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SELECTING ONLY THE BEST AND BRIGHTEST? AN ASSESSMENT OF MIGRATION POLICY SELECTIVITY AND ITS EFFECTIVENESS

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Selecting only the best and brightest? An assessment of migration policy selectivity and its effectiveness*

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Abstract

This paper introduces a new set of comprehensive and cross-country-comparable indexes of migration policy selectivity. Crucially, these reflect the multidimensional nature of the differential treatment of migrants. We use these indexes to study the evolution of migration policy selectivity and estimate how they affect migration flows. Combining all publicly available and relevant data since WWII, we build three composite indexes that identify selectivity in terms of skills, economic resources and nationality. First, we use these to characterise migration policies in 42 countries between 1990 and 2014. Second, we analyse the effectiveness of migration policy selectivity by estimating its impact on migration flows. Each of the three dimensions of selectivity is found to affect the size and structure of migration flows significantly.
Keywords: Migration Policy; International Migration; Selectivity; Effectiveness
JEL codes: F22, C43, P16, C32, 057

1 Introduction

The size and structure of international migration flows have changed significantly since the Second World War (De Haas et al. 2018). Government attempts to manage these flows have intensified, resulting in an increasingly complex set of migration policies. Most policies

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control who comes in, targeting the composition of flows more than their scale. In this light, (De Haas et al. 2018, p. 42-43) argue that modern migration policies 'work as filters rather than taps', aimed at selecting the 'right migrants'. Throughout this paper, we refer to this dichotomy as the restrictiveness versus the selectivity of migration policy. The former refers to the obstacles a migrant faces when entering a country and any limitations on her rights when staying there. The latter refers to the differences in restrictiveness that depend on the characteristics of the migrant.

A growing number of governments have developed selective migration policies that favour the high-skilled, aiming to fill labour market gaps resulting from economic shifts and structural ageing. This is often called the 'battle for the best and brightest' (Kapur and McHale 2005; Ruhs 2013; Czaika 2018; Boucher 2020). The growing preference for the high-skilled is largely driven by the general perception that they are more easily integrated and pose less of a burden on the welfare state than their low-skilled counterparts. In addition, high-skilled migrants are believed to foster innovation and promote long-term economic growth (Ruhs 2013; Czaika and Parsons 2018; Edo et al. 2018; Boucher 2020). While the bulk of the literature has focused on selectivity based on skills – typically defined in terms of education level[1] – a migrant's access to resources and her nationality also appear to be major selection criteria (see, for instance, bilateral labour agreements and immigration investment programs).

In spite of its central position in the debate on migration and the attention for migration policy in other disciplines, the *economic* analysis of its characteristics, drivers, and impact of migration policy is fairly young. This is mainly due to a lack of comparable quantitative indicators of migration policy, especially in terms of its selectivity (for a discussion, see Bjerre et al. 2015; Rayp et al. 2017).[2] The few studies that have measured selectivity in migration policy have focussed predominantly on skill selectivity. Two notable examples are Ruhs (2013) and Parsons et al. (2020). Ruhs (2013) constructed a database comparing the openness and selectivity of the migration policy of 46 countries in 2009. Focussed specifically on labour migration, the author reveals a trade-off between restrictiveness, skill selectivity and migrant rights. More recently, Parsons et al. (2020) argued that skill selectivity is a multidimensional concept that goes beyond the education level of the migrant. They constructed a database tracking various aspects of skill-selective policies.

Initial research concerning the effectiveness of migration policy, i.e., its impact on migration flows, focused on the *restrictiveness*. It showed that the estimated effect varies with the policy dimension that is considered (see Beine et al. 2011a; Hatton 2005a; Mayda 2010a; Ortega and Peri 2012; Hatton 2014). The few empirical studies dealing with the effects of selectivity on migration flows have predominantly focused on *skill* selectivity, for which find-

[1]While the high-skilled are usually defined as those with a tertiary degree (Koslowski 2018) alternative definitions have been developed based on occupational qualifications or even the combination of occupation and salary (see Boucher 2020, for a discussion). As pointed out by (Boucher 2020), how 'skill' is defined has immediate implications for who is accepted and who is rejected under skilled migration selection policies, as well as for the selection outcomes of these policies.

[2]The two main bottlenecks are (i) the difficulty of coding changes in migration policies such that they are comparable over countries and time (Beine et al. 2015b) and (ii) the question of how to subsequently aggregate this information into one or a few summary indicators (Hatton 2014).

ings have been mixed. Antecol et al. (2003); Jasso and Rosenzweig (2009); Bélot and Hatton (2012) are sceptical about the impact of policies favouring the high-skilled. Using a set of nine skill-selective measures, Czaika and Parsons (2017) conclude that supply-driven policies have a larger impact than demand-driven ones. Additionally, they question to what extent skill selection in migration is a judicious policy. These studies, however, largely ignore other dimensions of selectivity than skills. Their estimations also rely on a limited set of proxy variables. Indicators and assessments of the effectiveness of migration policy selectivity in terms of economic resources and nationality are much more scarce.

This paper contributes to the literature in two ways. First, we construct three indexes of migration policy selectivity capturing not only selectivity in terms of skill level but also in terms of economic resources and nationality.[3] This allows us to characterise the multidimensional nature of selectivity in migration policy for 42 countries (of which 33 are members of the OECD) between 1990-2014. The indexes are constructed by combining information from all publicly available migration policy databases and are much more comprehensive than those available in the literature. As such, we improve upon the strategy used by, e.g., Bélot and Hatton (2012) or Czaika and Parsons (2017), whose indexes of skill selectivity are constructed based on a more limited set of indicators.[4] Second, we use these indexes to analyse how selectivity has shaped the magnitude and composition of migration flows – while controlling for the overall restrictiveness of migration policy – hereby contributing to the ongoing discussion concerning the effectiveness of migration regulations (Czaika and De Haas 2013). By considering the multidimensional nature of migration policy selectivity, we are able to account for potential substitution effects between the different selection criteria, as migrants might reorient towards the entry channel that is the least restrictive (De Haas et al. 2018).

We find that non-EU OECD countries have the most selective migration policies. The main basis of selectivity for EU countries is nationality, though skill selectivity also gained importance during the sample period. Non-OECD countries are much less selective on nationality but primarily select migrants based on their skills and resources. Furthermore, there seems to be a trade-off in migration policy between selectivity and restrictiveness. I.e., countries that are more open towards migration in general also tend to have a stronger preference for certain migrants. The correlation between migration policy selectivity and restrictiveness is small, meaning that the characterisation of migration policy cannot be reduced to its degree of restrictiveness. Restrictiveness and selectivity should be considered as two separate dimensions of migration policy.

Furthermore, our empirical analysis shows that migration policy selectivity affects bilateral migration flows more than overall restrictiveness. Unlike migration policy restrictiveness, migration policy selectivity seems to consistently shape the scale or structure of migration flows. All three dimensions of skill selectivity appear to be equally influential. Selectivity in terms of resources positively affects migration flows of the economically well-endowed while reducing overall migration flows and the migration of the high-skilled. An increase in

[3] Available at `https://users.ugent.be/~sastanda/Data.html`.

[4] Specifically, Bélot and Hatton (2012) use three indicators of skill selectivity and Czaika and Parsons (2017) nine. In contrast, we consider 28 indicators in all policy areas except exit (i.e., entry, residence and integration).

selectivity based on nationality, e.g., through the signing of a bilateral labour agreement, is also associated with an increase in the size of the targeted flows and the number of high-skilled migrants. We also find evidence for substitution effects in skill and resource selectivity, where, e.g., easier access for investors and managers seems to crowd out high-skilled migrants and vice versa.

After a review of the related literature in the following section, Section 3 discusses the data used to construct our indexes of migration policy selectivity and the characterisation of country-level migration policies. Section 4 presents the empirical model we bring to the data and the estimation strategy. The estimation results are presented in Section 5, after which Section 6 concludes.

2 Related literature

Our paper speaks to the literature on the conceptualisation and measurement of migration policies and the literature on migration policies' effectiveness.

Regarding the conceptualisation and measurement of migration policies, several initiatives have been undertaken to provide an indicator of migration policy stance (for more general overviews, see Bjerre et al. 2015; Helbling 2016). This is not an easy task given the qualitative nature of migration policies, which has hindered the development of a systematic method for measuring and comparing migration policies across countries and over time by (Czaika and De Haas 2013). Indeed, most countries do not uniformly set their migration policy using, e.g., quotas but allow for different entry tracks based on multiple criteria (Rayp et al. 2017).

One strategy has been to track the evolution in migration policies over time by identifying major *changes* in different policy dimensions. Using the information on the change's timing and direction, these are combined into an index tracking a country's overall policy stance over time. A shift in the index value reflects a significant increase or decrease in the tightness of a particular dimension of migration law (e.g. Ortega and Peri 2009; Mayda 2010a; Hatton 2004, 2009b, or the UN's International Immigration Policies Database United Nations, 2013). Such indexes, however, do not provide information on the initial level of restrictiveness nor on the relative magnitude of the change, i.e., no distinction can be made between gradual policy adaptation versus big bang reforms (Czaika and De Haas 2013).

The Determinants of International Migration Policy (DEMIG) dataset describes the direction and magnitude of 6,500 changes in immigration and emigration policies in 45 countries, forming the largest change-tracking database completed to date (see de Haas et al. 2015). Unlike other policy change indicators, DEMIG does not amalgamate this information into an indicator of a country's policy stance in a given year. Instead, it studies the individual policy changes, often deconstructing a major revision into the specific changes in individual policy measures. Moreover, the dataset identifies for each alteration which migrant group was affected and to what extent. As such, DEMIG tracks the changes in the restrictiveness of migration policies at a very detailed level, describing, e.g., the magnitude of the change, the targeted origin country, and the migrants' characteristics. The International Migration Policy And Law Analysis (IMPALA) project takes this even one step further by registering relevant laws and regulations for each ‘entry track’, which can be considered the most elementary level in migration policy. It also presents aggregate measures of the restrictiveness of migration policy at the level of the country, year, and particular aspect of migration and migration law (Beine et al. 2016). So far, the IMPALA dataset has compiled pilot data for nine countries between 1999 and 2008.

Other initiatives developed indexes providing aggregate information on the absolute *levels* of restrictiveness that are comparable across countries.[5] Most of these indexes, however, are not publicly available and tend to focus on specific aspects of migration policy, such as citizenship, integration, or non-discrimination policies alone, thereby ignoring potential interaction or compensation effects. One exception is the Migration Policy Index (MPR) developed by Rayp et al. (2017) that measures countries' overall restrictiveness towards international migration, as well as the restrictiveness in terms of entry, stay and integration policies.

The large majority of the existing indexes provide information on migration policy restrictiveness. Conversely, initiatives to construct indexes of migration policy selectivity are much more scarce. Existing research on migration policy selectivity has therefore relied on study-specific indexes. Bélot and Hatton (2012), for instance, build an index of skill selectivity based on three proxies: the extent to which migration policy allows the hiring of foreign workers (as indicated by a survey of employers) (a standardised 10-point scale variable), the ease of skill transferability (using a set of policy rules for four professions) and a dummy for the presence of a points-based system. Ruhs (2013) categorises the labour immigration programs of 46 high and middle-income countries for a single year, 2009. Among other things, he distinguishes between programs that target low, medium and high-skilled workers. While his index is focused on skill selectivity and labour migration, the study also notes programs that select based on nationality, age, gender, marital status, language and self-sufficiency. Czaika and Parsons (2017) use a set of nine dummy indicators of skill selectivity for ten OECD destination countries (and 185 origin countries), reflecting skill selection in admission, post-entry policies towards the high-skilled and bilateral labour agreements. However, these indexes are neither publicly available nor extend beyond the relatively limited set of countries and years considered in the research. Most recently, Parsons et al. (2020, p. 299) argue that a migrant's skill level should be seen as a multidimensional concept. Most studies looking into skill-selective migration policy have focussed on supply-driven policies that admit all migrants who meet particular criteria, mostly concerning the migrant's level of education. However, skill-selective migration policies can also be demand-driven, i.e., responding to labour market shortages. While both can overlap, demand-driven policies can also target low- or median-skilled labour, like fruit pickers and truck drivers. To track the different dimensions

[5]These include but are not limited to the Migrant Integration Policy Index (MIPEX) developed by Niessen et al. (2007), the migration component of the Commitment to Development Index designed by Grieco and Hamilton (2004), the Multiculturalism Policy Index constructed by Queen's University Banting and Kymlicka (2013), the Immigration Policies in Comparison dataset by Helbling et al. (2017), the Inventory of Migration Policies by (Jacobs 2011), the Migration Institutional Index by (Bertocchi and Strozzi 2008), the Asylum Deterrence Index by (Thielemann 2004), the Migration Policy Openness Index and the Migrants Right Index by Ruhs (2013), and the index of openness towards labour migration for the high-skilled by Cerna (2016).

of supply and demand-driven policies, they construct a database describing the skill-selective policies of 19 OECD countries from 1970 to 2012.

There is considerable research on the impact of policies affecting the overall *restrictiveness* of migration policies. The evidence remains, however, inconclusive (Czaika and de Haas 2015). Some scholars argue that efforts by states to regulate and restrict migration have mostly failed as states are, to a large extent, bound by institutional and constitutional constraints. Moreover, changing the migration policies does not alter structural factors like income inequalities or conflict driving migration flows (Hollifield 1992; De Haas 2010; Czaika and de Haas 2015). Others counter that migration policies have mostly been effective (Brochmann and Hammar 2020; Geddes and Scholten 2016). As put forward by (Czaika and de Haas 2015, p. 34), 'despite extensive media and academic attention to irregular and other forms of officially unwanted migration, these scholars argue that the majority of migrants abide by the rules and therefore the bureaucratic systems that regulate migration are largely under control.' This optimistic view is backed by a growing number of quantitative empirical studies showing that migration restrictions effectively shape the magnitude and composition of migration flows (Hatton 2005b; Mayda 2010b; Beine et al. 2011b; Ortega and Peri 2013; Czaika and de Haas 2014).

