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RESEARCH PAPER

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 characterize migration policies in 42 countries between 1990 and 2014. Second, we examine the relationship between the selectivity of migration policy and migration flows. Each of the three dimensions of migration policy is found to correlate strongly and significantly with both the size and structure of migration flows.

Keywords: Effectiveness; international migration; migration policy; selectivity

JEL classification: 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 control who comes in, targeting the composition of flows more than their scale. In this light, De Haas *et al.* (2018, pp. 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 favor the high-skilled, aiming to fill labor 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 labor 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 focused 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. Focused specifically on labor 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, constructing 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, 2005; Mayda, 2010; 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 findings have been mixed. Antecol *et al.* (2003), Jasso and Rosenzweig (2009), and Bélot and Hatton (2012) are skeptical about the impact of policies favoring 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 characterize

[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, Burgoon, *et al.*, 2015) and (ii) the question of how to subsequently aggregate this information into one or a few summary indicators (Hatton, 2014).

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

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 analyze how selectivity relates to 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 toward 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 between selectivity and restrictiveness in migration policy. I.e., countries that are more open toward 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 characterization 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 reveals an intricate pattern of significant direct and indirect correlations between migration policy selectivity and the scale and structure of bilateral migration flows. For example, the number of high-skilled migrants is positively linked with an overall liberal migration policy, particularly when aimed at a specific origin country. An increase in selectivity based on nationality, e.g., through the signing of a bilateral labor agreement, is associated with an increase in the size of the targeted flows and the number of high-skilled migrants. Similarly, resource-based selectivity is positively associated with the number and fraction of incoming investors and managers. However, there seem to be substitution effects in skill- and resource-based selectivity, where, e.g., easier access for investors and managers seems to crowd out high-skilled migrants and vice versa. As such, migration policy selectivity cannot be reduced to just the dimension of skill selectivity.

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 characterization 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 conceptualization and measurement of migration policies and the literature on migration policies" effectiveness.

[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).

Regarding the conceptualization 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, 2010; Hatton, 2004, 2009, 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

[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 Migrant Rights Index by Ruhs (2013), and the index of openness toward labor migration for the high-skilled by Cerna (2016).

Migration Policy Index (MPR) developed by Rayp *et al.* (2017) that measures countries' overall restrictiveness toward 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 standardized 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) categorizes the labor 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 labor 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 toward the high-skilled and bilateral labor 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 focused 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 labor market shortages. While both can overlap, demand-driven policies can also target low- or median-skilled labor, like fruit pickers and truck drivers. To track the different dimensions 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, 2005; Mayda, 2010; 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 skeptical about the impact of policies that favor 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 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 labor migration flows – operationalized as the share of high-skilled in the total labor 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,

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

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 toward 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, Burgoon, *et al.*, 2015, 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 organized 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

[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.

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, regularization), 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 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 labor 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 programs (IIP) and economic citizenship programs (ECP) – the so-called "golden visas". These are programs 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

[9]In DEMIG, these are defined respectively as "workers who are either explicitly labeled as low-skilled or who will work in occupations that do not require more than secondary education" and "workers who are either explicitly labeled 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 the 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

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 programs 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 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/program 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.

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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.

[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

	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.

First, we select from the database all selective legislative changes and categorize 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]

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 toward 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-time 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.

After this re-categorization, 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. 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 regularization 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 categorizes 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 selectivity. E.g., it decreases when it becomes easier for low-skilled migrants to enter.

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 forward, 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 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 normalization 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 characterization 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

[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).

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 organized 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 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, labor 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 18,972 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

Figures 2, 3 and 4 plot the value of the three indexes of migration policy selectivity by skills, resources and nationality, respectively 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 colors 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]

[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-time couple is zero.

[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.

Focussing on the change in selectivity over time, Figure 5 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 B. Overall, policy selectivity in the three dimensions increases continuously throughout our sample. Migration policy moves from moderately *negatively* skill-selective (i.e., favoring low-skilled workers) to outspokenly *positively* skill-selective. Similarly, in 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 toward 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.

Summarizing 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 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 5 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.

