, 2020). This is particularly relevant for variables such as stocks of robots or networks of migrants that may include zero values (Mullahy and Norton, 2022). The arcsine transformation of a variable x is calculated as $arcsinh(x) = \ln\left(x + \sqrt{x^2 + 1}\right)$.

The data for this analysis are compiled from several sources. Migration data is collected from the OECD. Country-level variables such as GDP, population, persons employed, and human capital index are sourced from the Penn World Table (PWT 10.01), compiled by Feenstra, Inklaar and Timmer (2015). Unemployment rate, population and share of the population aged 15-64 are compiled from the World Development Indicators of the World Bank. ICT capital data is sourced from the OECD's STAN database and augmented by the EU KLEMS database. Stocks of industrial robots are obtained from the International Federation of Robotics. Data on distance and common language come from CEPII (Mayer and Zignago, 2011). Data on PTAs are collected from the World Bank's Deep Trade Agreements database (Hofmann, Osnago and Ruta, 2017).

Figure A1 in the Appendix illustrates the development of the main variables in the study sample over the years, distinguishing between net receivers and net senders of migration across countries. Net receivers and net senders are identified by calculating the aggregated inflows of migration minus the aggregated outflows of migration.

4. Estimation results

The results of our estimations are in Tables 1-4. Tables 1 and 3 present the results when the dependent variable refers to the ratio of migration flow from a country of origin to a country of destination divided by the size of the population of the country of origin, which is one way to control for an expected size of a flow from a particular country of origin. Tables 2 and 4 provide estimation results with the absolute flow of migrants from a country of origin to a country of destination as the dependent variable. This specification is in line with how gravity models are implemented in international trade analysis, and in this case the additional variable of the population sizes of the two economies (origin and destination) is added. Furthermore, results in Tables 3 and 4 differ from those in Tables 1 and 2 in that the former use only 'gap or ratio' variables between the countries of destination and the countries of origin (i.e. relative gap in GDP per capita, relative ratios of ICT per employee between destination and origin countries, etc.), while Tables 1 and 2 introduce these push and pull factors separately for the countries of destination and of origin of migrant flows. The various columns of the tables show a variety of specifications depending upon whether: only time fixed effects are introduced; or time fixed effects plus bilateral fixed effects; or time fixed effects and no bilateral fixed effects, but either origin country-time fixed effects or destination country-time fixed effects; or, finally, time fixed effects plus bilateral fixed effects plus either origin country-time fixed effects or destination country-time fixed effects. We check here for robustness of the estimates across these different specifications, and we shall attempt to explain when results differ across them.

4.1. PUSH AND PULL FACTORS SEPARATELY

Here we come to an interpretation of the results, starting with Table 1. We shall always check results in relation to what our *prior expectation* would be regarding the importance and sign for the various explanatory variables. In the following, we discuss the results for the explanatory variables in sequence as they are presented in the table.

› One-year lagged *share of the stock of migrants from a particular country of origin in the total population in a country of destination*: this serves as our 'migrant network' variable in that it shows to what extent migrants from a country of origin can benefit from the support of pre-existing migrants from the same country of origin in a particular country of destination. As we can see, we obtain consistent positive and significant parameter estimates for our 'migrant network' variable.

› *GDP per capita in the country of destination*: consistent positive and significant results for this important 'pull' variable, as was expected. According to the estimates of model M1, a 1% increase in the GDP per capita of a destination country could lead to a 1.97% increase in the share of migrant inflows to that country, relative to the population of the country of origin.

› *GDP per capita in the country of origin*: in this case, the prior expectation is not so clear-cut, as the literature suggests that there might be a non-linearity here, as at very low levels of income, the tendency to migrate can be low because of too high mobility costs; it then increases as income levels rise, but when there is still a significant income gap to potential countries of destination; and the incentive to migrate vanishes when the income gap closes. We see in this variable rather different results in Table 1 (very low significance and variable signs in different specifications) and Table 2 (consistently significant and negative parameter estimates). The difference in these two estimates must be the result of different weights given to migrant flows from different countries of origin in the specifications underlying the results in Table 1 (migrant flows relative to the size of the population in the country of origin) and Table 2 (absolute migrant flows; hence countries with large absolute migrant flows get higher weights).

› *Unemployment rate in the country of destination*: consistently negative and significant parameter estimates, as expected. This suggests that migrants tend to move to countries with lower unemployment rates, expecting better integration into the labour market when there is excessive labour demand.

› *Unemployment rate in the country of origin*: consistently positive and significant parameter estimates, as expected. This suggests that migrants often move from countries with high unemployment rates. In other words, these migrants are likely to be more easily separated from their positions and subsequently from the labour force in their home country when it is difficult to find a job back home.

› *Share of population of working age in total population*: here, our prior expectation would be that a society which has a low share of population of working age would attract migrants in order to make up for missing potential workers. Also, conversely, a high share of working-age population in potential countries of origin would stimulate the outflow of migrants. We get contradictory results with different specifications: the expected signs (negative for the country of destination and positive for the country of origin) are obtained in the specifications that leave out bilateral fixed effects, but the signs change once we introduce bilateral fixed effects. We interpret this result in the following way: as the share of working-age population does not differ very much over time (demographic characteristics change only very slowly), the bilateral fixed effects absorb much of the differences in the structural (i.e. long-term) bilateral demographic characteristics between the two (destination and origin) economies, and hence what is left are the time-dependent changes in the shares of working-age population, which are picked up when a specification with bilateral fixed effects is estimated. In the short-term (year-to-year) dynamics, the share of working-age population in total population is furthermore endogenous as migration flows might – in particular instances – significantly affect this short-term dynamic.

› *Human capital indicator in destination country*: a standard hypothesis here is that in countries of destination the human capital ‘endowment’ is relatively high, and hence such countries would attract migrants who would perform jobs that would not be performed by the domestic population with high educational attainment levels. This hypothesis is supported by the significant positive sign in the specifications without the bilateral fixed terms, while the estimates become insignificant when bilateral fixed terms are introduced. We would argue that this can again be explained by the bilateral fixed terms capturing much of the longer-term structural gaps in the human capital indicators between the two economies, and the coefficient then only captures the year-to-year effect of changes (around the longer-term gaps) in the human capital ratio of both countries on their bilateral migration. These changes might be moving erratically, and furthermore might – as in the case of the working-age population above – be endogenous (if migrants themselves change the human capital ‘endowment’ of a country).