Literature on the effectiveness of selective migration policies is much more scarce, mainly due to data limitations. The few empirical studies dealing with the effects of selectivity on migration flows have predominantly focused on the impact of *skill* selectivity on the inflow and selection of *high-skilled* migrants, for which findings have been mixed. Some studies (e.g. Antecol et al. 2003; Jasso and Rosenzweig 2009) are sceptical about the impact of policies that favour the high-skilled. Comparing the entry of high-skilled migrants in the U.S., Canada, and Australia, Antecol et al. (2003) conclude that the differences are largely explained by geographical factors – i.e., the proximity of the U.S. to Latin America. In other words, they find migration is determined more strongly by other country characteristics than by policy. This is confirmed by Jasso and Rosenzweig (2009), who compare the migration flows and selection system of the U.S. and Australia, and by Bélot and Hatton (2012), who estimate a selection model for 21 OECD destination countries and 70 origin countries. The latter study finds a significant effect of education and skill selectivity on the skill structure of migrants. However, these are dominated by other determinants like physical distance or cultural similarities. From a different perspective, i.e., without trying to identify policy selectivity as such, Helbling et al. (2020) consider the selection effects of migration policies aimed at restricting entry to migrants with a higher integration potential.[6] They find no significant impact of migration policy restrictiveness of 22 European destination countries – as measured by the migration Policies in Comparison (IMPIC) indicator – on the share of the higher educated. They instead observe an impact on the geographical composition of migrant flows, stemming from an increase in the number of migrants originating from OECD countries and a decrease in the number of those coming from non-OECD countries.

Furthermore, using data on bilateral flows of high-skilled migration to ten OECD destination countries, Czaika and Parsons (2017) assess the effectiveness of a set of nine skill-selective

[6] Considered as the higher-skilled or those sharing a more similar culture with natives.

measures on the scale and structure of the inflows. They conclude that supply-driven policies have a greater impact on both the scale and structure of the migration flows than demand-driven policies. Nevertheless, the authors question to what extent skill selection in migration is a judicious policy: '[e]ven if particular skill-selecting and skill-attracting policies are associated with larger inflows of high-skilled migrants, the overall effect on the composition of total labour migration flows – operationalised as the share of high-skilled in the total labour inflow – remains uncertain.'(Czaika and Parsons 2017, p. 619) The overall effect is influenced by the existence of migrant networks, which are known to reduce migration costs – typically high for the low-skilled – altering the selection of migrants over time (see e.g. Beine et al. 2011a; McKenzie and Rapoport 2010). Bertoli et al. (2016) show that in the presence of positive self-selection based on unobservable characteristics, increased screening on observable characteristics like skills or education can reduce migrants' quality. In other words, skill selection may actually be counter-productive in the global competition for the best and the brightest.

In conclusion, due to data limitations and the lack of a comprehensive index of migration policy selectivity, most of the above studies either focus on specific skill-selective policies – in particular on supply- and demand-driven policies like in Czaika and Parsons (2017) – or the analysis remains partial like in Bélot and Hatton (2012). The index of skill selectivity that we develop in this paper is much more comprehensive, covering more countries over a longer period and considering a broader set of legislative changes. In addition, we conjecture that selectivity is a multidimensional concept that considers various characteristics of potential migrants, which has mostly been ignored in the literature (except for partial controls, like the inclusion of a Schengen area dummy). To fully determine how selective migration policy alters the scale and structure of migration flows – and whether it works in the way intended by policymakers (cf. Bertoli et al. 2016) – its multidimensional nature needs to be taken into account. Failing to do so risks misidentifying the relationship between selective migration policy and the scale and structure of migration flows. In what follows, we first elaborate on the construction of the indexes of migration policy selectivity based on skills, economic resources and nationality. We subsequently evaluate the effectiveness of the different dimensions of migration policy selectivity.

3 Construction of the migration policy selectivity indexes

Migration policy is selective when its restrictiveness depends on the characteristics of the migrant. Hence, for the construction of our indexes, we will consider only those laws and regulations that purposefully target migrants with specific characteristics. Policies oriented towards the general migrant population are not considered as they should affect all migrants homogeneously. This is not to say that general policy cannot be *de facto* selective (see, e.g. Bianchi 2013). E.g., while Sweden's migration policy is open to all migrants, its 'requirement that all migrants are employed at collectively agreed upon wages is likely to act as a strong deterrent to [low-skilled] migration' (Ruhs 2013, p. 103). In some cases, legislators disguise their policies as generic even though they are meant to target a specific group (e.g., the proposed restriction on the length of hair).[7] Within these constraints, we make maximal use of existing cross-country comparable data to create indexes based on clearly identified migrant characteristics and accounting for as many dimensions of migration policy selectivity as possible.

As put forward in the introduction, selectivity is multidimensional. Data availability dictates that we can consider the following three characteristics: (i) the migrant's educational or skill level, (ii) her economic resources, and (iii) her nationality.[8] Given the focus on legislation, the resulting indexes will capture only *de jure* selectivity of migration policies. Admittedly, countries may not always fully implement migration policies as enacted (Koslowski 2018), but – as with any *de jure* indicator – we cannot take this into account. Assessing the extent to which governments fully implement and adopt the laws and regulations falls beyond the scope of this study.

3.1 Data on migration policy selectivity

Ideally, information on migration policy selectivity would be structured and made available according to *entry tracks*, which – as defined in the IMPALA project – are the specific ways of entering a country, distinguished by the purpose of migration and the characteristics of migrants (see Beine et al. 2015b, p. 9). These would allow a straightforward derivation of the extent to which the restrictiveness of migration policy depends on specific migrant characteristics. However, databases organised in this way are still under construction. Available data that comes closest to this format is the DEMIG database (see also DEMIG 2015). The dataset contains a comprehensive list of all changes to migration policy and identifies which migrant group was affected and to what extent for each change. As such, DEMIG serves as the primary source of data for this study.

The DEMIG project registered and coded 6,500 migration policy changes enacted since the 18th Century, most of which were between 1945 and 2013. It does this for 45 (destination) countries, forming the largest change-tracking database completed to date (see de Haas et al. 2015). For each measure, this database lists the country and year of application, level of legislation (national policy or international agreement), policy area (border control, legal entry, integration, exit), policy tool (e.g., recruitment agreements, work permit, expulsion, quota, regularisation), targeted origin countries (e.g., all foreign nationalities, EU citizens, specific nationalities), targeted migrant groups (e.g., low and high-skilled workers, family members, refugees, irregular migrants, students) and an assessment of how much it impacts the restrictiveness of the existing legal framework (magnitude of the change) on a four-point scale (for more information, see the DEMIG Policy codebook).

The target group variable distinguishes between 15 categories, of which three are relevant according to our definition of selectivity: (i) measures conditional upon the skill level of

[7]To keep out Chinese migrants, one Member of Parliament in British Columbia suggested forbidding railway companies from hiring anyone whose hair was longer than 14 cm, as Chinese men used to wear their hair long in a 'queue' such that this (general) policy would have been binding only for them (Li 1988, p. 7).

[8]Most situational characteristics, like marriage or student status, are left out as these tend to lead to different ways of entering the country. Our analysis also leaves out asylum seekers for the same reason.

the migrant (low and high-skilled),[9] (ii) measures applicable to 'investors, entrepreneurs and businesspeople', i.e., the economically well-endowed.[10], and (iii) measures targeting migrants of specific nationalities (for instance through bilateral agreements or aimed at EU citizens).[11]

While the DEMIG database offers a detailed comparison of the changes in migration policies for a large group of countries, several relevant changes are not included. We complement DEMIG with information from several additional sources to fill in the gaps. First, we rely on the Bilateral Labor Agreement (BLA) dataset compiled by Chilton and Posner (2018), which provides additional information on selectivity in terms of nationality. The authors compiled a list of bilateral labour treaties since the Second World War by bringing together information from the United Nations Treaty Series, the World Treaty Index, the website of the International Labour Organisation, foreign ministry databases and internet searches for academic articles. For each treaty, they list the year it was signed and the countries that signed it.

Second, we use and extend the work of Xu et al. (2015) and Džankić (2015), who collected information on immigrant investment programmes (IIP) and economic citizenship programmes (ECP) – the so-called 'golden visas'. These are programmes where countries offer migrants facilitated access to residence rights or citizenship in exchange for a (substantial) financial contribution. Our data come from both official country websites and from business (solicitor offices) websites.[12] For each IIP and ECP, we registered the minimal amount that was required to obtain either a residence permit or citizenship, as well as the year of application or modification. The earliest information on these schemes goes back to the 1990s. Whereas initially, only a few Anglo-Saxon countries had such programmes in place, IIP and ECP became popular after the financial crisis of 2007 in many (mostly small) countries like Greece, Portugal and Slovenia. As they offer easier access conditional upon financial investment, IIP and ECP are informative on selectivity in terms of economic resources.[13]

For each change in migration policy, DEMIG provides information on the direction of the change and its magnitude. I.e., whether the policy restricts or enables migrant flows

[9] In DEMIG, these are defined respectively as 'workers who are either explicitly labelled as low-skilled or who will work in occupations that do not require more than secondary education' and 'workers who are either explicitly labelled as skilled/high-skilled or who will work in occupations that require more than secondary education' (see DEMIG Policy codebook, p. 10).

[10] In DEMIG, such measures are defined as 'codes policy measures that target people based on wealth and trade, such as investors or businesspeople, including entrepreneurs' DEMIG Policy codebook, p. 10)

[11] See DEMIG Policy codebook, p. 12.

[12] https://immigrationeu.com/en/argentina-immigration-for-investors/
http://golden-investor-visa.com
https://www.second-citizenship.org/permanent-residence/investment-programs-in-comparison/
http://www.giic.uk
http://globalresidenceindex.com/wp-content/uploads/2015/12/GRC-Report-2016.pdf
https://corpocrat.com/2016/12/22/30-countries-for-buying-citizenship-through-investment/

[13] Recently, Parsons et al. (2020) made three databases available, two of which might be relevant for the indexes on migration policy selectivity. First, a database of 23 unilateral policy instruments aimed at high-skilled migration. Second, a database on bilateral agreements. Both cover 19 OECD destination countries from 1966-2012 (mainly for the last two decades). We did not include this information in the construction of our indexes. The first database had coding and compatibility issues with the DEMIG information on skill selectivity. The second database was restricted to bilateral agreements relevant to the high-skilled only rather than all the citizens of a specific nationality.

and how much it impacts the restrictiveness of the existing legal system. In contrast, the BLA and (extended) IIP/ECP databases only provide dichotomous information indicating the existence of an agreement/programme and – for the latter – also the required minimal financial contribution. To integrate them into the DEMIG database, we need to add an assessment of the magnitude of the change in restrictiveness stemming from these BLA and IIP/ECP. To do that, we used the partial overlap between the databases, i.e., the BLA and IIP/ECP that already appeared in DEMIG. Conveniently, they were all assigned identical scores, i.e., within the same policy area, with the same direction and order of magnitude. Therefore, we could assign identical scores to those BLA and IIP/ECP not yet included in the DEMIG database.

3.2 Indexes of migration policy selectivity

The combination of DEMIG with the BLA and IIP/ECP information provides a rich and comprehensive database, listing the legislative changes to migration policy in 42 countries since the end of the Second World War. For each legislative change, it lists the destination and origin countries, the year, the direction and magnitude, and the targeted migrant group.

However, in its raw format, the database does not allow us to compare the selectivity of the migration policies over time or between different countries. To enable this comparison, we construct indexes that express the extent to which a country's migration policy provides preferential access to certain migrants based on several specific characteristics. Specifically, we create indexes that track (i) how the skill and resource-based selectivity of each of the destination countries' migration policy changes over time; (ii) how the level of *restrictiveness* of migration policy for each origin-destination country pair changes over time; and (iii) how – based on (ii) – selective each destination country's migration policy is in terms of nationality globally, i.e., for all origin countries included. We consider all measures that had a differential impact based on nationality, skill, or economic resources, regardless of the channel of entry that they affect.[14] Figure 1 provides an overview of the entire data processing algorithm.

First, we select from the database all selective legislative changes and categorise them according to the basis for selectivity: migrants' skills, resources or nationality. Each measure that qualifies subsequently receives a score based on the direction and magnitude of the change. For skill-selective measures, a positive score is given to measures that ease access for high-skilled workers or restrict access for low-skilled workers, and a negative score otherwise.[15]

[14]To the extent that the measures target one or more nationalities, the index of selectivity by nationality includes measures affecting family reunion, asylum seekers and refugees, international students or irregular migration. Examples include the reduction of the family reunion waiting time for Italians in Switzerland in 1964; a facilitated entry into the US of children of US citizens born in Korea, Vietnam, Laos, Cambodia or Thailand in 1982; integration activities for Yugoslav refugees in Denmark in 1994; the regularisation of Zimbabweans by South-Africa in 2010 or the ad hoc resettlement program for Syrians of Germany in 2013. Of the 1,093 policy measures concerning nationality selectivity included in the DEMIG database, 280 refer to family reunification, international students, irregular migrants, refugees, and asylum seekers. For the skill and resource dimension of selectivity, similar examples do not exist. The DEMIG database categorises low and high-skilled workers, investors and business people, family members, international students or asylum seekers into exclusive target groups.

[15]In the framework of Parsons et al. (2020), our index of skill selectivity measures supply-driven skill

Similarly, for resource-selective measures, a positive score is attributed to measures that eased the access of investors, entrepreneurs or the well-endowed. For nationality-selective measures, we track whether the access is eased (positive) or restricted (negative) for each origin country. For example, if a country joined the Schengen area, this was coded as a positive change towards all other members of the Schengen area. As the group of Schengen countries changed over time, the change in access for the newly joined members was also updated.