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 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

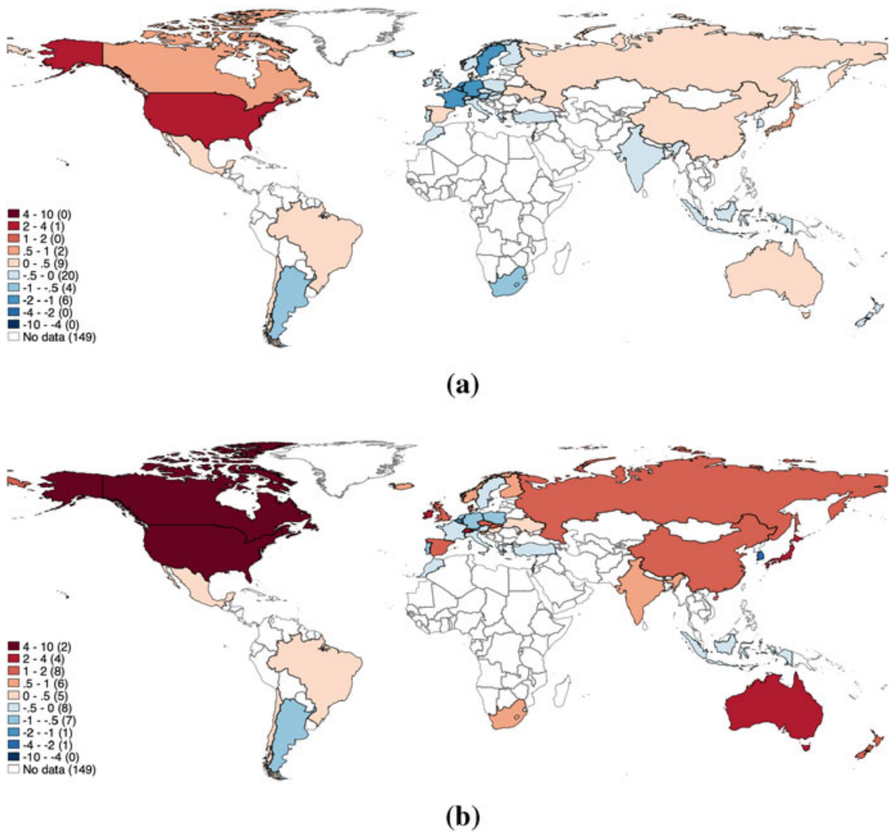


Figure 2. Migration policy selectivity scores in terms of skills by destination country 1990 and 2014.
Notes: Plot of the destination country-specific migration selectivity scores with respect to skills. (a) MPS^{skill} values in 1990, (b) MPS^{skill} values in 2014. Red (blue) values indicate a migration 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.

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 toward some migrants than toward others. This is in line with the findings of Ruhs (2013), who found a trade-off between the openness of (labor) migration policy and the level of (skill) selectivity. Moreover, the weakness of this correlation implies that the characterization 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. Migration policy selectivity and 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 analyze

