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Migration pathways into Europe — An assessment of drivers and policies

Deliverable 5.7

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1 Introduction

More than 2.5 million non-EU migrants entered the EU28 countries in 2019 by regular (legal) means (Eurostat, 2022). The main regular means by which non-EU migrants enter the EU is through a first residence permit or an asylum application. However, not all people who wish to migrate to the EU or an EFTA country are able to enter through a residence permit or the asylum route. In 2019, nearly 700,000 people tried to enter the EU by irregular means and were denied entry to the EU at the external borders (Eurostat 2022). That is to say, over three million non-EU third-country nationals migrated or tried to migrate to the EU and EFTA in 2019 through various regular or irregular entry routes.

Czaika, Bohnet and Soto Nishimura (2021) have analyzed spatial and categorical dependence of bilateral migration flows into Europe, indicating that migration flows of a particular migration category (labor, family, education, and asylum) are spatially associated with flows of the *same* legal migration category to other destination countries. Besides spatial dependence, they also found evidence for so-called categorical dependence between alternative migration flow of varying magnitudes between labor, asylum, education and family migration flows into 31 EU and EFTA countries. Similarly, Barslund, Di Salvo, and Ludolph (2019) found that the number of family and education permits issued was associated with a decrease in irregular migration from Africa to the EU-15 from 2009-2016.

This study aims to identify whether and to what extent different modes of entering a European destination country share similar sets of migration drivers or respond differently to migration policy changes. A significant body of literature has been devoted to the role of various drivers of migration and migration policy, but much of the large N empirical analysis of migration flows has been on total migration flows because migration data is often aggregated across alternative entry modes (Migali & Natale, 2017; Ortega & Peri, 2013). Less often have there been analyses investigating the drivers on specific legal categories of migration such as high-skilled migrants (Czaika & Parsons 2017), international students (Abbott & Silles, 2016), asylum seekers (Hatton, 2016), but also attempts for irregular entry (Czaika & Hobolth, 2016). The lack of comparative empirical analyses on multiple categories of migration flows is the reason for limited understanding of the relative importance of migration drivers for alternative forms of migration and modes of entry. Moreover, the relevance of specific migration drivers and policies is difficult to assess when, across migrant categories, time periods, countries, sets of drivers, and estimation techniques, analyses differ. To date there has been little systematic comparison of the effect of multiple drivers of migration across multiple legal migration flow categories.

This paper aims to fill this gap by assessing a comprehensive set of the most common migration drivers studied in the literature on the flow of international migrants through five regular and irregular modes of entry (i.e., legal categories) into 32 European countries of destination. The five modes of entry, identified by the type of entry permit, refer to family, labor, student, asylum, and irregular immigration. A second aim of this paper is to analyze the so-called categorical substitution or deflection effects (cf. Czaika & de Haas, 2013; de Haas et al., 2019) that migration policies may cause between these five legal categories of immigration. For example, we assess whether and to what extent migrants are more prone to migrate by means of one legal category over another category when certain migration policy areas turn more, or less, restrictive.

We aim to identify the effects of migration policy changes on the categorical composition of total immigration flows into 32 European destinations between 2008-2019. We further assess changes in (bilateral) visa policy restrictions on the number of immigrants by legal category. These policy effects are assessed in the context of broader structural changes across a large range of migration driver categories as reviewed and typologized in Czaika and Reinprecht (2022). Structural drivers may not only affect (i.e., facilitate or constrain) gross migration flows but may also affect their composition by influencing the choice of legal pathway migrants may (have to) decide upon their migration journey. We employ pseudo-poisson maximum likelihood as well as fractional multinomial logit models to assess the extent to which alternative configurations of migration policies and structural migration drivers affect category-specific, and consequently, the overall composition of total migration inflows into 32 European destination countries between 2008 and 2019.

We understand that reasons for migrating are multiple and complex regardless of what legal category an individual migrant may fall into (Aksoy & Poutvaara, 2019; Czaika, Bijak, & Prike, 2021). For instance, the decision to apply for a student visa could be because it was simply easier to obtain than, for example, a work visa. Migration categories are deeply politicized in the context of European migration particularly around the case of "real" refugees and "economic" migrants. Crawley and Skeparis (2018, 52) point out that "that there is nothing 'natural' or 'fixed' about the legal and policy categories associated with international migration: rather these categories are in a constant state of change, renegotiation and redefinition". The politicization of migrant categories is reflected in public attitudes towards immigrants which vary by category of migration (Abdelaaty & Steele, 2022) as well as the demographic characteristics of migrants (Ford, Jennings & Sommerville, 2015). Given this context we find it necessary to emphasize that we reject any notion that any category of migrant, including "irregular" migrants, is more deserving, more desirable, more legitimate, or better than another. We also wish to make it clear that any statistical effect that a certain driver of migration has on a particular category of migration does not illegitimatize a migrant category. For instance, economic drivers may be relevant in explaining inflows of asylum seekers, family, or student migrants, etc., yet statistically 'relevant drivers' are irrelevant to the definitions of these categories and does not mean that people who migrate through these categories are per se "bogus" asylum seekers, family migrants, or student migrants.

The remainder of the paper is structured as follows. Section 2 presents and discusses some relevant literature on migration policies and drivers on migration in general, and some more specific migration categories. We further discuss the existence and relevance of so-called categorical substitution between migration categories as a result of migration policy changes. Section 3 provides a description of data and the analytical strategy, Section 4 discusses the results of two alternative empirical strategies, and Section 5 concludes.