The next step in creating the indexes involves rearranging a dataset based on individual laws to one aggregated at the country-year level. We conjecture that the newly constructed database contains all relevant policy changes so we can attribute a score of zero to years without legislative changes. On the other hand, if multiple legislative changes took place within the same year, we take the sum of their scores. For skill and resource selectivity, this gives us the yearly change in selectivity in each destination country. For nationality-based selectivity, we end up with a dataset that tracks the yearly change in restrictiveness for each origin-destination pair.

	Group legislation that selects on	*Recode into destination-(origin-)year format*	*Running sum*	*Normalization*	*Gini*
List of legislative changes from DEMIG, BLA and IIP/ECP	Skills	Change in selectivity based on skills	Level of selectivity based on skills	MPS_{dt}^{skill}	
	Resources	Change in selectivity based on resources	Level of selectivity based on resources	MPS_{dt}^{res}	
	Nationality	Change in restrictiveness for each origin-destination	Level of restrictiveness for each origin-destination	MPS_{odt}^{nat}	MPS_{dt}^{nat}

Figure 1: Overview of the algorithm used to create the selectivity indexes

After this re-categorisation, our dataset lists the yearly *changes* in the selectivity of destination countries' migration policy. To get the yearly *level* of migration policy selectivity that can be compared across countries, we require at least one measurement comparing the (initial) level of these countries. Unfortunately, such data does not (yet) exist. However, we can reasonably approximate the yearly level of migration policy selectivity by looking at a long cumulative change (running sum) in migration policy selectivity. After summing up the yearly changes over a sufficiently large period, it is not unreasonable to assume that the initial level no longer determines the current level of restrictiveness. We take 1945 as our zero point since the end of the Second World War was a period of major political and institutional change. From that point forwards, we use the cumulative sum of the scores by dimension and policy area and discard the first 45 years of our data (i.e., from 1945 to 1989) as burn-in. To be clear, we do not mean to imply that the policies before 1945 are unimportant. Rather, they no longer determine the level of selectivity in migration policy 45 years later. For example, our chosen starting point excludes the 'White Australia Policy', which forbade non-Europeans from settling in the country, as this policy dates back to 1901. However, by the mid-1970s, this policy had been entirely dismantled. The choice of start date would only completely

selectivity. E.g., it decreases when it becomes easier for low-skilled migrants to enter.

distort our findings if a country had designed its migration policy entirely before 1945 and made no subsequent changes.[16]

Importantly, our choice of zero-point does not have any implications for the empirical analysis of the effectiveness of the migration policy measures (as reported in Section 4). This is because these analyses include origin-destination fixed effects, which account for the initial level of selectivity.[17]

The main drawback of using a running sum as a proxy of the selectivity level is that any errors in the dataset will be compounded. Measurement errors throughout the dataset imply that the results become less informative or trustworthy as we compute the running sum over a more extended period. As such, our indexes are contingent upon the dataset being (mostly) without errors. In Appendix A, we consider how the created indexes change when we instead allow the migration policies to fade out in the long run.

Our indexes of selectivity based on *skills* and *resources*, MPS^{skill} and MPS^{res}, are obtained after a normalisation that sets their standard deviation equal to one. This results in a yearly score for the skill and resource selectivity indexes that can be compared across all 42 destination countries in our sample. The closer the score lies to zero, the more equal the incoming migrants are treated. It is important to note that the skill and resource selectivity indexes can take negative values, which would signal that people with low skills or few resources gain easier access to the country.

Our selectivity index based on the *nationality* of the migrant, MPS_o^{nat}, differs from the previous two as it is bilateral, tracking the restrictiveness for each origin-destination pair. While we will use this bilateral variable directly in our gravity estimations, we also construct an aggregated version at the destination country level. This resulting index, MPS^{nat}, is compatible with the skill and resource selectivity indexes, allowing for a straightforward characterisation of migration policy selectivity. To that end, we compute the population-weighted Gini index of the cumulative nationality scores for each destination country and year. If a country treats all migrants equally, it will have a Gini score of zero, regardless of whether the country grants access to everyone or no one. As the Gini index rises, the inequality of the policy increases.[18] Unlike the skills and resources indexes, the nationality index cannot take negative values. However, it can otherwise be interpreted in the same way.

Overall, we rely on two main assumptions to compute the selectivity indexes: (i) the list of legislative changes is complete, and (ii) the dataset does not contain any errors. This allows us to go from a dataset organised according to legislative changes to one in which we track the yearly level of selectivity of destination countries' migration policy. While it is impossible to test the validity of these assumptions, we run various robustness checks to see how the indexes

[16] As a robustness check, we changed the anchor point from 1945 to 1960 and reduced the burn-in period to 30 years. See Appendix A for more details.

[17] Note that in the regressions explaining the scale and structure of migration flows of the high-skilled and the economically well-endowed, the inclusion of destination fixed effects would be enough. However, their inclusion is redundant as we already include origin-destination fixed effects (i.e., both approaches are equivalent in these equations).

[18] The Gini index is sensitive to negative values. However, as we are only interested in the inequality of the distribution, we rescale the values such that the lowest restrictiveness score for each destination-year couple is zero.

change when they are relaxed. A full description of these checks can be found in Appendix A, but the general conclusion is that the indexes remain robust.

Finally, we compare the newly constructed indexes with existing migration policy indicators. Unfortunately, a direct comparison with the source material, DEMIG, is impossible as they have a different unit of analysis. This leaves the indicators of skill selectivity constructed by Parsons et al. (2020). There are a few notable differences. First, Parsons et al. cover supply- and demand-driven policies, while our index is restricted to the former (cf. infra). Second, while Parsons et al. (2020) cover fewer destination countries (19 vs. 42), they cover a longer period (1970 to 2012). Third, Parsons et al. (2020) do not compute a composite index. Instead, for each type of policy (e.g., the presence of quota, labour market tests, or a points-based system of entry and residence permits), they provide information on the presence (extensive margin) and the impact of the provision (intensive margin). To compare the Parsons et al. (2020) indicators to our index of skill selectivity, we used the average of the 20 dummy variables (as described in their Section 4.1 Policy Systems).[19] Because of the differences in coverage, we could only match a third of our dataset: 6,391 out of the total 18,0972 observations. Nevertheless, the correlation between our skill selectivity index and Parsons et al. (2020) average is 0.471, which is quite high given the differences between both datasets.

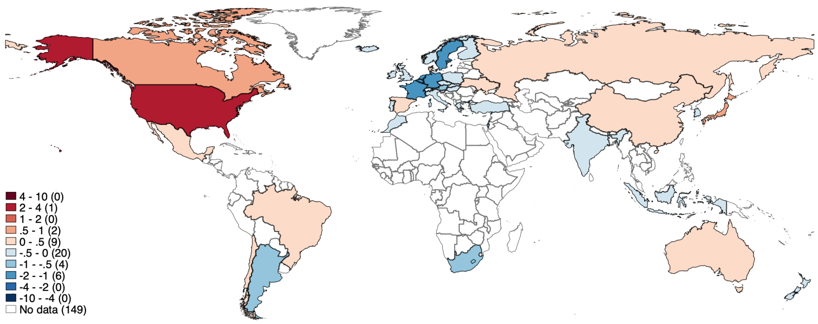
3.3 The characteristics of migration policy in terms of selectivity

Figure 2 plots the values of the three indexes of migration policy selectivity (by skills, resources and nationality) for the first and last year of our dataset (1990 and 2014) on a world map. For comparisons over time, the scale is fixed for each index, meaning that changes in the colours indicate a change in the selectivity scores. For each dimension, we notice an overall increase in the index values. The index also displays considerable variation between countries, but certain regional patterns emerge, particularly among European countries. Finally, despite noticeable similarities between the three indexes, their geographical distribution still differs considerably, confirming that selectivity cannot be reduced to a single dimension. This is also supported by the fairly weak cross-country correlation between MPS^{skill}, MPS^{res}, and MPS^{nat} (see Table 1).[20]

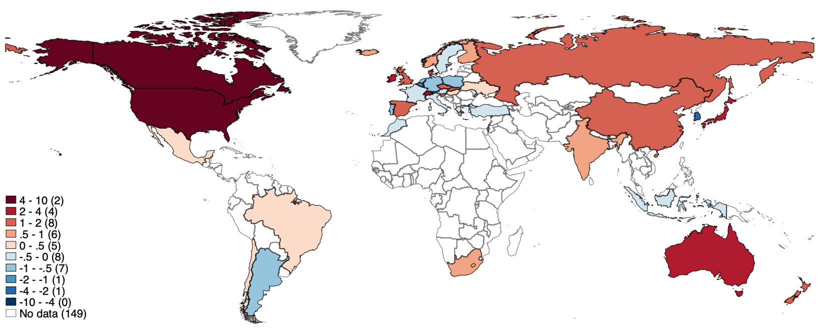
Focussing on the change in selectivity over time, Figure 3 maps the average selectivity score for all 42 countries in the database. It also shows the average scores of four sub-groups: OECD and non-OECD countries, with the former subdivided into EU and non-EU members. This split-up separates countries according to economic and institutional characteristics and filters out the popular and traditional migrant destinations. The composition of each group is listed in Appendix C. Overall, policy selectivity in the three dimensions increases continuously throughout our sample. Migration policy moves from moderately *negatively* skill-selective (i.e., favouring low-skilled workers) to outspokenly *positively* skill-selective. Similarly, in

[19] We considered only the extensive margin as details on the coding, scale and method used to construct the intensive margin were not provided.

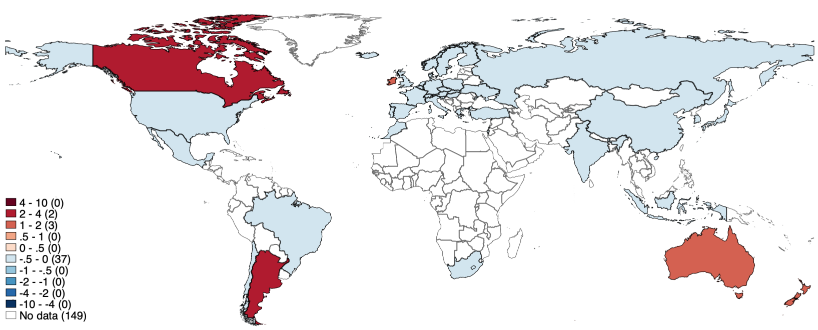
[20] Furthermore, their Cronbach's alpha coefficient is 0.19 which is well below even the lowest rule-of-thumb of 0.7, indicating heterogeneity between the three indexes.



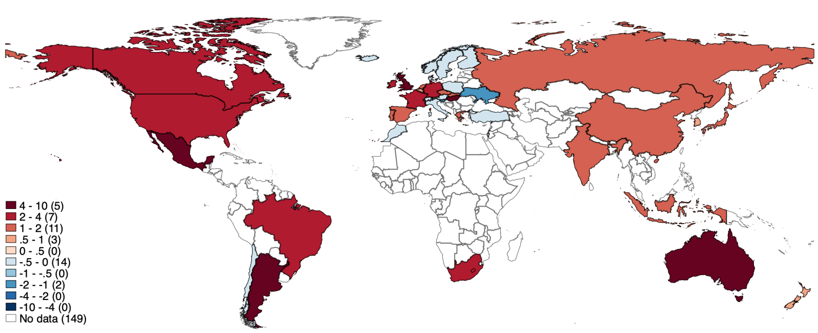
(a) MPS^{skill} values in 1990



(b) MPS^{skill} values in 2014

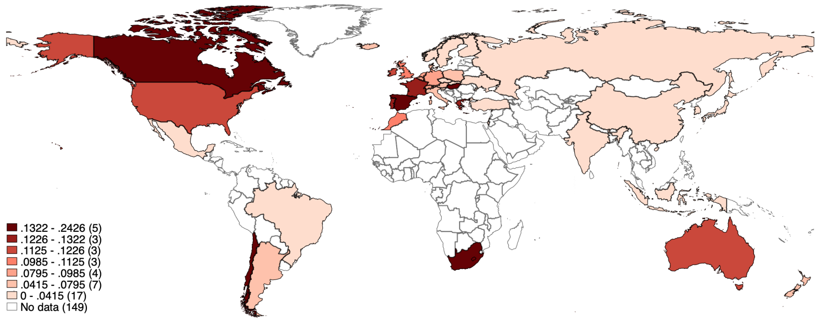


(c) MPS^{res} values in 1990

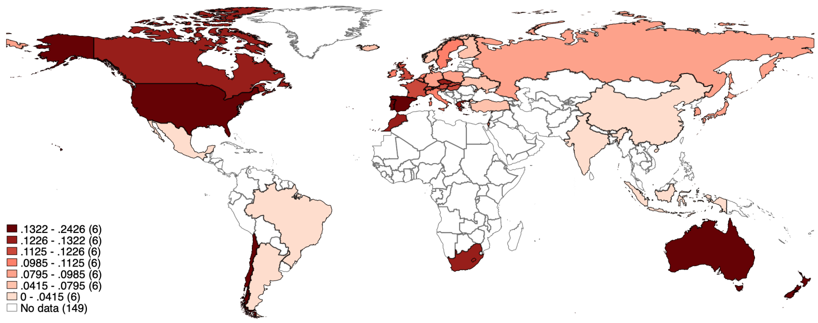


(d) MPS^{res} values in 2014

Figure 2: Migration policy selectivity scores by destination country 1990, 2014



(e) MPS^{nat} values in 1990



(f) MPS^{nat} values in 2014

Figure 2: Migration policy selectivity scores by destination country 1990, 2014

Notes: Plot of the destination country-specific migration selectivity scores with respect to skills (a,b), economic resources (c,d) and nationality (e,f). Red (blue) values indicate a migration policy that is more open to people with higher (lower) skills and more (fewer) resources. The intensity of the color correlates with the magnitude of the selectivity in policy

terms of economic resources, migration policy steadily changes from mildly to strongly selective. In contrast, nationality selectivity is initially limited, but access suddenly becomes much more unequal from the 2000s onwards.