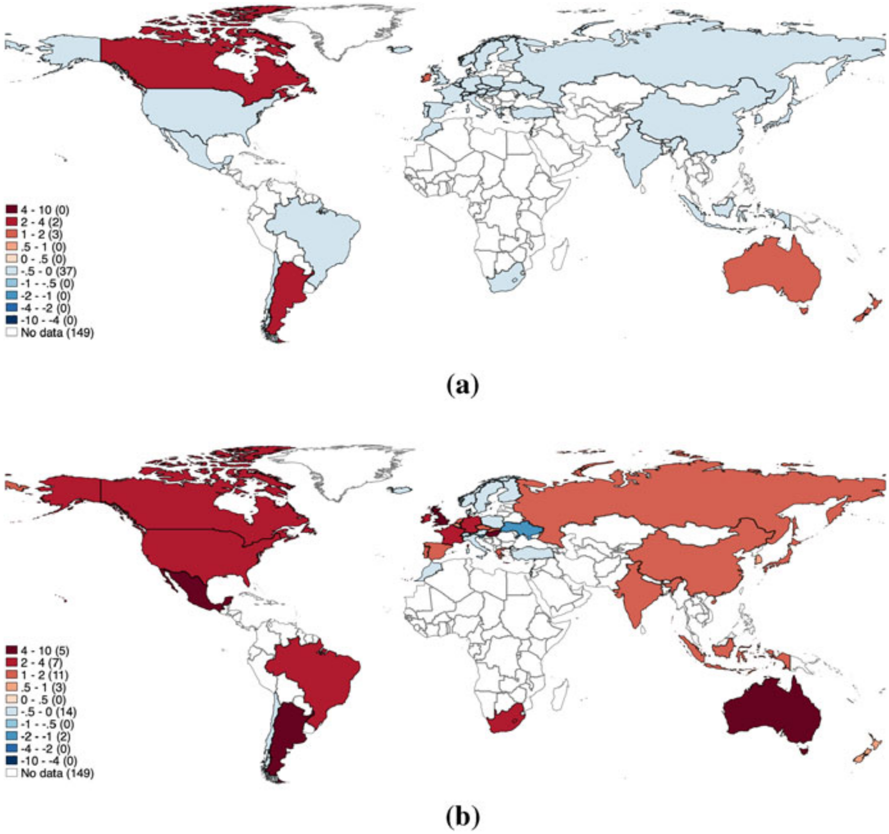


Figure 3. Migration policy selectivity scores in terms of resources by destination country 1990 and 2014.
Notes: Plot of the destination country-specific migration selectivity scores with respect to economic resources. (a) MPS^{res} values in 1990, (b) MPS^{res} values in 2014. Red (blue) values indicate 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.

the effectiveness of migration policies is derived from the standard random utility maximization (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]

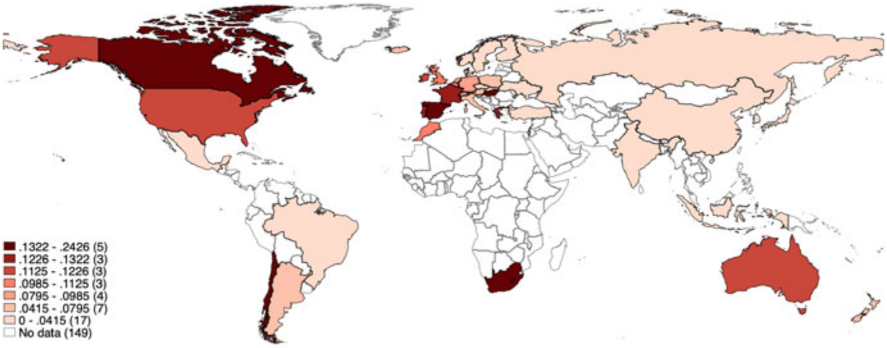
The general specification of the *scale* equation is as follows:

$$M_{odt}^{k} = \alpha_1^k MP_{odt-i} + \alpha_2^k Z_{odt-1} + \delta_{od}^k + \delta_{ont}^k + \varepsilon_{odt}^k, \qquad k = skill, res, nat \tag{1}$$

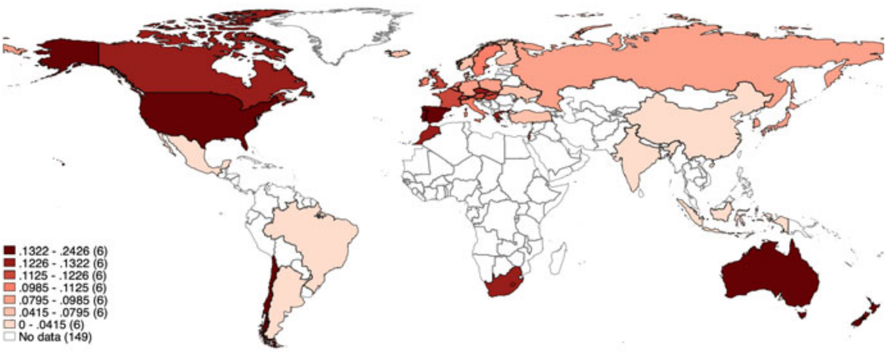
[21]See e.g., the references in Czaika and Parsons (2017). For more details, see e.g., Beine, Bertoli, *et al.* (2016).

[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.

 https://doi.org/10.1017/dem.2024.9



(a)



(b)

Figure 4. Migration policy selectivity scores in terms of nationality by destination country 1990 and 2014.
Notes: Plot of the destination country-specific migration selectivity scores with respect to economic resources. (a) MPS^{nat} values in 1990, (b) MPS^{nat} values in 2014. 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.