Table 1 / PPML estimation results on bilateral share of inflows of migration relative to the population of the origin country, using country-level variables

Dep. var.:	M1	M2	M3	M4	M5	M6
L.Log of population share of stock of	0.38***	0.25***	0.72***	0.31***	0.29***	0.22***
foreign-born population by country of birth	(0.015)	(0.050)	(0.019)	(0.043)	(0.016)	(0.050)
Log GDP per capita in destination	1.97***	1.36***	1.34***	1.65***		
	(0.18)	(0.36)	(0.17)	(0.26)		
Log GDP per capita in origin	0.20	0.21			-0.26**	0.31*
	(0.17)	(0.18)			(0.11)	(0.16)
Destination log of unemployment total	-0.23***	-0.64***	-0.37***	-0.56***		
(% of total labour force)	(0.082)	(0.073)	(0.075)	(0.054)		
Origin log of unemployment total	0.054	0.52***			0.030	0.53***
(% of total labour force)	(0.079)	(0.050)			(0.059)	(0.045)
Log of destination's share of	-15.5***	13.8***	-15.9***	11.9***		
15-64 population in total	(2.18)	(2.55)	(1.96)	(2.05)		
Log of origin's share of	0.38	-5.52***			3.42**	-5.66***
15-64 population in total	(0.78)	(2.01)			(1.57)	(1.81)
Human capital index based on years of schooling	1.17***	0.39	0.84***	-0.0047		
and returns to education in destination	(0.24)	(0.36)	(0.19)	(0.28)		
Human capital index based on years of	-0.074	-0.16			0.076	-0.33
schooling and returns to education in origin	(0.11)	(0.41)			(0.072)	(0.37)
Log of destination ICT capital	-0.53***	-0.045	-0.60***	-0.072		
per employees constant 2015 USD	(0.059)	(0.12)	(0.048)	(0.098)		
Log of origin ICT capital	-0.31***	-0.24***			-0.26***	-0.31***
per employees constant 2015 USD	(0.049)	(0.093)			(0.038)	(0.079)
Log of intensity of stock robots in	1.10***	0.42***	1.16***	0.52***		
thousand persons employed in destination	(0.073)	(0.10)	(0.062)	(0.093)		
Log of intensity of stock robots in	-0.94***	0.030			-0.92***	-0.020
thousand persons employed in origin	(0.060)	(0.062)			(0.046)	(0.056)
PTA dummy with visa provisions	0.78***	0.78***	1.03***	0.43***	0.65***	0.81***
legally enforced	(0.098)	(0.12)	(0.12)	(0.12)	(0.076)	(0.11)
Common language spoken by	0.63***		0.54***		0.37***	
at least 9% of the population	(0.073)		(0.076)		(0.082)	
Log of distance between the two countries	-0.11***		0.29***		-0.49***	
	(0.035)		(0.037)		(0.033)	
Constant	-7.70***	-16.5***	-4.88**	-19.6***	10.0***	6.86***
	(2.86)	(4.56)	(1.94)	(3.29)	(1.41)	(1.50)
Observations	8008	8008	8033	8008	8030	8004
Pseudo R-squared	0.599	0.965	0.742	0.975	0.813	0.973
AIC	2020731.7	177828.4	1322964.3	124647.0	959128.7	137201.6
BIC	2020850.5	177933.2	1323041.2	124709.9	959205.6	137264.5
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bilateral FE	No	Yes	No	Yes	No	Yes
Origin-time FE	No	No	Yes	Yes	No	No
Destination-time FE	No	No	No	No	Yes	Yes

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.

› *Human capital indicator in country of origin*: here, we do not obtain significant estimates in any of the specifications. This is not necessarily surprising as the evidence suggests that from countries of origin the composition of migrants could show both significant shares of migrants with higher educational attainment or of those with lower levels of educational attainment. Overall, therefore, migrants might come from both types of countries, where human capital is either relatively high or low, as long as income gaps or labour market conditions provide an incentive to both types of potential migrants to move.

› *ICT capital per employee in destination country*: here, just as in the case of the robotisation variable discussed below, there could be two competing hypotheses. On the one hand, digital technologies could substitute the need for migrant workers. On the other hand, they might attract migrants with skills that would be complementary to working with digital technologies. In our estimates, the substitution hypothesis is confirmed in the case of digital technologies.

› *ICT capital per employee in country of origin*: from the country-of-origin point of view, the results for digitalisation confirm also the substitution hypothesis, i.e. a higher level of digitalisation seems to have a tendency to 'eject' workers from potential countries of origin and hence contributes to migration flows.

› *Robots per employee in the destination country*: here – differently from the ICT variable – we get confirmation of the 'complementarity' hypothesis, i.e. that a higher stock of robots also attracts more migrants in the country of destination. This is a consistent result in all specifications. The difference between the ICT and the robotisation variable could result from the fact that the installation of robots so far is highly concentrated in a narrow set of industries (such as car manufacturing or mechanical engineering) and might be specifically conducive to attract migrant workers who can work in these industries. Given that this independent variable undergoes a hyperbolic sine transformation, which exhibits an asymptotic marginal effect similar to the logarithmic transformation, this can be interpreted – according to model M1 – that a 1% increase in newly installed robots per employee in a destination country could lead to a 1.1% increase in the share of migrant inflows to that country, relative to the population of the country of origin.

› *Robots per employee in the country of origin*: for the country of origin, however, we obtain the result that a higher level of robots per employee reduces possible employment opportunities and hence leads to more outward migration – again a case of a substitution effect. This is in line with the finding for the ICT variable for the country of origin.

› *Liberalisation of visa agreements*: this, as expected, increases migration flows on a bilateral basis where visa liberalisation between countries is taking place.

› *Common language spoken by at least 9% of the population*: as expected, this significantly contributes to migration flows between countries.

› *Distance between the two countries*: we can estimate this effect only when bilateral fixed effects terms are left out, and then we obtain the expected negative sign in most specifications. There is, however, an exception when we introduce an origin-time fixed effect; in this case, the sign becomes positive (and is significant). One would venture to argue that in certain circumstances (such as migration from Poland or the Baltic countries to the UK or Ireland in the wake of EU accession), countries which were further apart nonetheless might have had high flows of migrants bilaterally. This could have been a result of two factors: first, that over time transport costs did not matter very much any more (see, for example, the results obtained in the study by Bruecker (2007), which emphasises the increased affordability of charter flights); and second, that changes in country-specific migration policy restrictions might not have been sufficiently captured by the visa liberalisation variable – as was the case during the transition periods after Central and Eastern European (CEE) countries joined the EU in 2004 and 2007, respectively, which lasted for seven years.