Despite institutional, geographic and economic differences, the increase in policy selectivity is reasonably homogeneous across country groups. The ranking between the four groups remains stable for all but the nationality indexes. The non-EU OECD countries, like Australia, are consistently the most selective and the EU countries the least selective. The patterns are much less stable for selectivity based on nationality. The average non-OECD country remains close to its initial, low level. The OECD member countries, in contrast, witness a sudden spike in nationality-based selectivity from the 2000s onwards. That increase stops for the EU members after the 2004 expansion of the EU towards Central and Eastern European countries. Simultaneously, the non-EU OECD countries see another peak in their levels of selectivity by nationality, rapidly surpassing the levels of all other groups.

Summarising the overall pattern, we note that the non-EU OECD countries are the most selective in their migration policies. The primary basis for selectivity in the migration policy of EU countries is nationality, but this is not to say that EU countries do not select on resources or skills. Non-OECD countries primarily select migrants based on skills and resources, but this group also shows more heterogeneity. Only the selectivity in terms of economic resources

Table 1: Correlation between the indexes of migration policy selectivity and restrictiveness

	MPS^{skill}	MPS^{res}	MPS^{nat}
MPS^{res}	0.31^{***}		
MPS^{nat}	0.10^{***}	0.16^{***}	
MPR	-0.15^{***}	-0.21^{***}	0.04

Notes: The Table shows cross-country correlations between the different indexes of migration policy selectivity MPS^{skill}, MPS^{res}, and MPS^{nat} constructed in this paper, and the migration policy restrictiveness index MPR taken from Rayp et al. (2017). *,** and *** indicate significance at the 10%, 5% and 1% respectively.

displays a similar pattern for all groups in our dataset.

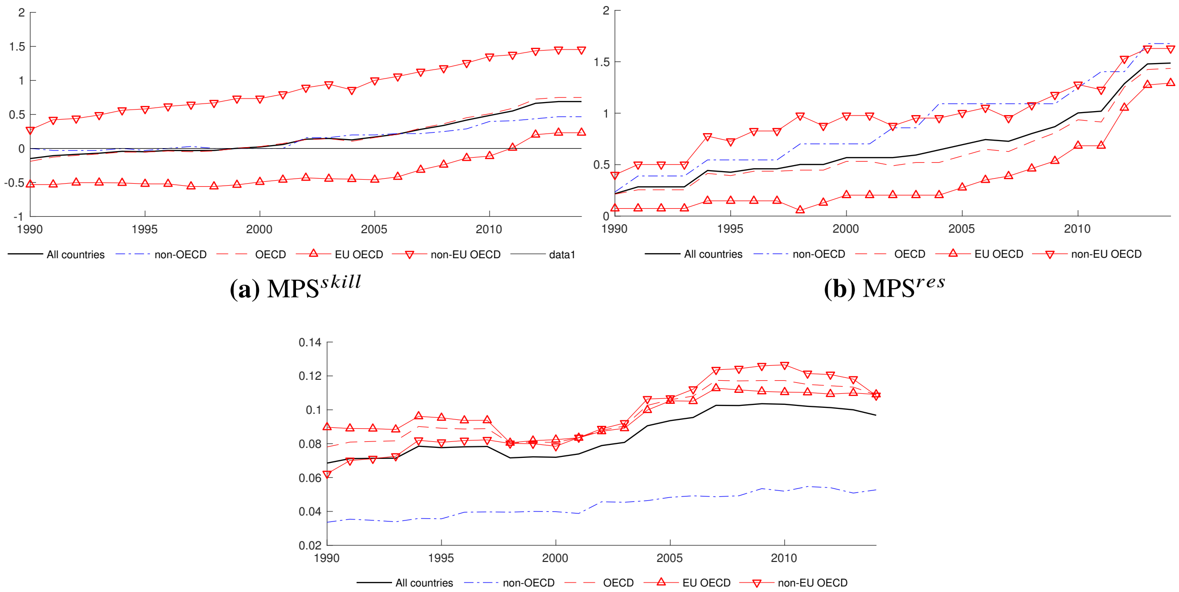
To assess the significance of the differences in average migration policy selectivity along the different dimensions between the country groups, we perform t-tests on the group mean differences for all indexes. Table 2 shows the results for four reference years (the first, final and two intermediate years). It shows that EU countries are consistently less selective on skills than non-EU OECD countries. However, the initial significant difference between the EU and the non-OECD countries disappears after the 2000s, as the EU countries increase their level of skill selectivity. In terms of economic resources, the t-tests confirm the pattern of convergence shown in Figure 3 as the differences are insignificant by the end of the period. Regarding nationality-based selectivity, OECD countries are significantly more selective than non-OECD countries for the whole period. The differences in nationality-based selectivity within OECD countries do not appear statistically significant.

Table 2: Differences in average selectivity along the different dimensions between country groups

			1990	2000	2010	2014
$\overline{MPS}^{skill}_{OECD}$	=	$\overline{MPS}^{skill}_{nOECD}$	-2.12	0.30	1.25	3.17
$\overline{MPS}^{skill}_{EU}$	=	$\overline{MPS}^{skill}_{nOECD}$	-5.38^{**}	-5.00^{*}	-4.59	-1.70
$\overline{MPS}^{skill}_{EU}$	=	$\overline{MPS}^{skill}_{OECD,nEU}$	-8.96^{***}	-14.58^{***}	-16.06^{***}	-13.39^{**}
$\overline{MPS}^{res}_{OECD}$	=	$\overline{MPS}^{res}_{nOECD}$	-0.06	-0.49	-0.89	-0.69
$\overline{MPS}^{res}_{EU}$	=	$\overline{MPS}^{res}_{nOECD}$	-0.48	-1.57^{*}	-1.79	-1.25
$\overline{MPS}^{res}_{EU}$	=	$\overline{MPS}^{res}_{OECD,nEU}$	-1.14^{**}	-2.99^{***}	-2.49^{*}	-1.56
$\overline{MPS}^{nat}_{OECD}$	=	$\overline{MPS}^{nat}_{nOECD}$	0.04^{**}	0.04^{***}	0.07^{***}	0.06^{***}
$\overline{MPS}^{nat}_{EU}$	=	$\overline{MPS}^{nat}_{nOECD}$	0.04^{**}	0.04^{**}	0.06^{***}	0.06^{***}
$\overline{MPS}^{nat}_{EU}$	=	$\overline{MPS}^{nat}_{OECD,nEU}$	0.01	-0.00	-0.02^{*}	-0.00

Notes: The Table displays the results of t-tests on the country group mean differences in migration policy selectivity for all indexes of selectivity MPS^{skill}, MPS^{res}, and MPS^{nat} for four different reference years (the first and final year in our sample and two intermediate years). *,** and *** indicate significance at the 10%, 5% and 1% respectively.

Finally, we may wonder how selectivity is related to and distinct from restrictiveness. We address this question by looking at the correlation between the different migration policy selectivity indexes and an index of migration policy restrictiveness (MPR). Specifically, we



(a) MPS^{skill} **(b)** MPS^{res} **(c)** MPS^{nat}

Figure 3: Evolution in migration policy selectivity

Notes: Plot of the yearly average values of the migration policy selectivity indexes with respect to skills (a), economic resources (b) and nationality (c) for all countries and subgroups.

use the index provided by Rayp et al. (2017), which covers a comparable period and country sample to ours but is limited to OECD countries. The correlations (for all years and countries) reported in the last row of Table 1 are either insignificant or weakly negative. This points to a trade-off in migration policy between selectivity and restrictiveness: i.e., more liberal countries to migration tend to be more open towards some migrants than towards others. This is in line with the findings of Ruhs (2013), who found a trade-off between the openness of (labour) migration policy and the level of (skill) selectivity. Moreover, the weakness of this correlation implies that the characterisation of migration policy cannot be reduced to its degree of restrictiveness alone. Restrictiveness and selectivity should be considered as separate dimensions of migration policy.

4 Impact of migration policy selectivity on migration flows

4.1 Model specification and estimation method

The three indexes of selectivity constructed in the previous Section allow us to expand the scope and depth of the analysis of migration policy. The model we use to analyse the effectiveness of migration policies is derived from the standard random utility maximisation (RUM) framework, which has become the consensus model used to understand the location decision of migrants.[21] As argued by Grogger and Hanson (2011), the effectiveness of policy selectivity refers to its impact on the scale or the structure of the targeted migration flows.[22]

The general specification of the *scale* equation is as follows:

$$M^k_{odt} = \alpha^k_1 MP_{odt-1} + \alpha^k_2 Z_{odt-1} + \delta^k_{od} + \delta^k_{ot} + \varepsilon^k_{odt}, \qquad k{=}skill, res, nat \tag{1}$$

where M^k_{odt} denotes the flow of migrants from country o to country d at time t with k indicating the inflow of skilled ($skill$), economically well-endowed (res), or all migrants (nat). MP_{odt-1} is the lagged vector of the migration policy variables and Z_{odt-1} represents the lagged vector of the control variables, with:

$$MP_{odt-1} = \begin{pmatrix} \text{MPS}^{skill}_{dt-1} \\ \text{MPS}^{res}_{dt-1} \\ \text{MPS}^{nat}_{odt-1} \\ \text{Migration Policy Restrictiveness (MPR)}_{dt-1} \end{pmatrix} \qquad Z_{odt-1} = \begin{pmatrix} \ln(\text{Relative GDP pc})_{odt-1} \\ \ln(\text{Migrant Stock})_{odt-1} \\ \ln(\text{Unemployment Rate})_{dt-1} \\ \ln(\text{Income Inequality})_{dt-1} \end{pmatrix}$$

The *structure* equation takes the following general form:

$$\frac{M^k_{odt}}{M_{odt}} = \beta^k_1 MP_{odt-1} + \beta^k_2 Z_{odt-1} + \mu^k_{od} + \mu^k_{ot} + \eta^k_{odt}, \qquad k{=}\ skill, res \tag{2}$$

where the dependent variable reflects the share of migrants from a specific category, i.e., either the high-skilled or the economically well-endowed. While not identical, equation (2) is equivalent to the structure equation *strictu sensu* of (Grogger and Hanson 2011). In case of positive selection, e.g., due to migration policy, the share of the targeted group in the total bilateral flow should be higher.

Both equations (1) and (2) are estimated using the Poisson pseudo-maximum likelihood (PPML) estimator, as this allows to include zero migration flows and controls for heteroskedasticity (Santos Silva and Tenreyro 2006). For the scale equation (1), we specify a model that applies to all groups of migrants that we consider.[23] We use the same specification for the structure equation (2) given that it is essentially the ratio of two scale equations. The policy component of bilateral costs (MP_{odt-1}) contains the three indexes of policy selectivity we constructed (MPS^{skill}, MPS^{res} and MPS^{nat}) as well as an index of policy restrictiveness (MPR). The migration policy variables are lagged one year to control for potential contemporaneous reverse causality and allow for the delay with which migration policy rules usually come into effect.

As control variables, we include the common explanatory variables in the literature on the determinants of international migration. Z_{odt-1} contains the difference in earnings between origin and destination as proxied by their relative GDP per capita;[24] the origin-specific stock

[21] See e.g., the references in Czaika and Parsons (2017). For more details, see e.g., Beine et al. (2015a).

[22] We restrict our analysis to these two components and do not consider like Grogger and Hanson (2011) the sorting of migrants, i.e., the distribution of the targeted group among destinations.

[23] Though our preferred specification of the scale equation for resource selectivity omits income inequality because of sample bias concerns. See below.

[24] Because the regressions also include origin-time fixed effects, this boils down to the GDP per capita of the destination country.

of migrants in each destination country as an indicator of the network component of migration costs; and the unemployment rate and income inequality in the destination country as proxies for economic opportunity, all lagged by one year and expressed in logs.[25] Other usual proxies for migration costs like bilateral distance, common colonial history, former colony and common language are captured by the origin-destination fixed effects (μ_{od}^k).

We include origin-time (δ_{ot}) and origin-destination fixed effects (μ_{od}) in both the scale and structure of migration. The former control for time-varying unobserved characteristics of the countries of origin (including the population size). The latter control for the unknown initial levels of the migration policy selectivity variables.[26] In addition, the origin-destination fixed effects correct for (time-invariant) multilateral resistance to migration Bertoli and Fernández-Huertas Moraga (2013). In a cross-sectional framework, Bertoli and Fernández-Huertas Moraga (2015) control for international correlation in migration policy – and hence, multilateral resistance to migration – by including nest-origin fixed effects. Considering that, e.g., international policy coordination is implemented in a destination-country-specific manner, the origin-destination fixed effects make the origin-nest fixed effects redundant. We do not include a time-varying component of multilateral resistance to migration in our benchmark regressions for two reasons. First, our time dimension is fairly short. For skill and resource selectivity, each country-pair only has ten years (maximum). Second, migration policy is commonly assumed to be the most prominent source of multilateral resistance to migration, and it is explicitly controlled for in our estimations. However, we also run our regressions in the robustness section using origin-nest-time fixed effects.

Finally, the scale and structure equations are estimated from origin-destination-year specific observations, but include destination-time determinants common to all origins (such as MPS^{skill}, MPS^{res} and MPR). In addition, as the number of origins is destination-specific, the residual errors of the estimated models are likely to be correlated by destination. To control for this, we cluster the standard errors by destination (see e.g. Angrist and Pischke 2009, p. 308-312).