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.

where M^k_{odt} denotes the flow of migrants from country o to country d at time t, and n groups together different sets of destination countries. The superscript k indicates the inflow of skilled (*skill*), economically well-endowed (*res*), or all migrants (*nat*). MP_{odt-i} and Z_{odt-1} are vectors containing lagged migration policy variables and control variables, respectively.

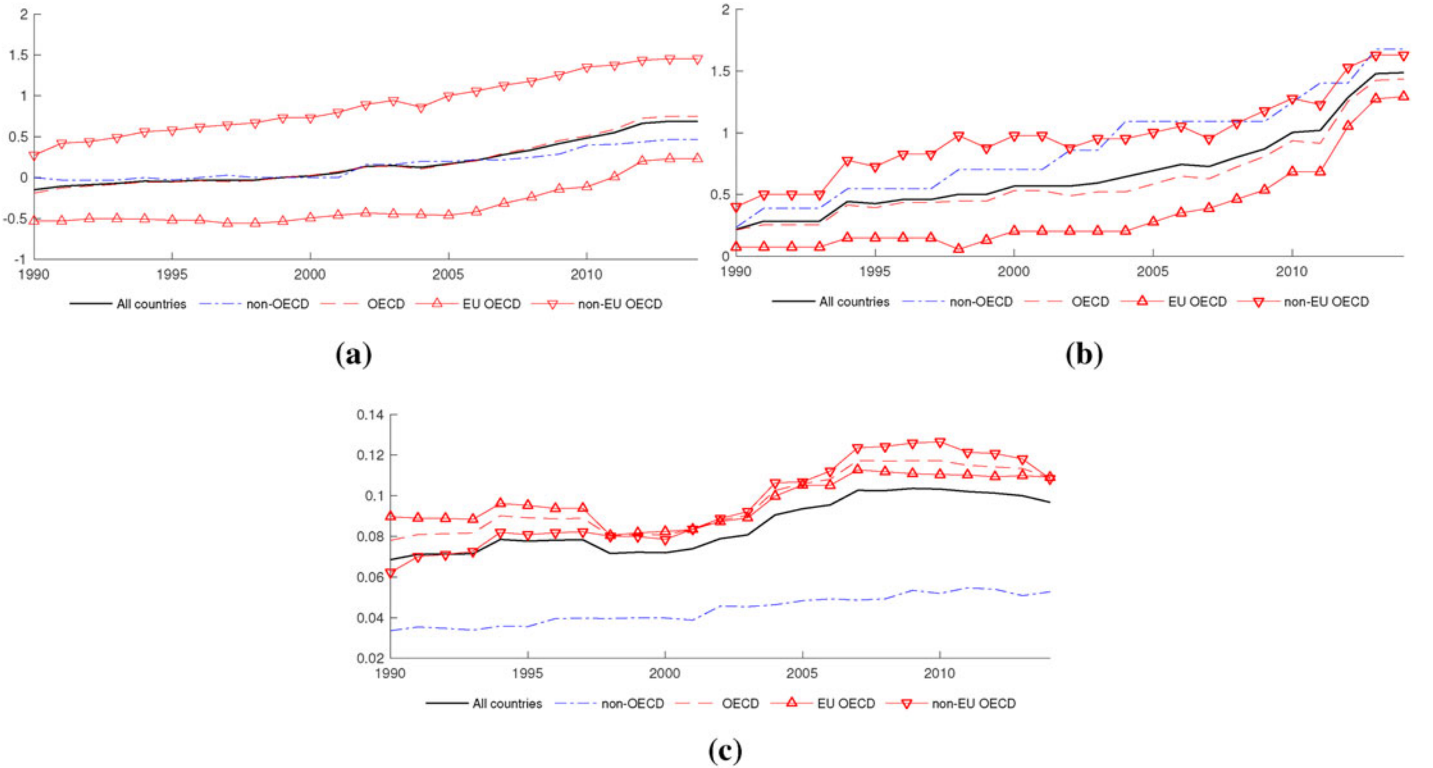


Figure 5. Evolution in migration policy selectivity, (a) MPS^{skill}, (b) MPS^{res}, (c) MPS^{nat}. Notes: Plot of the yearly average values of the migration policy selectivity indexes with respect to skills (a), economic resources (b) and nationality (c) for all countries and subgroups.