Table 2 / PPML estimation results on bilateral inflows of migration, using country-level variables

Dep. var.:	M1	M2	M3	M4	M5	M6
L.Log of population share of stock of foreign-born population by country of birth	0.69***	0.31***	0.70***	0.31***	0.80***	0.34***
	(0.011)	(0.054)	(0.013)	(0.054)	(0.012)	(0.046)
Log GDP per capita in destination	-0.19	1.43***			0.098	1.42***
	(0.16)	(0.30)			(0.13)	(0.26)
Log GDP per capita in origin	-0.66***	-0.72***	-1.09***	-0.74***		
	(0.11)	(0.18)	(0.088)	(0.17)		
Destination log of unemployment total (% of total labour force)	-0.81***	-0.47***			-0.78***	-0.46***
	(0.063)	(0.053)			(0.056)	(0.045)
Origin log of unemployment total (% of total labour force)	0.072*	0.33***	0.057	0.35***		
	(0.044)	(0.044)	(0.040)	(0.037)		
Log of destination's share of 15-64 population in total	4.20***	13.2***			10.9***	12.0***
	(1.60)	(2.47)			(1.51)	(2.11)
Log of origin's share of 15-64 population in total	-1.30	5.80***	-1.28	4.32***		
	(1.21)	(1.56)	(1.05)	(1.31)		
Human capital index based on years of schooling and returns to education in destination	-0.28***	0.14			-0.28***	-0.11
	(0.088)	(0.27)			(0.074)	(0.23)
Human capital index based on years of schooling and returns to education in origin	0.21***	-0.0099	0.28***	0.0019		
	(0.052)	(0.31)	(0.048)	(0.28)		
Log of destination ICT capital per employees constant 2015 USD	-0.12***	0.10			-0.098**	0.18**
	(0.042)	(0.090)			(0.040)	(0.080)
Log of origin ICT capital per employees constant 2015 USD	-0.085***	-0.13	0.014	-0.16**		
	(0.033)	(0.078)	(0.032)	(0.075)		
Log of intensity of stock robots in thousand persons employed in destination	0.35***	0.40***			0.27***	0.41***
	(0.035)	(0.086)			(0.030)	(0.078)
Log of intensity of stock robots in thousand persons employed in origin	-0.25***	0.031	-0.12***	0.023		
	(0.030)	(0.054)	(0.025)	(0.050)		
PTA dummy with visa provisions legally enforced	1.07***	0.62***	0.31***	0.64***	1.41***	0.49***
	(0.078)	(0.12)	(0.062)	(0.099)	(0.084)	(0.15)
Common language spoken by at least 9% of the population	0.25***		0.41***		0.12***	
	(0.046)		(0.041)		(0.039)	
Log of distance between the two countries	-0.000053		0.064***		-0.056***	
	(0.020)		(0.020)		(0.022)	
Log population (in millions) in destination d in year t	0.81***	-3.93***			0.90***	-3.26***
	(0.015)	(0.56)			(0.014)	(0.49)
Log population (in millions) in origin o in year t	0.27***	-0.19	0.20***	-0.31		
	(0.017)	(0.37)	(0.015)	(0.31)		
Constant	9.28***	1.30	13.0***	12.5***	-6.10***	-5.06*
	(2.42)	(3.97)	(1.04)	(1.81)	(1.48)	(3.05)
Observations	8008	8008	8004	8004	8008	8008
Pseudo R-squared	0.855	0.977	0.925	0.984	0.900	0.984
AIC	8629584.0	1352851.1	4437344.2	974406.4	5948063.1	929160.9
BIC	8629716.8	1352969.9	4437428.1	974476.2	5948146.9	929230.8
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bilateral FE	No	Yes	No	Yes	No	Yes
Origin-time FE	No	No	Yes	Yes	No	No
Destination-time FE	No	No	No	No	Yes	Yes

Robust standard errors in parentheses: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

We now come to the other specifications depicted in Tables 2-4, starting with Table 2, which differs from the specification in Table 1 in that the dependent variable refers to absolute migrant flows from a country of origin to a country of destination. Because we are dealing with absolute flows, the only added explanatory variables included here (but not in the specifications estimated in Table 1) are the absolute levels of the population in the country of origin and in the country of destination, as estimation of absolute migrant flows has to take account of the size of the populations in this bilateral relationship.

The results in Table 2 are in most cases consistent with those in Table 1, specifically in that most of the parameter estimates linked to the different explanatory variables keep the (positive or negative) signs, even though the size of the parameter estimates might differ. This latter difference is not surprising as the estimates in Table 2 (estimated in levels) give higher 'weights' to countries with higher bilateral migration flows and population sizes. Thus, the signs obtained for the variables GDP per capita (in destination and host countries), for the migrant network effect, for the unemployment rates, for visa liberalisation and for common language spoken by at least 9% of the populations in the destination and origin countries of migrants, are consistent between the two estimates depicted in Tables 1 and 2. Furthermore – and important for our study, with its focus on the impact of technology indicators (digital assets and robots) on migration flows – the estimated impacts of these two variables (as regards signs of estimated parameters) are also consistent between the two sets of estimates. As regards differences in the estimation results from the specifications depicted in Table 2 compared with those we obtained in Table 1, we want to mention the following.

› *Share of population aged 15-64 in total population in destination relative to origin country*: here, there are some differences in the estimates, as in Table 2 we now obtain consistently positive signs for the share of the working-age population in the destination country, which goes against a prior hypothesis that the availability of a large domestic potential labour force makes the country less dependent on migrant inflows. However, it could be the result, first, of an endogeneity that migrant inflows of working age affect this variable itself, and second, that a high share of a working-age population might reflect an active labour market situation and that this would be attractive to migrant inflows. For the share of working-age population in the country of origin, we obtain in Table 2 significant positive signs in the specification with bilateral fixed effects, which indicates that short-term dynamics in this variable acts as a 'push' factor for migrant outflows from countries of origin.
› *Human capital index in destination relative to origin country*: here, an interesting difference emerges between Table 2 and Table 1 estimates. In the latter, we obtain significant positive effects of the human capital indicator for the country of origin, which would indicate some evidence of brain drain (the higher the human capital 'endowment', the more outward migration). For the human capital indicator in the country of destination, however, we obtain opposite results regarding its effects on inward migration: in Table 1 we obtained a positive sign, which we interpreted above as indicating that migrants might be needed to undertake lower-skilled jobs, while in Table 2 we obtain a negative sign which – given the evidence found here for brain drain – might indicate competition between domestic well-educated workers and well-educated migrant workers from other countries. We should reiterate that these interpretations, and also other discrepancies between the results in Tables 1 and 2, are quite feasible and in line with the differences in weights given to bilateral relations between countries of origin and destination in the two sets of estimates which can give rise to such discrepancies.