4.2 Data

Except for the policy variables, all explanatory variables used to estimate equations (1) and (2) come from standard sources provided by the OECD, the World Bank and CEPII. In addition to the indexes of migration policy selectivity, we also use an indicator of overall restrictiveness from Rayp et al. (2017). Higher values of this index correspond to lower levels

[25]One might expect a high correlation between unemployment rates and the GDP per capita at the destination, which would make either relative GDP per capita or the unemployment rate redundant after including origin-year fixed effects. However, the pairwise correlation between both variables stands at -0.60 in the regressions considering migration by education and at -0.55 for those considering migration by nationality, which remain well below the usual cutoff of $|0.8|$. Moreover, repeating the estimations without unemployment (results available upon request) does give different results in some specifications, suggesting an omitted variable bias.

[26]See also footnote 17. Given that the skill and resource dimension of selectivity vary in the time and destination dimension but not in the origin country, destination country fixed effects would be sufficient to control for the unobserved initial selectivity levels in these dimensions. However, origin-destination fixed effects are needed to control for the unknown initial levels of selectivity that can vary bilaterally.

of restrictiveness. The complete list of sources can be found in Appendix D.

Data on migration flows, disaggregated by the migrant characteristics (e.g., skills and resources), is harder to come by. In particular, Czaika and Parsons (2017) expound on the difficulties in comparable cross-country statistics. They use different detailed national data sources to construct a harmonised dataset that, unfortunately, is not publicly available. Alternatively, Bélot and Hatton (2012) use the information on migrant stocks broken down by educational level for the year 2000 or 2001 taken from the DLM database of (Docquier et al. 2009).

In this study, we use migration data from two sources. First, to capture the bilateral flows by *skill level* and *economic resources*, we rely on the OECD's Database on Immigrants in OECD and non-OECD Countries (DIOC).[27] Based on population censuses and registers, DIOC provides information on demographic and labour market characteristics of the foreign population by country of birth for 34 OECD destination countries and 235 countries of origin. This data is collected at four different points: 2000/2001, 2005/2006, 2010/2011 and 2015/2016.[28] This dataset includes a variable listing the migrants' highest level of education, distinguishing between four broad aggregates based on the ISCED classification. The 'tertiary education' category (ISCED levels 5A, 5B and 6) is used as a proxy for the stock of skilled migrants. The bilateral inflow of skilled migrants is proxied by the change in the stock of high-skilled migrants. Negative values were dropped from the sample.

DIOC does not provide direct information on migration by economic resources connected to policy selectivity along this dimension – nor are we aware of any other dataset that does. However, DEMIG defines selectivity in terms of economic wealth as those policy changes that target 'investors, businesspeople and entrepreneurs' (see footnote 10). Therefore, to proxy the number of economically well-endowed migrants, we use the breakdown of immigrants by ISCO-88 occupation category provided in DIOC.[29] The closest match that can be found in DIOC for the DEMIG category of economically well-endowed migrants are the migrants classified in the ISCO-88 category 1 ('Legislators, senior officials, corporate managers and general managers').[30]

While the DIOC database is one of the most detailed and accurate sources for migration data broken down by education level or occupation category for the destination countries under consideration, it has several drawbacks. First, it only provides information on the stock of

[27]See Arslan et al. (2014) for a description and methodological details.

[28]The data of 2015/2016 were not included in the analysis because they do not identify bilateral migration flows.

[29]Or the national equivalents thereof in case of, e.g., Japan, the US and Turkey. However, the correspondence with the ISO-88 classification was straightforward at the lower level of detail in the occupation scheme relevant to this study.

[30]A reasonable concern might be that the category of well-endowed migrants – as proxied by legislators, senior officials, corporate managers and general managers – largely overlaps with that of skilled migrants. To test for this, we computed the share of the high-skilled within the ISCO-88 category 1. Reassuringly, this share remains relatively small: depending on the country, it ranges from 13% to 67% with a mean value of 46%. This mitigates the concern that the share of high-skilled among our category of well-endowed migrants is systematically high. Furthermore, it is not statistically significantly different from the aggregate of the other ISCO-88 categories (results available from the authors upon request).

migrants. As such, any flow data derived from it will measure net rather than gross migration flows. Second and more importantly, the DIOC database only provides information every five years and, at most, three measurements for each country pair. Taking the difference between two consecutive stock measurements results in a considerable reduction in sample size to about 1,500 observations.[31] In addition, the number of destination countries in the analysis is reduced to at most ten.[32] This limited sample size may compromise the representativeness and reliability of the analysis. To address this, we used the Bayesian state-space model of Standaert and Rayp (2022) to fill in the gaps in the DIOC database to obtain a more representative sample. The state-space model combines data on migration stocks and flows from different sources together with a model of demographic evolution to fill in missing observations with the most likely value. A full description of the imputation algorithm can be found in Appendix B. The yearly bilateral migrant stock series we obtain in this way significantly increases the sample size. Most importantly, it extends the range of destination countries included in the analysis to 27 for skilled migration and 24 for the economically well-endowed.

For the *nationality*-based selectivity, we can rely on the International Migration Database (IMD) of the OECD (see OECD 2021). In contrast to the DIOC data, the IMD provides annual data on the bilateral *gross* flow of migrants and bilateral migrant stocks (used in the analysis as a proxy for network effects) since 2000.

5 Results

Tables 3, 4 and 5 present the estimation results for the scale equation (columns 1 through 4) and structure equation (columns 5 through 8) for the three categories of migrants. The first specification (columns 1 and 5) includes only the control variables and overall migration policy restrictiveness. In the next columns, the three distinct dimensions of policy selectivity are added, starting with the dimension directly related to the migration flow considered (e.g., MPS^{skill} to explain high-skilled migration). Columns 4 and 8 display the preferred specification that includes all the dimensions of policy selectivity and the overall restrictiveness.

5.1 Skilled migration

First, columns 1-4 of Table 3 show that the estimated coefficients of the control variables in the *scale* equation for skilled migration have the expected sign (when significant). In particular, high-skilled migration is higher to destinations characterised by a higher skill premium, as proxied by income inequality.[33] However, many control variables do not have a significant impact. The estimated coefficient for the stock of migrants from the same country of origin, for instance, has the expected positive sign but remains insignificant. While this could indicate that high-skilled migrants may rely less on migrant networks, our regression analysis

[31] 2,000 in the case of migration by education and 1,500 for migration in terms of occupation.

[32] The number of origin countries in the sample is less affected by the data loss and remains around 180. However, the sample reduction still implies that we are left with just a few observations for many origin countries.

[33] The income range between the ninth and fifth decile.

Table 3: Estimation results for skilled migration (scale and structure)

	Scale equation				Structure equation			
	M_{odt}^{skill} (1)	M_{odt}^{skill} (2)	M_{odt}^{skill} (3)	M_{odt}^{skill} (4)	$\frac{M_{odt}^{skill}}{M_{odt}}$ (5)	$\frac{M_{odt}^{skill}}{M_{odt}}$ (6)	$\frac{M_{odt}^{skill}}{M_{odt}}$ (7)	$\frac{M_{odt}^{skill}}{M_{odt}}$ (8)
MPS_{dt-1}^{skill}	-	-0.06***	-0.03	-0.03	-	0.001	0.001	-0.003
		(0.02)	(0.02)	(0.02)		(0.03)	(0.03)	(0.03)
MPS_{dt-1}^{res}	-	-	-0.1**	-0.09**	-	-	-0.002	-0.01
			(0.05)	(0.05)			(0.06)	(0.06)
MPS_{odt-1}^{nat}	-	-	-	0.06**	-	-	-	-0.09***
				(0.03)				(0.03)
MPR_{dt-1}	0.5	0.4	0.5*	0.6*	0.6**	0.6**	0.6**	0.6**
	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
$lnGDPpc_{odt-1}$	-0.2	-0.4	-1.2	-1.4	-2.6***	-2.6***	-2.6***	-2.3***
	(1.7)	(1.6)	(1.6)	(1.6)	(0.7)	(0.7)	(0.7)	(0.8)
$lnMigstock_{odt-1}$	0.1	0.1	0.1	0.1	-0.09	-0.09	-0.09	-0.06
	(0.1)	(0.1)	(0.1)	(0.1)	(0.05)	(0.06)	(0.06)	(0.05)
$lnUnemp_{dt-1}$	-0.4	-0.4	-0.4*	-0.4	0.3	0.3	0.2	0.3
	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
$lnInterdec9050_{dt-1}$	2.5	2.5	3.3*	3.4*	1.2	1.2	1.2	1.1
	(1.9)	(1.9)	(1.9)	(1.9)	(1.5)	(1.5)	(1.6)	(1.6)
Origin-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Origin-dest FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	7,417	7,417	7,417	7,417	7,417	7,417	7,417	7,417

Notes: Standard errors clustered by destination country in parentheses. *,** and *** indicate significance at the 10%, 5% and 1% respectively. Estimations with Stata© ppmlhdfe.

is unlikely to identify strong network effects. The slow variation of the stock of migrants over time means that most variation in the variable is captured by the origin-destination fixed effects, particularly as the time dimension of our panel is relatively short. The same reason may explain the insignificance of the GDP per capita, where the large set of fixed effects already account for the variation in the origin's GDP, the average GDP in the destination and any worldwide shocks to GDP.

Both the restrictiveness and selectivity of migration policy affect the flow of high-skilled migrants. A more liberal migration policy (higher values of the restrictiveness index) is associated with a rise in the scale of the skilled inflow (at the 10% level). Somewhat surprisingly, we do not find a significant impact of skill selectivity on the inflow of skilled migrants, in particular when the other components of policy selectivity are taken into account. Instead, the scale of high-skilled migration is negatively affected by selectivity in terms of economic resources and positively by nationality-based selectivity. Bélot and Hatton (2012) already hinted at the importance of other (migration) policies next to skill selectivity, which our estimations seem to confirm. An increase in the index of resource selectivity by one unit, corresponding to what DEMIG terms a fine-tuning change, implies an expected decrease in the inflow of high-skilled migrants of 9%. This reduction may coincide with an increase in the average quality of the higher educated, as only those with higher expected earnings will continue to move. In other words, the inflow of skilled migrants may be smaller but consist of 'brighter' people. However, this cannot be verified because we lack an indicator of the expected earnings of the migrants. Vice versa, a more selective policy in terms of nationality increases the number of high-skilled migrants. Concluding, for instance, a bilateral labour agreement (considered in DEMIG as a mid-level legislative change) is expected to raise the number of skilled migrants by approximately 20%.[34]

The positive effect of nationality selectivity on the *scale* of skilled migration does not pass through to the *share* of skilled migrants in the net inflow. On the contrary, as can be seen in columns 5-8 in Table 3, its effect is negative and significant at the 1% level. The reason for this is that the influence of nationality selectivity on total bilateral migration flows is stronger than that on skilled migration (Table 5). Since the share equation of skilled migrants is essentially the ratio of the scale equations of skilled migration and the total bilateral migration flow, the share of high-skilled migrants falls when selectivity in terms of nationality increases.

The negative scale effect of resource selectivity also does not extend to the share of skilled migrants because of its negative effect on the total bilateral migration flows. The share of skilled migrants, however, increases with overall policy liberalism (higher values of MPR_{dt-1}) due to its positive effect on the scale of skilled migrants while leaving the total bilateral flow essentially unaltered.[35]

The diverging effect of overall policy restrictiveness and nationality-based selectivity on the share of high-skilled migrants suggests that these two policy dimensions have a differential impact on the mobility of the low-skilled. A non-discriminatory liberalisation increases the competition in the destination country's labour market, which primarily affects the employment probability of the less demanded skills. Therefore, lower-skilled may be expected to respond less to a fall in overall policy restrictiveness than to a preferential liberalisation. When a country grants preferential access to people with a particular nationality, the low-skill migrants of that origin country enjoy preferential access to the employment opportunities of the destination country. As such, they have a stronger incentive to move.

In contrast with the more recent contributions on the impact of skill selectivity (in particular Bélot and Hatton 2012; Czaika and Parsons 2017), we do not find a significant effect of skill selectivity on the inflow of the high-skilled, neither in their scale nor in their share in total migration. There are several differences in the analysis that may explain the different findings. Firstly, different definitions are used for high-skilled migrants; e.g., Czaika and Parsons (2017) use an occupation criterion rather than education. Second, our study also examines a different

[34] A 'mid-level change' is a measure that affects part of a migrant category, introducing or removing a new policy instrument and is assigned a score of three (DEMIG Policy codebook, p. 3). As such, the estimated effect of this agreement is equal to $\mathbb{E}(\hat{y}) = e^{0.06*3} = 1.197$.

[35] The parameter estimates of the other variables of the structure equation (column 8) are also coherent with those of the respective scale equations. The income gap has a significant negative effect resulting from a positive effect on the total migration flows and an insignificant effect on high-skilled migration. Similarly, the migration network has an (insignificant) negative effect on the share of high-skilled migrants due to its positive impact on total flows. Finally, the existence of economic opportunities increases the share of high-skilled migrants. The unemployment rate has a weaker negative effect, and income inequality has a stronger positive effect on high-skilled migrants than the total migrant flow. Except for the relative income gap, none of these estimates is significant.

period and different destination countries. E.g., Bélot and Hatton (2012) use a single cross-section, while Czaika and Parsons (2017) only consider ten countries. Third, the estimation model is also different, with Bélot and Hatton (2012) using a log-linear model. Finally, how policy measures are categorised also differs considerably. E.g., in their definition of supply-oriented skill selectivity, Czaika and Parsons (2017) include bilateral labour agreements and permanency rights, which they find to positively affect the inflow of the high-skilled. However, in our analysis, these policies are part of nationality-based selectivity and overall restrictiveness. Both have a (significant) positive effect on the inflow of high-skilled migrants.

Notwithstanding, our results suggest that overall, skill selectivity policies were either ineffective in attracting higher educated foreigners or aimed at a broader, not neatly delineated, category of migrants.[36] The concept of skill selectivity used in our analysis is more encompassing compared to previous studies. It includes all relevant measures in the skill dimension, i.e., for the high and the low-skilled (see page 10). As such, our finding of an insignificant impact for a broader definition of skill selectivity does not contradict the claim that specific, well-targeted individual measures can increase high-skilled migration.