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.

For the migration of the high-skilled and economically well-endowed, we also estimate the *structure* equation, which takes the following general form:

$$\frac{M^k_{odt}}{M_{odt}} = \beta^k_1 MP_{odt-5} + \beta^k_2 Z_{odt-1} + \mu^k_{od} + \mu^k_{ont} + \eta^k_{odt}, \qquad k = skill, res \tag{2}$$

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 Eqn (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 to control for potential contemporaneous reverse causality and allow for the delay with which migration policy rules usually come into effect. In the skill and resources regressions, this necessitates 5-year lags ($i = 5$) as the dependent variable captures the net five year migration flow. As the nationality regressions have yearly migration flow data, we only require a one-year lag ($i = 1$).

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

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

capita;[24] the origin-specific stock 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.

Both the scale and structure equations include origin-nest-time (δ^k_{ont} and μ^k_{ont}) and origin-destination fixed effects (δ^k_{od} and μ^k_{od}). The first control for international correlation in migration policy across destinations and time. For example, the European Union often implements European-wide migration policy measures and ignoring this would bias the results downward.[26] To control for this, we group the destinations into different nests and use those to construct origin-nest-time fixed effects (cf. Bertoli and Fernández-Huertas Moraga, 2013, 2015). 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.[27] This results in 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.[28] The origin-destination fixed effects control for the unknown initial levels of the migration policy selectivity variables,[29] as well as any residual, time-invariant multilateral resistance to migration that varies between the destination countries within a nest.

Finally, the scale and structure equations are estimated from origin-destination-time 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

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

[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 around -0.14 in the sample considered in Tables 3 and 4.

[26]We opt for nested fixed effects to address the potential violation of the independence of irrelevant alternatives assumption, which arises from correlated unobservable factors across origins and destinations. Supplementary results from a model solely utilizing origin-year and origin-destination fixed effects are provided in Table Appendix A-4. This choice of incorporating nested fixed effects in our baseline analysis represents a more cautious approach aimed at obtaining unbiased estimates.

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

[28]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 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.

[29]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.

correlated by destination. To control for this, we cluster the standard errors by destination-time (see e.g. Angrist and Pischke, 2009, pp. 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 of restrictiveness. The complete list of sources can be found in Appendix C.

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 harmonized 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).[30] Based on population censuses and registers, DIOC provides information on demographic and labor 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.[31] 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.[32] 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").[33]

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

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

[32]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.

[33]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

While the DIOC database is one of the most detailed and accurate sources of 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 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 a significant fraction of country-pairs are missing in the 2005/2006 sample. Taking the difference between two consecutive stock measurements results in a considerable reduction in sample size, and in the number of destination countries.[34] 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 and 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 D. The bilateral migrant stock series we obtain in this way extends the range of destination countries to 30 for skilled migration and to 27 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. The choice of yearly data for these regressions allows us to make maximum use of the available information and variation in our data so as to capture any short-term impact of changes in migration policies.

5. Results

Tables 3, 4 and 5 present the estimation results for the scale equation (columns 1 through 3) and structure equation (columns 4 through 6) for the three categories of migrants. The first specification (columns 1 and 4) 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 3 and 6 display the preferred specification that includes all the dimensions of policy selectivity and the overall restrictiveness.

5.1 Skilled migration

First, columns 1–3 of Table 3 show that the estimated coefficients for most of the control variables in the *scale* equation are insignificant. The only significant effect is

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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).

[34]The number of destination countries is reduced to 14 for the occupation data. The number of origin countries remains around 200. However, the sample reduction still implies we are left with just a few observations for many origin countries.