- *Distance between the two countries*: we pointed out in the interpretation of the results in Table 1 that we can expect unstable estimates depending on specifications (with and without bilateral fixed effects) and now, in Table 2, this emerges again, in line with the result in Table 1.
- *Population sizes* (these are only included in the specification estimated in Table 2): here, we obtain the expected signs (larger population sizes lead to higher migration flows, *ceteris paribus*) in the estimates without bilateral fixed effects. The negative signs when bilateral fixed effects are introduced can again be explained by the fact that in this case the relative sizes of the two populations in the longer run are captured by the bilateral fixed terms; the parameter estimates then only capture short-term changes in population sizes, which could be spurious.

4.2. RELATIVE PUSH AND PULL FACTORS

We now come to the estimates depicted in Tables 3 and 4. In these specifications only 'relative' or 'gap' variables are introduced between the countries of destination and origin. This means we can no longer separately identify whether the variable is moved by changes in the value of the variable in the country of destination or of the country of origin. Nevertheless, it is interesting to see which results remain robust in this specification. Let us first name the variables for which the results are easy to interpret and are consistent with what we found in Tables 1 and 2: the migration network effect remains significant, so does the gap variable in GDP per capita between country of destination and the country of origin, as do the relative unemployment rates, the impact of visa liberalisation, and common language spoken in the two types of countries. We also again obtain unstable sign estimates for the distance variable when we introduce origin-time or destination-time fixed effects (in Tables 3 and 4 specifications, we cannot include bilateral fixed effects as geographical distance between two countries does not change over time).

This leaves three variables (log of difference in the human capital indicator, relative absolute gap in non-ICT capital to labour ratio, and log of ratios of ICT capital per employee; in each case specified as destination country relative to origin country) for which we obtain rather unstable parameter estimates, mostly depending on whether we introduce origin-country or destination-country fixed effects. For the last variable (relative stock of robots per employee), we obtain consistent, significantly positive parameter estimates. This latter result supports the hypothesis that adoption of robots in a country of destination relative to that of the country of origin attracts migrants, which is also consistent with the estimates obtained in Tables 1 and 2.

As regards the other three variables, while not wanting to overstretch the interpretation of our results, it is nonetheless possible to infer from the results obtained in Tables 1 and 2 which of the two countries' (destination or origin) variables might drive the results obtained for the 'gap' or 'relative' variables in Tables 3 and 4.

Table 3 / PPML estimation results on bilateral share of inflows of migration relative to the population of the origin country, using bilateral explanatory variables

Dep. var.:	M1	M2	M3	M4
L.Log of population share of stock of foreign-born population by country of birth	0.77*** (0.017)	0.29*** (0.042)	0.37*** (0.016)	0.34*** (0.043)
Log of the absolute gap in GDP per capita of both countries	0.24*** (0.032)	0.032** (0.013)	0.28*** (0.037)	0.078*** (0.014)
Log of destination to origin unemployment rates	-1.02*** (0.086)	-0.99*** (0.073)	-0.067 (0.080)	-0.63*** (0.050)
Log of absolute difference of human capital index	0.31*** (0.035)	0.0019 (0.011)	-0.021 (0.017)	-0.063*** (0.015)
Log of destination to origin ICT capital per employees constant 2015 USD	-0.47*** (0.043)	-0.55*** (0.12)	0.23*** (0.029)	0.25*** (0.083)
Log of destination to origin relative intensity of stock robots in thousand persons	1.04*** (0.058)	0.36*** (0.077)	0.32*** (0.018)	-0.017 (0.020)
PTA dummy with visa provisions legally enforced	1.01*** (0.13)	0.55*** (0.12)	0.81*** (0.064)	0.89*** (0.11)
Common language spoken by at least 9% of the population	0.50*** (0.080)		0.45*** (0.070)	
Log of distance between the two countries	0.37*** (0.039)		-0.41*** (0.033)	
Constant	-6.46*** (0.52)	4.49*** (0.49)	1.73*** (0.39)	2.58*** (0.41)
Observations	7524	7522	7520	7518
Pseudo R-squared	0.748	0.976	0.825	0.975
AIC	1166046.0	110010.9	812157.2	113901.5
BIC	1166115.2	110066.3	812226.5	113956.9
Bilateral FE	No	Yes	No	Yes
Origin-time FE	Yes	Yes	No	No
Destination-time FE	No	No	Yes	Yes

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.

Take the example of the variable relative ICT capital per employee (destination-to-origin country), which is of particular interest to us: we obtain a significant negative sign estimate when country-of-origin time fixed effects terms are included and a significant positive sign estimate when destination-country time fixed effects are included. How can we explain or interpret such a result? If we look at the results in Tables 1 and 2, we obtain – as discussed earlier – for ICT per employee a ‘substitution’ result in the country of destination (i.e. more ICT per employee reduces the need for migrant inflows) but a ‘complementarity’ result in the country of origin (i.e. the use of more digital assets in the country of origin acts as an incentive not to migrate). Hence, when we then estimate the impact of the ratio of ICT per employee (destination divided by country of origin) we would anticipate – from the results in Tables 1 and 2 – that if both countries’ digital assets per employee increase, this would act as a deterrent to migrate to the destination country (substitution effect) and an incentive to stay at home in the country of origin (because of the complementarity effect). This would lead to a consistent result, and one would expect a negative sign for the parameter estimate for the ‘ratio’ variable in Tables 3 and 4. But what if they move in the opposite direction from each other? In that case, migrants would still be deterred from migrating to the country of destination, but in the numerator of the ratio a fall in digital assets in the country of origin would indicate that there would be an incentive for migrants to leave the country. Then, depending on the size of the two effects, there could be a positive migration flow associated with an increase in the ratio, that is if the incentive effect (to leave the country) outweighs the deterrent (or substitution) effect in the destination country. From this, we can see that in this case an estimate that relies on combining these two effects into one ratio might lead to rather unstable results. If, on top of that, we include country-time fixed effects, we de facto introduce country-specific time trends which can absorb some of the trend effects in the digital asset per employee movements in the destination relative to the origin country. Then, for this country, what is left are only the effects of the fluctuations around this trend. This, in our view, explains why adding a country-time fixed effect into these ('gap' or 'ratio') estimates of certain variables in Tables 3 and 4 can lead to the changes in the estimated signs.