5.2 Migration of the economically well-endowed

Table 4 reports the estimation results for migration of the economically well-endowed. These estimations were run with a slight change in the control variables. Specifically, the regressions do not include income inequality in the destination country to avoid sample selection bias. Due to gaps in its coverage, its inclusion would reduce the sample size to less than 5,000 observations. Reassuringly, it has an insignificant effect in all specifications run on this reduced sample. Moreover, its omission does not affect the coefficients on the other variables, implying no omitted variable bias.

The remaining control variables have the expected signs when significant. Both relative income per capita and the network variable have a positive and significant effect in all the scale equations. In contrast, unemployment and overall policy restrictiveness seem to have little effect on the migration of the economically well-endowed.

Migration policy selectivity affects the scale and structure of the migration of managers and businesspeople. As we expect, migration of the economically well-endowed is positively associated with selectivity based on economic resources. A fine-tuning change, implying a change in the resource selectivity index by one unit, is expected to change the inflow of managers and businesspeople by 10%. Second, migration of the economically well-endowed is negatively associated with skill selectivity. Together with the negative effect of resource selectivity on the migration of the high-skilled (see Table 3), this confirms the existence of skill substitution effects from migration policies as discussed, e.g., by Stark et al. (2017).

Similar to what we saw in Table 3, the estimated parameters of the scale regressions only partially resemble those of the migration structure regressions (columns 5-8). First, the

[36]Note that Parsons et al. (2020) point out that states use a rather implicit definition of 'high-skilled' meaning in practice everyone who contributes to economic growth and development or the easing of labour market shortages.

Table 4: Estimation results for migration of the economically well-endowed (scale and structure)

	Scale equation				Structure equation			
	M^{res}_{odt}	M^{res}_{odt}	M^{res}_{odt}	M^{res}_{odt}	$\frac{M^{res}_{odt}}{M_{odt}}$	$\frac{M^{res}_{odt}}{M_{odt}}$	$\frac{M^{res}_{odt}}{M_{odt}}$	$\frac{M^{res}_{odt}}{M_{odt}}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MPS^{skill}_{dt-1}	-	-	-0.1***	-0.1***	-	-	-0.1***	-0.1***
			(0.02)	(0.02)			(0.02)	(0.03)
MPS^{res}_{dt-1}	-	0.2***	0.1**	0.1**	-	0.1	0.01	0.01
		(0.05)	(0.03)	(0.03)		(0.05)	(0.05)	(0.03)
MPS^{nat}_{odt-1}	-	-	-	0.01	-	-	-	-0.1***
				(0.07)				(0.04)
MPR_{dt-1}	-0.1	-0.2	-0.001	0.01	-0.1	-0.2	-0.1	-0.2
	(0.5)	(0.5)	(0.4)	(0.4)	(0.2)	(0.2)	(0.2)	(0.2)
$lnGDPpc_{odt-1}$	4.6**	3.7*	3.6*	3.5*	-1.002	-1.05	-1.5**	-1.02
	(2.0)	(2.0)	(1.9)	(1.9)	(0.9)	(1.0)	(0.7)	(0.7)
$lnMigStock_{odt-1}$	0.4***	0.4***	0.2**	0.2**	0.006	0.01	-0.003	0.01
	(0.1)	(0.1)	(0.1)	(0.1)	(0.05)	(0.05)	(0.05)	(0.05)
$lnUnemp_{dt-1}$	-0.3	-0.1	0.002	0.004	0.003	0.07	0.1	0.1
	(0.2)	(0.2)	(0.2)	(0.2)	(0.1)	(0.1)	(0.1)	(0.1)
Origin-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Origin-dest FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	6,304	6,304	6,304	6,304	6,304	6,304	6,304	6,304

Notes: Standard errors clustered by destination in parentheses. *,** and *** indicate significance at the 10%, 5% or 1% levels respectively. Estimations obtained with Stata© ppmlhdfe.

control variables and overall policy restrictiveness are insignificant in the structure equation.[37] Similar to skilled migration, the share of managers and businesspeople is mainly determined by migration policy. The negative scale effect of skill selectivity is repeated in the structure equation, which makes sense as the skill selectivity has no significant effect on the total migration flows. In contrast, the positive scale effect of resource selectivity is no longer significant in the structure equation, although its sign remains consistent with our expectations. Lastly, the share of the economically well-endowed falls with selectivity in terms of nationally due to its positive influence on the total bilateral flows.

[37]The signs of the control variables are consistent with the scale equations from which the structure equation is derived (except for the income gap). Policy restrictiveness has a higher impact on the total migrant flows than on the number of managers and businesspeople, explaining the negative sign in the structure equation. In the scale equation, the migrant network has a positive and significant effect. However, it is comparable in size to its effect on the total bilateral flows, which explains why the coefficients are close to zero in the structure equation. Unemployment has a stronger (and negative) impact on overall migration than on the migration of businesspeople and managers, explaining its positive (but insignificant) coefficient in the structure equation. Finally, as the relative income gap has a stronger effect on the number of businesspeople and managers than it does on overall migration, we would have expected a positive coefficient in the structure equation. However, the coefficient in column 8 is negative but not significant. This might be caused by their relatively small share in the total flows.

5.3 Migration by nationality

Table 5 shows the estimation results for the impact of migration policy selectivity on the scale of bilateral migration. We only consider the scale equation, as the estimation of a structure equation is redundant when the dependent variable is the total bilateral migration flow.

For the scale equation's estimations, we use the bilateral selectivity index MPS_{odt}^{nat}, which tracks the differential restrictiveness a migrant faces for each origin-destination pair. We do not use the destination-specific Gini index of selectivity that was used in the characterisation (Section 3.3). The scale equations in this study are similar to the empirical specifications used in the literature to explain international bilateral migration flows in a push-and-pull framework. The main difference is that we include a more exhaustive and disaggregated migration policy component.

Again, the control variables have the expected sign (see columns 1-4 in Table 5). Bilateral migration flows are larger between countries with more dissimilar incomes. In contrast, significantly fewer migrants move to destinations with less favourable economic prospects (as proxied by the unemployment rate) and more to destinations where income inequality is high. The stock of migrants from the same origin country appears with a significant, positive effect, indicating the presence of network effects. The estimated coefficients are in line with the effects reported in the literature, e.g., a 1% increase in the relative GDP per capita is associated with a 2% increase in the bilateral migrant inflow.

Table 5: Estimation results for migration by nationality (scale)

	M^{nat}_{odt} (1)	M^{nat}_{odt} (2)	M^{nat}_{odt} (3)	M^{nat}_{odt} (4)
MPS^{skill}_{dt-1}	-	-	-0.005	-0.01
			(0.01)	(0.01)
MPS^{res}_{dt-1}	-	-	-	-0.05**
				(0.02)
MPS^{nat}_{odt-1}	-	0.1***	0.1***	0.1***
		(0.03)	(0.03)	(0.03)
MPR_{dt-1}	0.2*	0.2*	0.2	0.1
	(0.1)	(0.1)	(0.1)	(0.1)
$lnGDPpc_{odt-1}$	1.7**	1.6*	1.6*	1.7**
	(0.8)	(0.8)	(0.8)	(0.9)
$lnMigStock_{odt-1}$	0.1***	0.1***	0.1***	0.1***
	(0.04)	(0.04)	(0.04)	(0.04)
$lnUnemp_{dt-1}$	-0.5***	-0.5***	-0.5***	-0.6***
	(0.09)	(0.09)	(0.09)	(0.1)
$lnInterdec9050_{dt-1}$	1.3*	1.4*	1.5*	1.6**
	(0.8)	(0.8)	(0.8)	(0.7)
Origin-year FE	yes	yes	yes	yes
Destination FE	yes	yes	yes	yes
Observations	22,248	22,248	22,248	22,248

Notes: Standard errors clustered by destination in parentheses. *,** and *** indicate significance at the 10%, 5% or 1% levels respectively. Estimations with Stata© ppmlhdfe.

The results reported in Table 5 confirm the importance of migration policy selectivity when explaining the size of migration flows. While overall policy restrictiveness has no significant impact, bilateral migration flows are affected by selectivity in terms of nationality and economic resources. A rise in migration policy selectivity in terms of nationality increases the corresponding migration flows, while selectivity in terms of resources decreases them. Policy measures such as the signing of a bilateral labour agreement or the EU enlargement (respectively a 3-point 'mid-level' and a 4-point 'major' change according to DEMIG) are expected to raise bilateral migration flows by 30 to 40%.[38]

For all the flows considered, the effect of selectivity is consistently more significant for both the scale and structure of migration flows than that of restrictiveness. The overall policy restrictiveness only significantly affects the migration of the high-skilled. This supports the claim that migration policies work '*as filters rather than taps*' (De Haas et al. 2018, p. 43), particularly when selection is viewed from a broader perspective than just skills.

[38] 'Major changes are measures that affect an entire migrant category and introduce or remove a new policy instrument' DEMIG Policy codebook, p. 3.

5.4 Robustness

As noted in Section 3.2, our selectivity indexes might suffer from measurement errors stemming from several sources. To build our indexes, we assumed that the data is complete and without error, and neither assumption is likely to hold perfectly true. First, there could be general migration policies that, purposefully or not, end up being highly selective. Our empirical specification tried to control for this by including the overall restrictiveness of migration policy. This might be part of why the overall restrictiveness of migration policy has a positive effect on the fraction of skilled migrants.

Second, while we are unaware of any non-random patterns of missing or erroneous information in the underlying databases, it cannot be excluded that some legislative changes have been missed or wrongly recorded. It should be noted that the DEMIG dataset was entirely encoded by the same team, making country-specific error terms less likely. Moreover, we made a substantial effort to fill in any remaining missing values. Overall, the robustness checks on the construction of the indicators (Appendix A) showed that its values are relatively stable.[39]

Third, it is important to keep in mind that we consider only *de jure* regulations and not the extent to which they have been effectively implemented. As far as we know, cross-country databases that provide information on the implementation of migration regulations do not exist. However, any potential delay in the implementation of regulations is accounted for as our constructed indexes capture cumulative policy changes.

Fourth, we only considered the first lag of the migration policy variables. While deeper lags might allow us to disentangle the implementation gap or uncover the dynamics in the migration response to policy changes, their inclusion has little added value for the following reasons. First, our indexes are the cumulative sum of all legislative changes, meaning that the regression results measure the long-term impact of *de jure* policy changes.[40] As such, it is unclear what increasing the number of lags would reveal. Second, the auto-correlation of the migration policy variables is more than 95%. As such, incorporating multiple lags would result in a serious multicollinearity problem, completely undermining the reliability of any differences between the parameters on the lags. To thoroughly test the dynamics of the policy impact, we would have to estimate a much more complex model. E.g., a local projection approach incorporating the potential dynamics between migration policy, migration flows and their lagged values. Unfortunately, we lack the data for such a regression model and leave this for further research.

To test the sensitivity of our estimation results, we also performed a number of robustness checks in which we varied our empirical specification. To start, our baseline estimations controlled for multilateral resistance to migration by including origin-destination fixed effects.

[39] Another way to evaluate any potential bias stemming from measurement error is to re-estimate the model using alternative indexes. While we could not find alternatives for the resources and nationality-based selectivity, we replaced the skill selectivity index by the average of the indicators of Parsons et al. (2020). However, the differences in coverage reduced our sample size by 60%, making it impossible to distinguish measurement errors from sample selection effects. Results are available upon request.

[40] I.e., $MPS_t = \sum_{i=0}^{t} pm_i$, where MPS_t is the measure of policy selectivity and pm_t indicates the policy measures taken at time t.

However, migration policies might be correlated across destinations and time, which would bias the results downwards. For example, the European Union often implements European-wide migration policy measures. In order to test the robustness of our results, we group the destinations into different nests and re-estimate the model using origin-nest-year fixed effects. We identify destination-nests using two criteria: (i) the likelihood of correlation between migration policies, i.e., the likelihood that destinations are substitutes for potential migrants; and (ii) keeping the number of nests small to reduce the risk of an incidental parameter problem.[41] Table A-5 presents the results using the following nest definition: 1) Europe (including the UK), 2) the New World (US, Canada, Australia and New Zealand), and 3) the rest of the world.[42] As can be seen from Table A-5, rerunning our model with origin-nest-year effects gives very similar results to those obtained in our benchmark regressions. Apart from a switch in significance for skill selectivity (column 2), all estimated coefficients keep their original sign and significance.

Second, while the baseline specification included destination-specific fixed effects, it did not control for time-varying unobserved heterogeneity in the destination countries. This can be solved by including destination-time fixed effects. However, these are collinear with the resources and skill selectivity indexes (as well as most control variables), removing most variables from the estimations. As seen in Table A-6, the results remain unaffected except for the loss of significance in the nationality regressions.

Lastly, our baseline model clustered the error terms at the level of destination countries. However, clustering could also be done at the destination-time level, the variation level of two of the migration policy indexes. Furthermore, in the context of RUM-based models, it makes sense to cluster at the origin-time level, which is the level of aggregation from a theoretical point of view. Re-estimating our model with clustered standard errors at the destination-time (Table A-7) or origin-time level (Table A-8) had no meaningful impact on our results.[43]

6 Conclusions

Using data from the DEMIG Policy database, augmented with data on bilateral labour agreements, immigrant investor programmes and economic citizenship programmes, we constructed indexes that track the selectivity of migration policy for 42 (mostly OECD) countries between 1990 and 2014. These revealed that selectivity should be considered a multidimensional concept covering not only selectivity in terms of skills – which has been chiefly the focus so far – but also nationality and economic resources. The characterisation of migration policy selectivity revealed considerable heterogeneity across countries in their migration policies. For almost all country groups and dimensions of selectivity, the constructed indexes increase

[41] Note that changing the nest structure - and particularly increasing the number of nests - impacts the number of observations.