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

	Scale equation			Structure equation		
	M_{odt}^{skill}			M_{odt}^{skill}/M_{odt}		
	(1)	(2)	(3)	(4)	(5)	(6)
MPS_{dt-5}^{skill}		−0.0730	−0.0018		0.119***	0.127***
		(0.076)	(0.069)		(0.026)	(0.022)
MPS_{dt-5}^{res}			−0.0885			0.108
			(0.099)			(0.077)
MPS_{dt-5}^{nat}			0.777***			0.318**
			(0.215)			(0.137)
MPR_{dt-5}	1.545***	1.240***	1.324***	0.346	1.087***	1.081***
	(0.501)	(0.396)	(0.301)	(0.332)	(0.302)	(0.278)
$lnGDPpc_{odt-1}$	22.60***	9.295	16.95	24.99***	36.94***	28.87***
	(7.297)	(19.21)	(12.73)	(4.917)	(4.900)	(6.412)
$lnMigStock_{odt-1}$	0.209	0.254	0.100	0.0231	−0.0008	−0.175
	(0.324)	(0.264)	(0.243)	(0.0967)	(0.0966)	(0.114)
$lnUnemp_{dt-1}$	−0.325	−0.736	−1.122	0.0569	−0.069	−0.148
	(0.934)	(1.259)	(1.075)	(0.527)	(0.298)	(0.270)
$lnInterdec9050_{dt-1}$	−2.169	5.018	0.958	−12.87**	−15.68***	−14.73***
	(4.996)	(11.51)	(8.864)	(6.551)	(5.203)	(4.487)
Constant	−32.83**	−11.57	−22.69	−32.55***	−50.18***	−37.48***
	(12.80)	(31.09)	(20.13)	(7.036)	(6.526)	(9.003)
Origin-nest-time FE	yes	yes	yes	yes	yes	yes
Origin-dest FE	yes	yes	yes	yes	yes	yes
Observations	1,020	1,020	1,020	1,020	1,020	1,020
Pseudo R^2	0.988	0.989	0.991	0.123	0.129	0.131

Notes: Standard errors are clustered at the destination-time level. ***, **, and * indicates significance at the 1%, 5%, and 10% level.

that destination countries with higher GDP per capita (relative to the origin country) see a greater inflow of skilled migrants, which carries over to a higher percentage of skilled migrants in the total migrant inflow. Low unemployment rates, low inequality, and a high stock of migrants from the same country of origin in the destination country are all associated with an increase in skilled migration, but none of them are significant. While this could indicate that, e.g., high-skilled migrants may rely less on migrant networks, our regression analysis 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 each panel only has three observations.

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_{odt}		
	(1)	(2)	(3)	(4)	(5)	(6)
MPS^{skill}_{dt-5}			−0.00531			−0.0293**
			(0.00534)			(0.0121)
MPS^{res}_{dt-5}		0.205***	0.217***		0.227***	0.166***
		(0.0158)	(0.0208)		(0.0358)	(0.0477)
MPS^{nat}_{dt-5}			−0.172***			0.0886
			(0.0563)			(0.0885)
MPR_{dt-5}	0.804***	0.0871	0.0262	0.111	−0.389*	−0.582***
	(0.135)	(0.0618)	(0.060)	(0.299)	(0.207)	(0.217)
$lnGDPpc_{odt-1}$	5.963***	−1.003*	−0.498	7.857***	−2.012	−1.142
	(1.360)	(0.569)	(0.654)	(2.876)	(1.789)	(2.022)
$lnMigStock_{odt-1}$	0.353***	−0.0571	−0.0477	0.157	−0.0717	−0.0543
	(0.0728)	(0.0600)	(0.0602)	(0.131)	(0.111)	(0.145)
$lnUnemp_{dt-1}$	−1.383***	−0.0570	0.0401	−0.397	0.691*	0.595
	(0.257)	(0.134)	(0.140)	(0.444)	(0.371)	(0.403)
Constant	−3.395	10.02***	9.455***	−13.12**	−1.362	−1.444
	(3.156)	(1.752)	(1.735)	(5.141)	(3.082)	(3.499)
Origin-nest-time FE	yes	yes	yes	yes	yes	yes
Origin-dest FE	yes	yes	yes	yes	yes	yes
Observations	878	878	878	878	878	878
Pseudo R^2	0.993	0.994	0.994	0.213	0.215	0.215

Notes: Standard errors are clustered at the destination-time level. ***, **, and * indicates significance at the 1%, 5%, and 10% level.