Table 4 / PPML estimation results on bilateral inflows of migration, using bilateral explanatory variables

Dep. var.:	M1	M2	M3	M4
L.Log of population share of stock of foreign-born population by country of birth	0.83*** (0.014)	0.27*** (0.046)	0.77*** (0.014)	0.32*** (0.048)
Log of the absolute gap in GDP per capita of both countries	-0.022 (0.026)	0.034** (0.013)	0.065** (0.026)	0.097*** (0.017)
Log of destination to origin unemployment rates	-0.60*** (0.075)	-0.86*** (0.052)	-0.17*** (0.063)	-0.64*** (0.041)
Log of absolute difference of human capital index	0.049*** (0.018)	-0.020 (0.014)	-0.031*** (0.011)	-0.032*** (0.011)
Log of destination to origin ICT capital per employees constant 2015 USD	-0.27*** (0.035)	0.028 (0.10)	0.16*** (0.028)	0.24*** (0.078)
Log of destination to origin relative intensity of stock robots in thousand persons	0.46*** (0.041)	0.42*** (0.071)	0.054*** (0.016)	0.057*** (0.021)
Summation of both countries' population (in millions)	1.26*** (0.026)	-9.27*** (1.00)	0.24*** (0.024)	-1.18* (0.62)
PTA dummy with visa provisions legally enforced	1.23*** (0.089)	0.37*** (0.13)	0.40*** (0.076)	0.80*** (0.11)
Common language spoken by at least 9% of the population	0.067 (0.057)		0.21*** (0.049)	
Log of distance between the two countries	-0.012 (0.026)		0.13*** (0.023)	
Constant	-4.33*** (0.38)	47.9*** (4.63)	-0.58* (0.32)	10.3*** (2.95)
Observations	7524	7522	7520	7518
Pseudo R-squared	0.838	0.986	0.912	0.984
AIC	9293846.6	819309.2	5047915.4	918642.8
BIC	9293922.8	819371.5	5047991.5	918705.1
Bilateral FE	No	Yes	No	Yes
Origin-time FE	Yes	Yes	No	No
Destination-time FE	No	No	Yes	Yes

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.

When we examine the variable of the absolute gap in the human capital index between destination and origin country, we obtain a significant positive estimate when a country-of-origin time fixed effect is introduced but an insignificant (Table 3) or significant negative parameter estimate (Table 4) when a destination-country time fixed effect is introduced. If we go back to the results obtained in Tables 1 and 2, when the effects of the human capital index were estimated separately for the destination and the origin countries, we had obtained rather contradictory results: in the estimate in Table 1, we found a positive and significant effect when human capital in the destination country was increasing, while we found no significant effect when human capital was increasing in the country of origin. In Table 2, on the other hand, we found a negative effect of a human capital increase in the country of destination, and a significant positive effect associated with a human capital increase in the country of origin, which we interpreted as evidence of brain drain. Now, we see that in Table 3 the result is perfectly explainable by the strong positive effect that has been found in Table 1 for the increase in the human capital index in the destination country, while no significant effect was found for the country of origin. And there is no significant change of sign found when country-time fixed effects are introduced. In Table 4, however, there is a change of sign when the destination country-time fixed effect is introduced. This severely weakens the impact of the first term in the difference (human capital in the destination country), because – using the already familiar argument – the trend effect of the destination country human capital index is in parts absorbed by introducing this country-time fixed effect, and hence we are left with the stronger brain drain effect from an increase in human capital in the country of origin (the negative term in the difference between the two human capital indicators); this results in a switch of the sign from positive (when no destination country-time fixed effect is included) to negative (when a destination country-time fixed effect is included).

5. Summary and concluding remarks

The focus of this paper was on the impact of technology adoption – proxied by two variables: digital assets per employee and robots per employee – on migration flows. We set up a model which is commonly used in migration research, representing the main ‘push’ and ‘pull’ factors such as GDP per capita and labour market conditions (unemployment rates and the share of working-age population), human capital indicators that can proxy the likely composition of migrants in terms of educational attainment levels, commonality of language, migration/mobility restrictions (proxied by a visa liberalisation variable), migrant network effects, distance and population sizes. To these, we added the two ‘technology adoption’ variables. All of these variables were defined for countries of origin and (potential) countries of destination: in one set of estimations these were independently introduced, and in the other set these were included as ‘gap’ or ‘ratio’ variables. We applied estimation methods which are well-established in gravity modelling, such as taking account of zero-flow entries and dealing with ‘multilateral resistance’ through the inclusion of country-time fixed effects and bilateral fixed effects terms. The results obtained with the various specifications were carefully analysed and discussed. We should keep in mind that the set of countries included in the estimations for this paper were EU27 economies (except Romania) and other more advanced (OECD) economies: Australia, the UK, Japan, Norway and the US. Let us now recapitulate the most interesting results.

As regards the more traditional variables introduced into this enlarged migration ‘push and pull’ model, we obtained the expected results for GDP per capita, as well as for unemployment rates in the destination relative to origin country of migrants; the same was the case for the variables visa liberalisation and commonality of language. For human capital indicators and the share of working-age population, slightly more complex results were obtained, which could be interpreted by reference to the possibility (and hence competing hypotheses) that migrants might be allocated to lower-skilled jobs or are indeed also attracted to higher-skilled employment opportunities in the country of destination; and by brain drain features for the countries of origin. A high share of working-age population in the country of origin means a bigger pool of migrants that could look for jobs abroad, while a higher share of working-age population in the destination country could either mean less need for migrants or could also reflect a more active labour market that could be attractive for migrants.

This leaves us with the interesting results obtained for the technology adoption indicators in our study: overall, we found that the two technology variables (digital assets and robots per employee) gave us different results: for digital assets per employee in the destination country, we found mostly evidence for a ‘substitution effect’. In other words, a higher level of digital assets per employee in the destination country led to lower migration flows, while a higher level of robots per employee in the destination country exerted a positive ‘migrant pull’ effect – i.e. there was evidence of ‘complementarity’ here. We interpreted this difference as reflecting the more concentrated use of robots in a few selected industries (specifically transport equipment and mechanical engineering), which encouraged migrant employment in those industries, while the use of digital assets was much more widespread across a wide range of industries. As regards the impact of the degree of digitalisation and robotisation in the (potential) country of origin, this pointed consistently in the direction of ‘complementarity’, i.e. less incentive to migrate when the level of technology adoption (for both types of technologies) was higher.

References

Abreu, A. (2012), ‘The new economics of labor migration: beware of neoclassicals bearing gifts’, *Forum for Social Economics*, Vol. 41(1), pp. 46-67.

Acemoglu, D. and P. Restrepo (2017), ‘Robots and jobs: evidence from US labor markets’, National Bureau of Economic Research, Working Paper No. 23285.

Adovor, E., M. Czaika, F. Docquier and Y. Moullan (2021), ‘Medical brain drain: how many, where and why?’, *Journal of Health Economics*, Vol. 76: 102409.

Adserà, A. and M. Pytliková (2015), ‘The role of language in shaping international migration’, *The Economic Journal*, Vol. 125(586), pp. F49-F81.

Anderson, J.E. (1979), ‘A theoretical foundation for the gravity equation’, *American Economic Review*, Vol. 69(1), pp. 106-116.