[42] During the period of our analysis (2000-2010 or 2014) migration policy between the European countries in our dataset was increasingly coordinated. As such, we prefer to group all the European countries in one cluster rather than, for example, distinguishing EU-15 from the newer EU-27 and non-EU members. Our results are robust to changes in this definition, like limiting the nests to European and non-European countries.

[43] Results available upon request.

steadily over time, confirming the impression of steadily intensifying migration management during our sample period. In general, the non-EU OECD countries in our sample were found to have the most selective migration policies. While EU countries were initially less selective on skills and economic resources, by 2014, they were as selective as non-OECD countries and even more selective based on nationality. Despite this increase, the skill selectivity of EU countries is still lower than that of non-EU OECD countries. Since 1990, the prevailing pattern has been convergence in economic resource selectivity but divergence in nationality. Given the weak correlation between migration policy selectivity and overall restrictiveness, we conclude that migration policy is multidimensional.

A potential limitation of our indexes of migration policy selectivity is that they measure *de jure* selectivity of migration policies but not how existing regulations are adopted in practice. Also, when building the migration policy selectivity indexes, we do not consider general (non-selective) migration policies even though these can *de facto* be selective (see Bianchi 2013). Furthermore, our data allows us to identify selectivity in three dimensions. However, there are surely other dimensions of selectivity that play an essential role. To some extent, that is an intrinsic characteristic of any index that intends to be comprehensive and comparable for a large group of countries. These issues could be much easier accommodated when constructing country-specific (non-comparable) indicators.

Using these selectivity indexes, we subsequently investigated how migration policy has shaped the size and structure of migration flows. In general, selectivity in migration policy was found to be more effective than overall restrictiveness. The only exception was skilled migration, which did not appear significantly influenced by skill selectivity, while restrictiveness did matter. Hence, migration policy plays a substantial role in shaping the size and structure of migration flows. Interestingly, we find that the effect of resource and nationality selectivity is similar to that of skill selectivity, underlining the multidimensional nature of selectivity in migration policy. Furthermore, we also find evidence for substitution effects in skill and resource selectivity. E.g., easier access for investors and managers seems to crowd out high-skilled migrants and vice versa.

The finding of significant effects of selectivity in other dimensions than skills raises the question of why countries would be selective in these respects. The rationale for skill selectivity in social welfare terms is straightforward. Destination countries want to attract skilled migrants because of the expected positive impact on economic growth or fiscal revenues and the greater political and social acceptance of skilled migration by the native population. At first sight, a social welfare argument for economic resource selectivity is less straightforward. The negative selection effect for high-skilled migrants may indicate adverse selection effects. However, it might be an instrument to influence the average skill quality of the migrants or positively select migrants based on other, unobservable characteristics than their level of education. Furthermore, selectivity in terms of nationality may be part of countries' broader international commercial policy. As shown by Limão (2016), half of the preferential trade agreements signed include clauses on international migration. As one of the four freedoms of a common market, the interregional mobility of people may be part of a regional integration strategy. This could also play for selectivity in terms of resources, which could be aimed at stimulating the mobility of investors and businesspeople in a regional integration framework.

An exploration of the latter forms an interesting pathway for future research.

Appendix A Robustness of the migration policy selectivity indexes

In this section, we check the sensitivity of our indexes of selectivity to our modelling choices. We specifically focus on the main assumption, namely that our list of legislative changes is complete and without errors. The following robustness checks by no means constitute a formal test of these assumptions, but instead gauge the sensitivity of the selectivity indexes to the purposeful introduction of errors.

A.1 Scaling errors

The first robustness check looks at the impact of the DEMIG encoded scale of legislative changes. Each legislation is assigned a magnitude score between 1 and 4 by de Haas et al. (2015) categorising them as either fine-tuning, minor, mid-level or major change. In order to see how errors in this scoring affect the selectivity indexes, we gave all changes the same magnitude score of one, leaving only the direction of the effect (increase or decrease in restrictiveness) intact. However, this barely impacted the indexes, as can be seen from Table A-1. The correlations between the baseline results and the robustness checks is in excess of 96% for all indexes, regardless of whether we looked at the overall correlation or only considered the correlation between counties (between) or over time (within).

Table A-1: Correlation with the baseline index values

	Overall	Between	Within
MPS^{skill}	0.96	0.96	0.96
MPS^{res}	0.97	0.98	0.97
MPS^{nat}	0.99	1.00	0.98

A.2 Missing data

The second robustness check gauges the sensitivity of our indexes to missing data. To that end, we randomly deleted 10% of the legislative changes and recomputed the index. This process was repeated 50 times. Table A-2 shows the average correlation between the baseline results and those with randomly missing values. This table clearly shows that a random deletion of 10% of the data has no significant impact on the index values, making it unlikely that our results are significantly distorted by any actual missing legislative changes.

Table A-2: Correlation with the baseline index values

	Overall	Between	Within
$MPS^{skill}_{i,t}$	0.98	0.98	0.98
$MPS^{res}_{i,t}$	0.97	0.96	0.96
$MPS^{nat}_{ij,t}$	0.97	0.98	0.95

A.3 Initial anchor values

The third robustness verifies the importance of taking the year 1945 as the initial anchor value of zero given that the initial value of policy selectivity is unknown. To start with, we changed the anchor point from 1945 to 1960 to see how this impacts the indicator values. In both the baseline and the alternative scenario, the start date of the dataset was kept in 1990, meaning that the alternative scenarios reduced the burn-in period from 45 to 30 and even 10 years. As can be seen in Table A-3, the effect on the indicator values was minimal.

Table A-3: Correlation with the baseline index values

startyear	1960	1980
$MPS_{i,t}^{res}$	0.9937	0.9752
$MPS_{i,t}^{skill}$	0.9740	0.8470
$MPS_{ij,t}^{nat}$	0.9539	0.8484

There are a number of reasons why the choice of anchor point has a modest impact on the resulting indicator. To start, the number of legislative changes per year listed in the DEMIG database is heavily skewed towards the latter years. only about 35% of changes happens in the 45 years between 1945 and 1989, while the next 25 years hold the remaining 65%. Furthermore, the effect of a single legislative change is also fairly limited, with the maximum impact capped at a plus or minus four. Finally, there is also a strong positive correlation between the legislative changes over time. For example, countries that strongly increase the restrictiveness in one year are more likely to continue doing so. For the starting values to have a significant distorting effect, you would need some countries to radically alter the restrictiveness of their policies from one year to the next.

A.4 Policy decay

The final robustness check is focused specifically on our use of a running sum. As was explained above, using a running sum means that all errors in the dataset are compounded. As a result, the longer the running sum, the larger the uncertainty of the estimates becomes. As an alternative modelling choice, we replace our computation of the level of migration policy from $L_{i,t} = L_{i,t-1} + C_{i,t}$ to one where the effects fade over time: $L_{i,t} = \delta L_{i,-1} + C_{i,t}$. Lacking any information on the speed with which policy should decay, we set the value of δ such that the effect of a legislative change is reduced to only 5% after 20 years. This gave us a relatively short half-life of 4.6 years, which serves as a lower bound as the actual persistence of policy is likely much higher. It should also be noted that the DEMIG dataset does contain information on the role-back of legislation, which conflicts with the fade-out.

The effect of allowing policy to fade out over time is slightly larger than that of our first two robustness checks. However, the correlation with our baseline results remains high as can be seen form Table A-4. Overall, our selectivity indexes seem to be highly robust to our modelling choices as well as potential errors or omission in the dataset.

Table A-4: Correlation with the baseline index values

	Overall	Between	Within
$MPS_{i,t}^{skill}$	0.71	0.83	0.74
$MPS_{i,t}^{res}$	0.81	0.95	0.80
$MPS_{ij,t}^{nat}$	0.87	0.93	0.80

Appendix B Imputing the DIOC education and occupation migration data

As explained in the main body of the paper, our regression models require data on the number and share of high-skilled migrants and managers and businesspeople migrating each year. However, the DIOC data we have at our disposal cover only the stock of migrants at a rather low frequency: three times in five-year intervals for half the dataset and two times in ten-year intervals. The number of non-missing migration stock data is slightly less than $12,000$ for education and $10,500$ for occupation.[44] To obtain net migration flows, we have to take the differences of the stock data, which compounds the data loss. For education, only some $2,000$ observations remain, whereas for occupation, the number of observations falls to about $1,500$. In addition, the range of destination countries included in the analysis falls substantially (to ten for migration in terms of education and eight for occupation). While it is possible to run the regression with this dataset, it limits the use of our new indicators of migration selectivity, for which the data are complete for all destination countries and long time range (1990 to 2014).

For this reason, we use a statistical model to fill in the gaps in the DIOC data, allowing us to make full use of the new indicators of migration policy selectivity. Following Standaert and Rayp (2022), we construct a (Bayesian) state-space model consisting of two main sets of equations. The state equations describe the dynamic behaviour and relationships between our main variables of interest (the latent state variables). In this case, our state variables are the stock and flows of high-skilled migrants in the first model and the stock and flow of managers and businesspeople in the second. The relationship between the stock and flows is described in a demographic model. The second set of equations is the measurement equations, which describe the relationship between these state variables and our observed data, e.g., how the flow of high-skilled migrants relates to the overall flow of migrants. See Durbin and Koopman (2012) or Kim and Nelson (1999) for more information on state-space models.

Using a state-space model allows us to combine data on migration stocks and flows of different sources with a demographic model to help estimate the most likely value for our missing data. This technique is related to some extent to the demographic accounting technique employed by (Abel 2013; Abel and Cohen 2019) to impute net migration flow data, in which differences in stock data are combined with demographic data. The demographic accounting technique requires close-to complete information on the stock of migrants. These are used to build contingency tables that describe where the population of a particular origin country is distributed around the world. Given the paucity of data on managers or high-skilled, we instead use the state-space approach, allowing us to estimate the missing data for each country pair separately.

[44] The tables of migration stock data according to education and occupation are constructed separately using census and labour force survey data, which explains the difference in data availability.

B.1 Imputation algorithm

We used two different models to impute both the occupation and education DIOC data. However, as both models are very similar, we will focus our explanation on the imputation of high-skilled migrants. The only difference between both regressions occurs in the measurement equation (A-5), where the share of high-skilled migrants in the origin country is replaced by the share of managers in the origin country.

The state equation is built on a demographic identity: the only way in which the stock of migrants based on country of birth can change is if migrants enter the country, leave the country or if they die.[45] If $S^h_{ij,t}$ is the stock of high-skilled migrants from i in j at time t, $N^h_{ij,t}$ are the net flows from i to j and $D^h_{ij,t}$ is number of high-skilled migrants from i in j that have died in year t, this gives us the following equation:

$$S^h_{ij,t} \equiv S^h_{ij,t-1} + N^h_{ij,t} - D^h_{ij,t} \tag{A-1}$$

For the vast majority of countries, the information on how many migrants have died per origin country is not available. We follow the approach of Abel and Cohen (2019) and assume that the deaths equal to the stock of migrants already in the country multiplied by a destination-country-specific death rate.

$$D^h_{ij,t} = \delta_{i,t}\, S^h_{ij,t-1}, \tag{A-2}$$

As many of the variables that influence the flow of migration are highly persistent (e.g., size of the migrant population, population size of the sending country), we also want to allow for this persistence in the net migration flows. To that end, we model this variable as an autoregressive process with one lag process. The level of persistence in these flows is estimated within the model.

$$\begin{aligned} N^h_{ij,t} &= \tau_{ij}\, N^h_{ij,t-1} + \mu_{ij,t} \\ \mu_{ij,t} &\sim N(0, \sigma^{\mu}_{ij}) \end{aligned} \tag{A-3}$$

The measurement equation consists of two parts. To anchor our results, we impose that the available migration stock data from DIOC is correct.

$$DIOC_{ij,t} = S^h_{ij,t} \tag{A-4}$$

The second equation relates the flow of high-skilled migrants to the total migration flow and the share of high-skilled individuals in the origin country. If the choice to migrate was independent of skill level, then multiplying both variables would provide a good approximation of the flow of high-skilled migrants. However, as skill level is likely to influence the likelihood (and ability) to migrate, we embed this relationship in a linear error model.

[45] Depending on the legal system, babies born from migrant mothers are counted as an increase in the domestic population, or as an increase in the net migration flow. Either way, the births are already taken into account.

$$\begin{aligned} hs_{j,t} * N_{ij,t} &= zN^h_{ij,t} + c_{ij} + \epsilon_{ij,t} \\ \epsilon_{ij,t} &\sim N(0, \sigma^{\epsilon}_{ij}) \end{aligned} \tag{A-5}$$

c_{ij} and z capture the persistent differences between the flow of high-skilled migrants, N^h, and the error term ϵ accounts for any stochastic deviations. As the magnitude of the flow and stock of migrants can be very different depending on the countries in question, the constant c_{ij} and variance of the error term σ^{ϵ}_{ij} can differ for each country-pair.

Putting these equations together, we get the following state-space model:

$$\begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} S^h_{ij,t} \\ N^h_{ij,t} \end{bmatrix} = \begin{bmatrix} 1-\delta_{j,t} & 0 \\ 0 & \tau^N \end{bmatrix} \begin{bmatrix} S^h_{ij,t-1} \\ N^h_{ij,t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ \mu_{ij,t} \end{bmatrix} \tag{A-6}$$

$$\begin{bmatrix} DIOC_{ij,t} \\ hs_{ij,t}N_{ij,t} \end{bmatrix} = \begin{bmatrix} 0 \\ c_{ij} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & Z \end{bmatrix} \begin{bmatrix} S^h_{ij,t} \\ N^h_{ij,t} \end{bmatrix} + \begin{bmatrix} 0 \\ \epsilon_{ij,t} \end{bmatrix} \tag{A-7}$$

B.2 Data sources

In addition to the DIOC dataset, several other databases were used in the computations. We collected information on the yearly flow of migrants from the OECD's International Migration Database. To proxy the inflow of managers, we multiplied the total inflows with the share of managers in the total population of the origin country (proxied by the ISCO-1 occupation category, using population and labor force data from the ILO (ILO 2021).[46] Unfortunately, a similar indicator for education was harder to come by. While the World Bank has a variable measuring the share of highly educated people in the total population, this variable is missing for most of the dataset. As a result, we used the average number of years of schooling from the UNDP Human Development Report 2020 instead. Finally, death rates of the destination countries from the WHO's Global Health Observatory.