As far as migration policies are concerned, 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 (significant at the 1% level). Somewhat surprisingly, we do not find a significant association between skill selectivity and the inflow of skilled migrants. However, it does significantly raise the fraction of the highly skilled in the bilateral flows (column 6). The reason for this is that the skill selectivity seems to decrease the total bilateral migration flows (Table 5). Since the structure 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 increases when countries select more strongly based on skill level. Specifically, a mid-level legislative change is associated with an increase in the fraction of the high-skilled of 8% per year.[35]

[35] 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

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

	Scale equation		
	M_{odt}		
	(1)	(2)	(3)
MPS^{skill}_{dt-1}			−0.00237
			(0.0035)
MPS^{res}_{dt-1}			−0.0250***
			(0.0066)
MPS^{nat}_{dt-1}		0.0604***	0.0624***
		(0.0225)	(0.0214)
MPR_{dt-1}	0.0564	0.0434	−0.0461
	(0.0609)	(0.0602)	(0.0730)
$lnGDPpc_{odt-1}$	2.406***	2.353***	2.645***
	(0.576)	(0.585)	(0.601)
$lnMigStock_{odt-1}$	0.203***	0.204***	0.196***
	(0.0353)	(0.0353)	(0.0346)
$lnUnemp_{dt-1}$	−0.451***	−0.442***	−0.481***
	(0.0824)	(0.0844)	(0.0838)
$lnInterdec9050_{dt-1}$	1.747**	1.765**	1.738**
	(0.776)	(0.778)	(0.765)
Constant	3.793***	3.660***	3.704***
	(0.904)	(0.903)	(0.916)
Origin-nest-time FE	yes	yes	yes
Origin-dest FE	yes	yes	yes
Observations	27,839	27,839	27,839
Pseudo R^2	0.984	0.984	0.984

Notes: Standard errors are clustered at the destination-time level. ***, **, and * indicates significance at the 1%, 5%, and 10% level.

As postulated by Bélot and Hatton (2012), we find that other aspects of migration policy play an important role in determining high-skilled migration flows. The scale of high-skilled migration is positively affected by nationality-based selectivity. This positive effect of nationality selectivity on the *scale* of skilled migration also passes through to the *share* of skilled migrants in the net inflow. Resource selectivity has a small, albeit insignificant, negative association with the scale of high-skilled migrants.

estimated effect of this agreement is equal to $\mathbb{E}(\hat{y}) = (e^{0.27*3}) - 1 = 46\%$ over 5 years, or $(1.46)^{1/5} - 1 = 7.9\%$ per year.

However, because it has a much stronger negative impact on the total bilateral migration flows, it still raises the share of high-skilled migrants.[36]

In contrast with a number of recent contributions on the impact of skill selectivity (in particular Bélot and Hatton, 2012; Czaika and Parsons, 2017), our results hence do not affirm a significant correlation between skill selectivity and the total inflow of the high-skilled, even though their share in total migration does increase. There are several differences in the analysis that may explain these disparate findings. First, different definitions are used for high-skilled migrants; e.g., Czaika and Parsons (2017) use an occupation criterion rather than education. Second, our study examines a different 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 different, with Bélot and Hatton (2012), for instance, estimating a log-linear model. Finally, there is substantial disparity in how policy measures are categorized. For instance, in their definition of supply-oriented skill selectivity, Czaika and Parsons (2017) include bilateral labor 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, more selective skill-based policies are not associated with an increase in the number of higher educated foreigners.[37] 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 3.2). As such, our finding of an insignificant effect 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 by almost 40%. When included, it has no significant impact in the scale equation and its omission leaves most other variables unaffected.[38]

The remaining control variables have the expected signs when significant. The relative income per capita and migration networks have a positive and significant

[36]The parameter estimates of the other variables of the structure equation (column 6) are also coherent with those of the respective scale equations. The income gap has a significant positive effect, resulting in a positive effect on high-skilled migration and a positive but much smaller effect on total migration flows. The migration network has a negative effect on the share of high-skilled migrants due to its positive impact on total flows. Income inequality has a significant negative impact on the structure of high-skilled migrants that follows from a strong positive effect on the total flows. Finally, the unemployment rate's negative impact on both the scale of high-skilled migration and the total flows results in the insignificant impact on the structure of high-skilled migration.

[37]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 labor market shortages.

[38]Including inequality does remove skill selectivity's significance, although this is at least in part due to sample selection effects. Results are available upon request.

effect, while unemployment in the destination country has a negative effect. These do lose their significance in our preferred specification (columns 3 and 6).