Anderson, J.E. (2011), ‘The gravity model’, *Annual Review of Economics*, Vol. 3(1), pp. 133-160.

Anderson, J.E. (2016), ‘The gravity model of economic interaction’, Boston College and National Bureau of Economic Research, No. 3, pp. 391-397.

Anderson, J.E. and E. van Wincoop (2003), ‘Gravity with gravitas: a solution to the border puzzle’, *American Economic Review*, Vol. 93(1), pp. 170-192.

Arango, J. (2000), ‘Explaining migration: a critical view’, *International Social Science Journal*, Vol. 52(165), pp. 283-296.

Arif, I. (2020), ‘The determinants of international migration: unbundling the role of economic, political and social institutions’, *The World Economy*, Vol. 43(6), pp. 1699-1729.

Arntz, M., T. Gregory and U. Zierahn (2019), ‘Digitalization and the future of work: macroeconomic consequences’, in: K.F. Zimmermann (ed.), *Handbook of Labor, Human Resources and Population Economics*, Springer International Publishing, Berlin.

Autor, D.H. (2015), ‘Why are there still so many jobs? The history and future of workplace automation’, *Journal of Economic Perspectives*, Vol. 29(3), pp. 3-30.

Autor, D.H., F. Levy and R.J. Murnane (2003), ‘The skill content of recent technological change: an empirical exploration’, *The Quarterly Journal of Economics*, Vol. 118(4), pp. 1279-1333.

Baldwin, R. (2019), The Globotics Upheaval: Globalization, Robotics, and the Future of Work, Oxford University Press, Oxford and New York.

Baldwin, R. and R. Forslid (2020), ‘Globotics and development: when manufacturing is jobless and services are tradable’, National Bureau of Economic Research, Working Paper No. 26731.

Basso, G., G. Peri and A.S. Rahman (2020), ‘Computerization and immigration: theory and evidence from the United States’, *Canadian Journal of Economics/Revue canadienne d'économique*, Vol. 53(4), pp. 1457-1494.

Beerli, A., R. Indergand and J.S. Kunz (2023), ‘The supply of foreign talent: how skill-biased technology drives the location choice and skills of new immigrants’, *Journal of Population Economics*, Vol. 36(2), pp. 681-718.

Beine, M. and C. Parsons (2015), ‘Climatic factors as determinants of international migration’, *The Scandinavian Journal of Economics*, Vol. 117(2), pp. 723-767.

Beine, M., S. Bertoli and J. Fernández-Huertas Moraga (2016), ‘A practitioners’ guide to gravity models of international migration’, *The World Economy*, Vol. 39(4), pp. 496-512.

Bellemare, M.F. and C.J. Wichman (2020), ‘Elasticities and the inverse hyperbolic sine transformation’, *Oxford Bulletin of Economics and Statistics*, Vol. 82(1), pp. 50-61. https://doi.org/10.1111/obes.12325

Bertoli, S. and J. Fernández-Huertas Moraga (2013), ‘Multilateral resistance to migration’, *Journal of Development Economics*, Vol. 102, pp. 79-100.

Bertoli, S. and J. Fernández-Huertas Moraga (2015), ‘The size of the cliff at the border,’ *Regional Science and Urban Economics*, Vol. 51, pp. 1-6.

Borjas, G.J. (1989), ‘Economic theory and international migration’, *International Migration Review*, Vol. 23(3), pp. 457-485.

Borjas, G.J. and R.B. Freeman (2019), ‘From immigrants to robots: the changing locus of substitutes for workers’, *RSF: The Russell Sage Foundation Journal of the Social Sciences*, Vol. 5(5), pp. 22-42.

Botezat, A. and R. Ramos (2020), ‘Physicians’ brain drain – a gravity model of migration flows’, *Globalization and Health*, Vol. 16(1):7.

Bruecker, H. (2007), ‘Labor mobility after the European Union's eastern enlargement. Who wins, who loses?’, GMF Paper Series, Washington, DC.

Carbonero, F., E. Ernst and E. Weber (2020), ‘Robots worldwide: the impact of automation on employment and trade’, Institute for Employment Research (IAB), Discussion Paper No. 7/2020.

Cattaneo, C. and G. Peri (2016), ‘The migration response to increasing temperatures’, *Journal of Development Economics*, Vol. 122, pp. 127-146.

Collin, S. and T. Karsenti (2012), ‘Facilitating linguistic integration of immigrants: an overview of ICT tools’, *Issues in Informing Science and Information Technology*, Vol. 9, pp. 243-251.

Correia, S., P. Guimarães and T. Zylkin (2019a), ‘ppmlhdfe: fast Poisson estimation with high-dimensional fixed effects’, arXiv.org.

Correia, S., P. Guimarães and T. Zylkin (2019b), ‘Verifying the existence of maximum likelihood estimates for generalized linear models’, arXiv preprint arXiv:1903.01633.

Czaika, M. and H. de Haas (2014), ‘The globalization of migration: has the world become more migratory?’, *International Migration Review*, Vol. 48(2), pp. 283-323.

Czaika, M. and H. de Haas (2015), ‘Evaluating migration policy effectiveness’, in: A. Triandafyllidou (ed.), *Routledge Handbook of Immigration and Refugee Studies*, Routledge, London, pp. 34-40.

Czaika, M. and C.R. Parsons (2017), ‘The gravity of high-skilled migration policies’, *Demography*, Vol. 54(2), pp. 603-630.

de Haas, H. (2010), ‘Migration and development: a theoretical perspective’, *International Migration Review*, Vol. 44(1), pp. 227-264.

de Haas, H. (2011), ‘The determinants of international migration: conceptualizing policy, origin and destination effects’, University of Oxford International Migration Institute, Working Paper No. 32.

de Haas, H. (2021), ‘A theory of migration: the aspirations-capabilities framework’, *Comparative Migration Studies*, Vol. 9(1):8.

de Haas, H., M. Czaika, M.-L. Flahaux, E. Mahendra, K. Natter, S. Vezzoli and M. Villares-Varela (2019), ‘International migration: trends, determinants, and policy effects’, *Population and Development Review*, Vol. 45(4), pp. 885-922.

Fasani, F., J. Llull and C. Tealdi (2020), 'The economics of migration: labour market impacts and migration policies', *Labour Economics*, Vol. 67: 101929.

Feenstra, R.C., R. Inklaar and M.P. Timmer (2015), 'The next generation of the Penn World Table', *American Economic Review*, Vol. 105(10), pp. 3150-3182.

Fei, J.C. and G. Ranis (1961), 'Unlimited supply of labour and the concept of balanced growth', *The Pakistan Development Review*, Vol. 1(3), pp. 29-58.