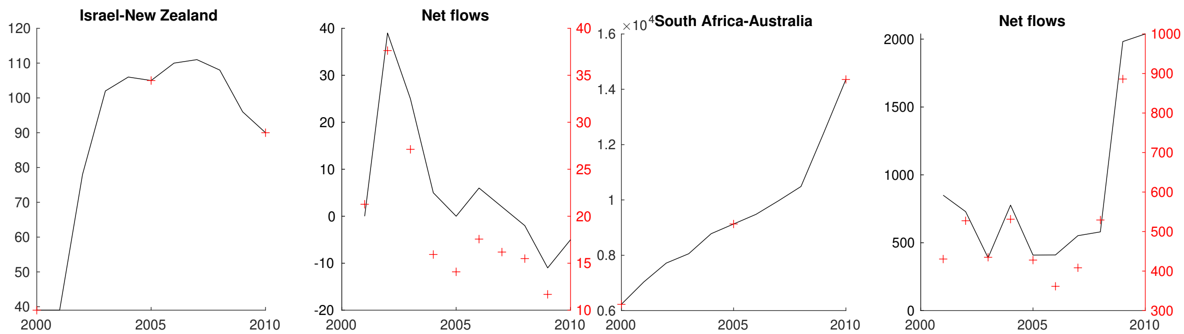
B.3 results

The estimation model ran for 5,000 iterations, of which the first 4,000 were discarded as burn in.[47] The remaining iterations were used to compute the most likely bilateral stock and net flows of high-skilled migrants and managers and businesspeople. In this way, the data set for migration according to education increases to more than 37,000 observations (resulting in a sample for the estimations of some 8,000 observations ranging over 27 destination countries, after adding the control variables) and approximately 23,000 observations for occupation (giving a final data set of 6,300 observations for 25 destination countries).

[46]See for concepts, definitions and a description of the methodology https://ilostat.ilo.org/resources/concepts-and-definitions/description-employment-by-occupation

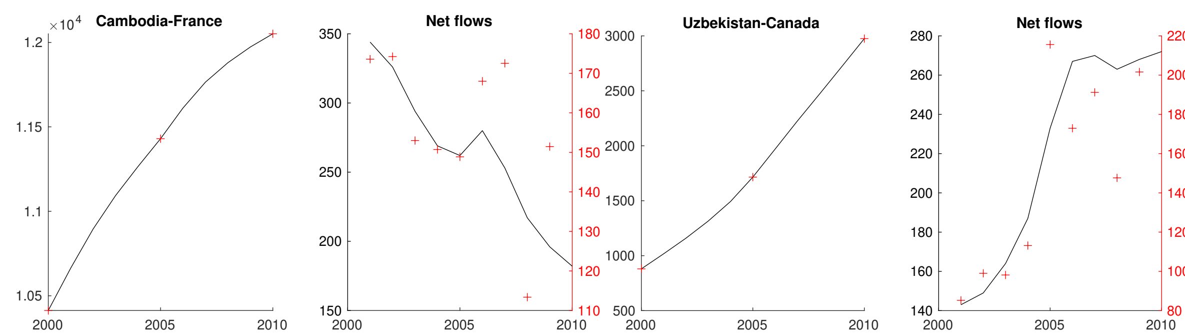
[47]We used uninformative priors and checked the model's convergence using a visual inspection of the parameters plots, autocorrelation function and CUMSUM graphs.

Figures 4 and 5 compare the imputed values of the occupation and education data to the source data. In both cases we see that the DIOC stock data anchors the imputed stock values (left panel), while the flows try to follow the pattern in the $hs_{j,t} * N_{ij,t}$ variable (right panel). However, this is not the case for all country-pairs. For example, according to the DIOC data, no high-skilled migrants were migrating from Poland to Chile in 2005 or 2010. As a result, the model returns all zeros for the intervening years as well.



(a) From Israel to New Zealand **(b)** From South Africa to Australia

Figure 4: Comparison of the imputed occupation and source data
Comparison of the imputed migration by occupation (black lines) with the source data (red crosses). The left-hand panel shows the stock data and DIOC data, while the right-hand panel shows the net flows and our proxy for the inflow of managers.



(a) From Cambodia to France **(b)** From Uzbekistan to Canada

Figure 5: Comparison of the imputed education data and source data
Comparison of the imputed migration by education level (black lines) with the source data (red crosses). The left-hand panel shows the stock data and DIOC data, while the right-hand panel shows the net flows and our proxy for the inflow of high-skilled migrants.

Appendix C List of countries by sub-groups

OECD				non-OECD
EU		non-EU		
Austria	Hungary	Australia	South Korea	Argentina
Belgium	Ireland	Canada	Mexico	China
Czech Rep.	Italy	Switzerland	Norway	Brazil
Germany	Luxembourg	Chile	New Zealand	Indonesia
Denmark	Netherlands	Iceland	Turkey	India
Spain	Poland	Israel	USA	Morocco
Finland	Portugal	Japan		Russia
France	Slovakia			Ukraine
UK	Slovenia			South Africa
Greece	Sweden			

Appendix D Data sources for the explanatory variables

Variable	Source
Income inequality	Labour force Statistics (OECD)
Interdecile earnings ratio (P90P50)	Decile ratios of gross earnings
GDP per capita (PPP)	World Development Indicators (World Bank)
Bilateral migrant stocks	International Migration Database (OECD)
Unemployment	World Indicators of Skills for Employment OECD)
Migration policy restrictiveness	Rayp et al. (2017)
Migration policy selectivity	Own computation

Appendix E Robustness regressions

Table A-5: Origin-nest-time fixed effects

	M_{odt}^{skill} (1)	$\frac{M_{odt}^{skill}}{M_{odt}}$ (2)	M_{odt}^{res} (3)	$\frac{M_{odt}^{res}}{M_{odt}}$ (4)	M_{odt}^{nat} (5)
MPS_{dt-1}^{skill}	-0.028	0.007	-0.092***	-0.106***	-0.008
	(0.032)	(0.033)	(0.035)	(0.034)	(0.010)
MPS_{dt-1}^{res}	-0.219***	-0.098**	0.081***	0.005	-0.056**
	(0.040)	(0.049)	(0.025)	(0.035)	(0.026)
MPS_{odt-1}^{nat}	0.053	-0.117***	-0.039	-0.010	0.071**
	(0.033)	(0.040)	(0.082)	(0.061)	(0.033)
MPR_{dt-1}	0.421	0.549**	0.118	-0.136	0.055
	(0.338)	(0.244)	(0.334)	(0.199)	(0.136)
$lnGDPpc_{odt-1}$	-0.761	-2.08**	1.805	-0.536	1.889**
	(1.756)	(0.911)	(1.334)	(0.846)	(0.960)
$lnMigStock_{odt-1}$	0.211**	-0.006	0.064	0.034	0.103*
	(0.086)	(0.052)	(0.167)	(0.060)	(0.055)
$lnUnemp_{dt-1}$	-0.305	0.403	-0.234	0.192	-0.607***
	(0.279)	(0.357)	(0.298)	(0.185)	(0.109)
$lnInterdec9050_{dt-1}$	4.267**	-0.467	-	-	0.668
	(2.05)	(2.251)			(0.834)
Constant	4.889***	1.046	6.061*	-0.563	6.667***
	(1.859)	(1.763)	(3.524)	(0.915)	(1.295)
Origin-nest-year FE	yes	yes	yes	yes	yes
Origin-destination FE	yes	yes	yes	yes	yes
Observations	6,502	6,502	5,523	5,523	21,523

Notes: Standard errors clustered by destination in parentheses. *,** and *** indicate significance at the 10%, 5% or 1% levels respectively. Estimations obtained with Stata© ppmlhdfe.

Table A-6: Three-way fixed effects (origin-time, origin-destination and destination-time)

	M^{skill}_{odt} (1)	$\frac{M^{skill}_{odt}}{M_{odt}}$ (2)	M^{res}_{odt} (3)	$\frac{M^{res}_{odt}}{M_{odt}}$ (4)	M^{nat}_{odt} (5)
MPS^{nat}_{dt-1}	0.076**	-0.065*	-0.019	-0.070*	0.0334
	(0.032)	(0.039)	(0.056)	(0.039)	(0.044)
$lnMigStock_{odt-1}$	0.001	-0.048	0.383*	0.147**	0.037
	(0.108)	(0.070)	(0.196)	(0.073)	(0.062)
Constant	6.402**	-0.427	2.730	-2.940***	8.897***
	(2.863)	(1.755)	(2.531)	(0.671)	(0.803)
Destination-time FE	yes	yes	yes	yes	yes
Origin-time FE	yes	yes	yes	yes	yes
Origin-destination FE	yes	yes	yes	yes	yes
Observations	10,189	10,189	6,304	6,304	32,386

Notes: Standard errors clustered by destination in parentheses. *,** and *** indicate significance at the 10%, 5% or 1% levels respectively. Estimations obtained with Stata© ppmlhdfe.

Table A-7: Destination-year clustered standard error

	M_{odt}^{skill} (1)	$\frac{M_{odt}^{skill}}{M_{odt}}$ (2)	M_{odt}^{res} (3)	$\frac{M_{odt}^{res}}{M_{odt}}$ (4)	M_{odt}^{nat} (5)
MPS_{dt-1}^{skill}	-0.032	-0.003	-0.102***	-0.102***	-0.008
	(0.022)	(0.032)	(0.022)	(0.026)	(0.010)
MPS_{dt-1}^{res}	-0.094**	-0.006	0.066	0.009	-0.047**
	(0.042)	(0.058)	(0.041)	(0.026)	(0.021)
MPS_{odt-1}^{nat}	0.062	-0.087***	0.010	-0.109***	0.102***
	(0.056)	(0.033)	(0.077)	(0.041)	(0.032)
MPR_{dt-1}	0.550*	0.562**	0.008	-0.172	0.073
	(0.296)	(0.251)	(0.430)	(0.164)	(0.094)
$lnGDPpc_{odt-1}$	-1.424	-2.227***	3.525	-1.023	1.697*
	(2.203)	(0.790)	(2.166)	(0.743)	(0.884)
$lnMigStock_{odt-1}$	0.135	-0.064	0.219	0.014	0.118**
	(0.125)	(0.049)	(0.143)	(0.047)	(0.054)
$lnUnemp_{dt-1}$	-0.423*	0.259	0.004	0.137	-0.569***
	(0.247)	(0.321)	(0.280)	(0.124)	(0.094)
$lnInterdec9050_{dt-1}$	3.391	1.093	-	-	1.610**
	(2.484)	(1.570)			(0.742)
Constant	7.021***	1.091	1.470	0.343	5.891***
	(2.470)	(1.416)	(4.209)	(0.755)	(1.160)
Origin-year FE	yes	yes	yes	yes	yes
Origin-destination FE	yes	yes	yes	yes	yes
Destination-year clustering	yes	yes	yes	yes	yes
Observations	7,417	7,417	6,304	6,304	22,248

Notes: Standard errors clustered by destination in parentheses. *,** and *** indicate significance at the 10%, 5% or 1% levels respectively. Estimations obtained with Stata© ppmlhdfe.

Table A-8: Origin-year clustered standard error

	M^{skill}_{odt} (1)	$\frac{M^{skill}_{odt}}{M_{odt}}$ (2)	M^{res}_{odt} (3)	$\frac{M^{res}_{odt}}{M_{odt}}$ (4)	M^{nat}_{odt} (5)
MPS^{skill}_{dt-1}	-0.032	-0.003	-0.102***	-0.102***	-0.008
	(0.021)	(0.027)	(0.028)	(0.023)	(0.011)
MPS^{res}_{dt-1}	-0.094**	-0.006	0.066	0.009	-0.047**
	(0.044)	(0.031)	(0.083)	(0.060)	(0.021)
MPS^{nat}_{odt-1}	0.062	-0.087***	0.010	-0.109***	0.102***
	(0.060)	(0.030)	(0.093)	(0.041)	(0.013)
MPR_{dt-1}	0.550***	0.562***	0.008	-0.172	0.073
	(0.208)	(0.091)	(0.387)	(0.147)	(0.090)
$lnGDPpc_{odt-1}$	-1.424	-2.227**	3.525**	-1.023	1.697***
	(2.011)	(0.992)	(1.797)	(0.907)	(0.605)
$lnMigStock_{odt-1}$	0.135	-0.064	0.219	0.014	0.118**
	(0.104)	(0.068)	(0.220)	(0.060)	(0.051)
$lnUnemp_{dt-1}$	-0.423***	0.259**	0.004	0.137	-0.569***
	(0.159)	(0.103)	(0.295)	(0.169)	(0.124)
$lnInterdec9050_{dt-1}$	3.391	1.093	-	-	1.610
	(2.524)	(0.965)			(0.986)
Constant	7.021***	1.091	1.470	0.343	5.891***
	(2.046)	(1.643)	(4.410)	(1.221)	(0.973)
Origin-year FE	yes	yes	yes	yes	yes
Origin-destination FE	yes	yes	yes	yes	yes
Origin-year clustering	yes	yes	yes	yes	yes
Observations	7,417	7,417	6,304	6,304	22,248

Notes: Standard errors clustered by destination in parentheses. *,** and *** indicate significance at the 10%, 5% or 1% levels respectively. Estimations obtained with Stata© ppmlhdfe.

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