Migration policy selectivity affects the scale and structure of the migration of managers and businesspeople. As expected, 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 4% per year. Second, migration of the economically well-endowed is negatively associated with skill selectivity. Together with the negative (but insignificant) effect of resource selectivity on the migration of the high-skilled (see Table 3), this hints at the existence of skill substitution effects from migration policies as discussed, e.g., by Stark *et al.* (2017).

The estimated parameters of the structure regressions (columns 4-6) closely resemble those of the scale regressions. Similar to skilled migration, after controlling for fixed effects, 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 and even becomes significant at the 5% level, which makes sense as the skill selectivity has no significant effect on the total migration flows. The positive scale effect of resource selectivity also retains its sign and significance. Lastly, the impact of selectivity in terms of nationally loses its significance.

5.3 Migration by nationality

Table 5 shows the estimation results for the association between migration policy selectivity and 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. Moreover, the regressions for migration by nationality rely on yearly instead of 5-yearly data, allowing the use of shorter lags on the migration policy variables.

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 characterization (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 1-3 in Table 5). Bilateral migration flows are larger between countries with more dissimilar incomes. In contrast, significantly fewer migrants move to destinations with less favorable 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 2.5% increase in the bilateral migrant inflow.

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 effect, 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 labor 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 20 to 30%.[39]

Overall, the effect of the selectivity tends to outweigh that of the overall restrictiveness in both the scale and structure regressions. Overall policy restrictiveness only seems to consistently affect 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.

5.4 Robustness

This section provides an overview of the various robustness checks that were performed on the computation of the selectivity indexes and their subsequent analysis.

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.

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.

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 with the average of the indicators created in Parsons *et al.* (2020). Appendix Table A-5 shows the results for each of the three migration flows using the preferred specification. There are two notable differences. First, the parameter values are higher than those using our skill index, but this is entirely due to the differences in the range of the indexes. Parsons' index is 15 times larger than our skill selectivity index over the sample considered in the regressions. Second, when using Parsons' index, the impact of skill selectivity on the scale of the high-skilled migration flows is now positive and

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

significant. However, if we repeat the analysis using our index on the sample used in Table A-5, we find a similar positive and significant impact (see Appendix Table A-6).

Fifth, our policy variables were lagged such that they capture the policy stance at the starting period of the change in migration stocks: i.e., we used the 5-year lags for the skills and resources regressions and the 1-year lag for the nationality regressions. Shortening the lags on the first two specifications is not advisable as this could lead to simultaneity issues. Using longer lags resulted in qualitatively similar results (Appendix Table A-7). In addition, 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 effect, we would have to estimate a much more complex model, e.g., taking a local projection approach to incorporate 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. First, re-estimating our model with the standard errors clustered at the origin-time level had no meaningful impact on our results (see Appendix Table A-8).

Second, while the baseline specification included origin-nest-time fixed effects, it did not completely 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 Appendix Table A-9, the impact on the nationality coefficients is not negligible, particularly in the nationality regressions where it loses its significance. However, this is at least in part due to sample selection issues since the parameter remains positive and significant when we restrict the sample to that used in the baseline estimations (see Appendix Table A-10).

Third, we also accounted for other ways of grouping the destination countries. In particular, two alternative nest definitions were considered: the first one only distinguishes between European and non-European countries; the second one groups together the Anglo-Saxon, Scandinavian, other European Union countries, and the rest of the world.[40] As both alternative definitions give the same results, we only present those using this last definition in Appendix Table A-11. The only notable change compared to the baseline results is that the selectivity based on nationality loses its significance in column 5.

Finally, we also ran the model using the original DIOC data. As can be seen in Appendix Table A-12 the results are mostly unaffected except for the exclusion of some of the control variables due to data availability issues.

6. Conclusions

Using data from the DEMIG Policy database, augmented with data on bilateral labor agreements, immigrant investor programs and economic citizenship programs, 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

[40]This last group consists of Mexico, Japan, Chile and Israel.

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 characterization 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 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 relates to the size and structure of migration flows. These regressions uncover intricate interconnections between migration policy selectivity and the scale and structure of bilateral migration flows. All three types of selectivity reveal both direct and indirect interactions with the targeted migration flows, and we find evidence for substitution effects in skill and resource selectivity.

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. 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.

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