Ferrie, J.P. and T.J. Hatton (2015), 'Two centuries of international migration', in: B.R. Chiswick and P.W. Miller (eds), *Handbook of the Economics of International Migration, (Vol. 1)*, Elsevier, Amsterdam, pp. 53-88.

Frey, C.B. and M. Osborne (2013), 'The future of employment: how susceptible are jobs to computerisation?', University of Oxford Working Paper. Available at: https://sep4u.gr/wp-content/uploads/The_Future_of_Employment_ox_2013.pdf

Ghodsi, M., I. Mara and A. Barišić (in progress), 'Technological revolution and international labour migration: a literature review'.

Goos, M. and A. Manning (2007), 'Lousy and lovely jobs: the rising polarization of work in Britain', *The Review of Economics and Statistics*, Vol. 89(1), pp. 118-133.

Goos, M., A. Manning and A. Salomons (2014), 'Explaining job polarization: routine-biased technological change and offshoring', *American Economic Review*, Vol. 104(8), pp. 2509-2526.

Graetz, G. and G. Michaels (2018), 'Robots at work', *The Review of Economics and Statistics*, Vol. 100(5), pp. 753-768.

Greenwood, M.J. (2019), 'The migration legacy of E.G. Ravenstein', *Migration Studies*, Vol. 7(2), pp. 269-278.

Greenwood, M.J. and G.L. Hunt (2003), 'The early history of migration research', *International Regional Science Review*, Vol. 26(1), pp. 3-37.

Grieveson, R., S.M. Leitner and R. Stehrer (2019), 'EU faces a tough demographic reckoning', wiiw Policy Note/Policy Report No. 30, The Vienna Institute for International Economic Studies (wiiw), Vienna, June.

Grigg, D.B. (1977), 'E.G. Ravenstein and the "laws of migration"', *Journal of Historical Geography*, Vol. 3(1), pp. 41-54.

Head, K. and T. Mayer (2014), 'Gravity equations: workhorse, toolkit, and cookbook', in: G. Gopinath, E. Helpman and K. Rogoff (eds), *Handbook of International Economics, (Vol. 4)*, Elsevier, Amsterdam, pp. 131-195.

Head, K. and T. Mayer (2021), 'The United States of Europe: a gravity model evaluation of the four freedoms', *Journal of Economic Perspectives*, Vol. 35(2), pp. 23-48.

Hofmann, C., A. Osnago and M. Ruta (2017), 'Horizontal depth: a new database on the content of preferential trade agreements', Policy Research Working Paper No. 7981. World Bank, Washington, DC.

ILO (2021), 'ILO global estimates on international migrant workers – results and methodology', International Labour Organization, Geneva. Available at: https://www.ilo.org/global/topics/labour-migration/publications/WCMS_808935/lang--en/index.htm

IMF (2024), 'Gen-AI: artificial intelligence and the future of work', International Monetary Fund, Washington, DC. Available at: https://www.imf.org/en/Publications/Staff-Discussion-Notes/Issues/2024/01/14/Gen-AI-Artificial-Intelligence-and-the-Future-of-Work-542379

IOM (2021), *World Migration Report 2022*, International Organization for Migration, Geneva. Available at: https://publications.iom.int/books/world-migration-report-2022

Kahanec, M., A. Zaiceva and K.F. Zimmermann (2009), 'Lessons from migration after EU enlargement', in: M. Kahanec and K.F. Zimmermann (eds), *EU Labor Markets after Post-enlargement Migration*, Springer, Berlin, pp. 3-45.

Katz, L.F. and K.M. Murphy (1992), 'Changes in relative wages, 1963-1987: supply and demand factors', *The Quarterly Journal of Economics*, Vol. 107(1), pp. 35-78.

Kim, K. and J.E. Cohen (2010), 'Determinants of international migration flows to and from industrialized countries: a panel data approach beyond gravity', *International Migration Review*, Vol. 44(4), pp. 899-932.

Krenz, A., K. Prettner and H. Strulik (2021), 'Robots, reshoring, and the lot of low-skilled workers', *European Economic Review*, Vol. 136: 103744.

Kurekova, L. (2011), 'Theories of migration: conceptual review and empirical testing in the context of the EU East-West flows', paper prepared for Interdisciplinary Conference on Migration: Economic Change, Social Challenge, University College London, 6-9 April 2011.

Lee, E.S. (1966), 'A theory of migration', *Demography*, Vol. 3(1), pp. 47-57.

Leitner, S.M. and R. Stehrer (2019a), 'Demographic challenges for labour supply and growth', wiiw Research Report No. 439, The Vienna Institute for International Economic Studies (wiiw), Vienna, March.

Leitner, S.M and R. Stehrer (2019b), 'The automatisation challenge meets the demographic challenge: in need of higher productivity growth', wiiw Working Paper No. 171, The Vienna Institute for International Economic Studies (wiiw), Vienna, December.

Lewer, J.J. and H. Van den Berg (2008), 'A gravity model of immigration', *Economics Letters*, Vol. 99(1), pp. 164-167.

Lewis, W.A. (1954), 'Economic development with unlimited supplies of labour', *The Manchester School*, Vol. 22(2), pp. 139-191.

Liu, L. and A. Portes (2021), 'Immigration and robots: is the absence of immigrants linked to the rise of automation?', *Ethnic and Racial Studies*, Vol. 44(15), pp. 2723-2751.

Mandelman, F.S. and A. Zlate (2022), 'Offshoring, automation, low-skilled immigration, and labor market polarization', *American Economic Journal: Macroeconomics*, Vol. 14(1), pp. 355-389.

Massey, D.S., J. Arango, G. Hugo, A. Kouaouci, A. Pellegrino and J.E. Taylor (1993), 'Theories of international migration: a review and appraisal', *Population and Development Review*, Vol. 19(3), pp. 431-466.

Mayda, A.M. (2010), 'International migration: a panel data analysis of the determinants of bilateral flows', *Journal of Population Economics*, Vol. 23(4), pp. 1249-1274.

Mayer, T. and S. Zignago (2011), 'Notes on CEPII's distances measures: the GeoDist database', CEPII Working Paper No. 2011-25.

Mullahy, J. and E.C. Norton (2022), 'Why transform Y? A critical assessment of dependent-variable transformations in regression models for skewed and sometimes-zero outcomes', National Bureau of Economic Research, Working Paper No. 30735.

Ortega, F. and G. Peri (2013), 'The effect of income and immigration policies on international migration', *Migration Studies*, Vol. 1(1), pp. 47-74.

Pesando, L.M., V. Rotondi, M. Stranges, R. Kashyap and F.C. Billari (2021), 'The internetization of international migration', *Population and Development Review*, Vol. 47(1), pp. 79-111.

Pesaran, M.H. (2006), 'Estimation and inference in large heterogeneous panels with a multifactor error structure', *Econometrica*, Vol. 74(4), pp. 967-1012.

Poprawe, M. (2015), 'On the relationship between corruption and migration: empirical evidence from a gravity model of migration', *Public Choice*, Vol. 163(3-4), pp. 337-354.

Ramos, R. (2016), 'Gravity models: a tool for migration analysis', IZA World of Labor.

Ramos, R. and J. Suriñach (2017), 'A gravity model of migration between the ENC and the EU', *Tijdschrift voor economische en sociale geografie/Journal of Economic and Human Geography*, Vol. 108(1), pp. 21-35.

Santos Silva, J. and S. Tenreyro (2006), 'The log of gravity', *The Review of Economics and Statistics*, Vol. 88(4), pp. 641-658. https://doi.org/10.1162/rest.88.4.641

Sjaastad, L.A. (1962), 'The costs and returns of human migration', *Journal of Political Economy*, Vol. 70(5, pt. 2), pp. 80-93.

Stark, O. and D.E. Bloom (1985), 'The New Economics of Labor Migration', *American Economic Review*, Vol. 75(2), pp. 173-178.

Tinbergen, J. (1962), Shaping the World Economy. Suggestions for an International Economic Policy, The Twentieth Century Fund, New York.

Todaro, M.P. (1969), 'A model for labor migration and urban unemployment in less developed countries', *American Economic Review*, Vol. 59(1), pp. 138-148.

Van Hear, N., O. Bakewell and K. Long (2018), 'Push-pull plus: reconsidering the drivers of migration', *Journal of Ethnic and Migration Studies*, Vol. 44(6), pp. 927-944.

Warin, T. and P. Svaton (2008), 'European migration: welfare migration or economic migration?', *Global Economy Journal*, Vol. 8(3): 1850140.

Wesselbaum, D. and A. Aburn (2019), 'Gone with the wind: international migration', *Global and Planetary Change*, Vol. 178, pp. 96-109.

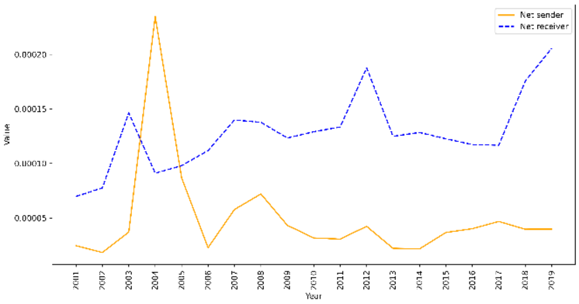
Wu, N. (2022), '"Restrict foreigners, not robots": partisan responses to automation threat', *Economics & Politics*, Vol. 35(2), pp. 505-528.

Xiang, B. and J. Lindquist (2014), 'Migration infrastructure', *International Migration Review*, Vol. 48, pp. S122-S148.

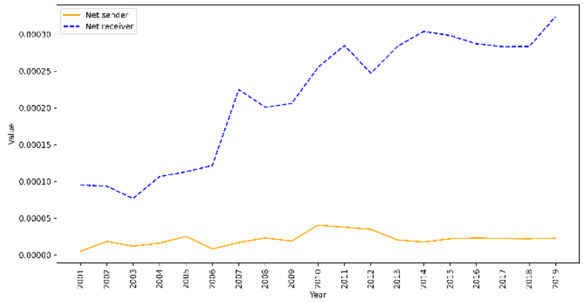
Appendix

Figure A1 / Development of main variables in the sample of study over years

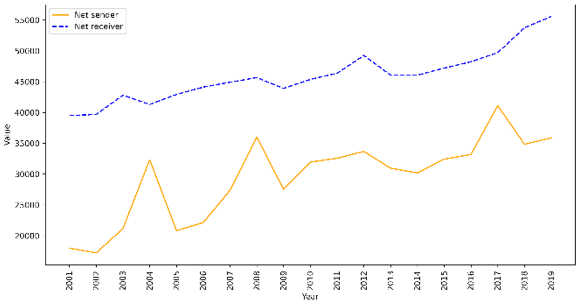
Migration to host population



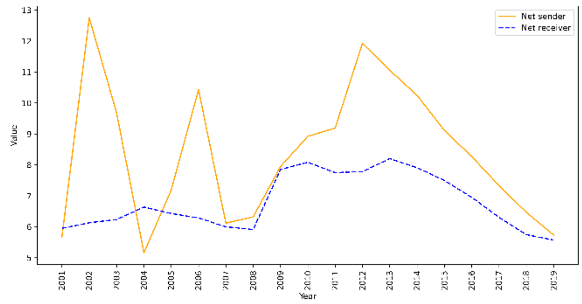
Migration to origin population



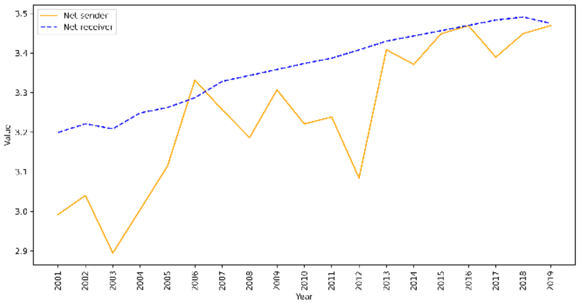
GDP per capita



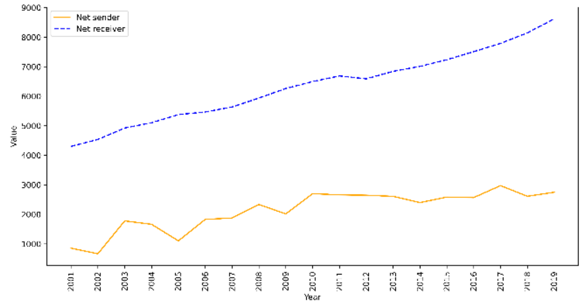
Unemployment rate



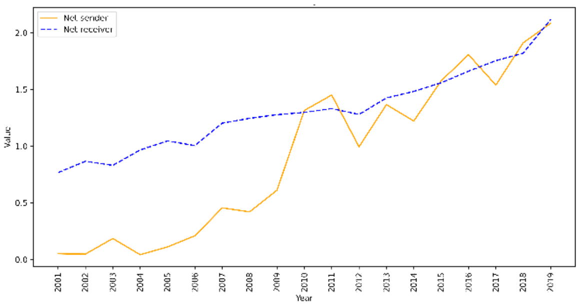
Human capital index



ICT capital per employee



Robots per thousand employees



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