2 Migration drivers and policies: effects on modes of entry

2.1 Migration driver effects

Migration drivers usually operate in complex combinations or configurations. A recent meta-analysis of a large body of migration driver analyses has identified and typologized at least two dozen of distinct migration drivers operationalized in hundreds of small and large N empirical analyses (Czaika & Reinprecht 2022). Depending on the legal category of migration, or mode of entry, the underlying driving factors may differ in their configuration and relative importance. Nevertheless, many studies that analyzed different categories of migration often still use similar migration driver indicators. For example, Qi and Bircan (2021) analyze overall migration flows, Nowak-Lehmann et al. (2022) analyze asylum applications, and Didisse et al. (2019) analyze student migration, but all studies include GDP per capita as the contextual economic indicator in their analysis. What typically differentiates analyses that focus on a particular migrant category from analyses of other categories is, in addition to a core set of drivers, the inclusion of a few supplementary drivers that are hypothesized to be specifically important to the particular migrant category. Two such examples would be, for instance, university rankings for explaining international student migration, or asylum recognition rates as indicator for explaining the number of asylum applicants (Didisse et al., 2019; Nowak-Lehmann et al., 2022). Such category-specific drivers are usually not included in the analysis of other migrant categories or for overall migration flows.

In summarizing a large body of migration driver analyses, Czaika and Reinprecht (2022) propose a taxonomy of nine driver dimensions including economic, demographic, environmental, developmental, politico-institutional, security-related, socio-cultural, and supranational, which are incorporated and tested in our empirical driver analysis (cf. Table 1). Migration drivers are usually not equally relevant to all forms of migration but found to have some greater relevance to certain legal migration categories. For instance, labor market conditions in destination countries are known to influence labor immigration flows as difficult conditions make it harder for labor migrants to find work (Martin, 2009). However, it is less obvious what effect labor market conditions may have on the inflow of student migrants, family migrants, or asylum seekers, who are often classified as non-economic migrants. It is assumed that economic drivers are of secondary importance to asylum and irregular migrants (Van hear et al., 2018). Similarly, political terror and repression in countries of origin is thought to increase asylum applications and irregular migration, but it is less clear what effect that has on labor, family, and student migrants (Hatton, 2012; Hatton 2020). It is well established that migrant networks, usually measured by the magnitude of bilateral migration stocks, facilitate overall inflows as well as inflows of specific migrant categories like labor migration (Migali & Natale, 2017), family members (ibid), asylum seekers (Keogh, 2013; Nowak-Lehmann et al., 2022; Toshkov, 2014), students (Abbott & Silles, 2016; Beine, NoÎl, & Ragot, 2014; Didisse et al., 2019; Kaushal & Lanati, 2019; Ovchinnikova et al., 2022; Perkins & Neumayer, 2014), and irregular migrants (Czaika & Hobolth, 2016). While highly relevant for all groups, we hypothesize that it is most relevant for asylum, irregular, and family migrants who may need to draw on the resources of their compatriots more so than other groups of migrants.

The five major migration categories that are often studied and that we also study in the subsequent analysis, and therefore review here, are asylum, labor, family, student, and irregular migration. Asylum migration is widely studied empirically, Hatton (2012, 2020) provides a comprehensive review of the literature. Conflict, violence, networks, livelihood conditions, bilateral asylum recognition rates, which is a driver not found in the analysis of other categories, is found to be as an important driver (Keogh, 2013; Nowak-Lehmann et al., 2022; Toshkov, 2014). Policy specific to asylum is also considered an important driver but less featured in the literature due to difficulty in operationalizing the variable (Di Iasio & Wahba, forthcoming). War, political and civil repression, and democracy are not unique to the analysis of asylum flows but are emphasized more here than in other migration categories. In the analysis of asylum applications to OECD or EU countries, conflict and war have not been consistently found to be significant drivers. There is more support for political terror and repression of civil liberties as a driver than war, which is often operationalized by battle deaths (Abel et al., 2019; Hatton, 2016; Nowak-Lehmann et al., 2022). Or the influence of democratic institutions in either origin or destination countries is not consistent across studies. Like for other (non-asylum) forms of migration, drivers such as distance, bilateral migration stock, and destination unemployment are consistently found to be relevant in explaining (or, predicting) the number of asylum applications (Hatton, 2020; Nowak-Lehmann et al., 2022; Paniagua, et al., 2021). Origin country income levels have not found consistent support as a driver of asylum applications (Hatton, 2020), while destination income levels (GDP per capita) have found some support but appear to be less relevant compared to non-asylum migration flows (ibid).

Several studies analyze the drivers of migration, or 'mobility' of international students enrolled in higher (tertiary) education programs. Findings for certain drivers are consistent with the analysis of other migration categories. For instance, social networks, usually operationalized by the bilateral stock of migrants, colonial ties, shared or proximate language, are robustly found to increase international student flows, while geographical distance tends to decrease those flows (Abbott & Silles, 2016; Beine, NoÎl, & Ragot, 2014; Didisse et al., 2019; Kaushal & Lanati, 2019; Ovchinnikova, Mol, & Jones, 2022; Perkins & Neumayer, 2014). Findings are mostly mixed regarding economic factors. For instance, higher origin GDP is associated with increased outflows in the analysis of Kaushal and Lanati (2019), but the opposite effect was found in the analysis of Didisse et al. (2019). Perkins and Neumayer (2014) and Abbott and Silles (2016) find opposite effects for the economic gap between origin and destination GDP on student migration flows with the latter (former) finding a positive (negative) effect of an income gap on student migration flows. Both studies find for the category-specific driver 'university rankings' a positive but not consistently significant effect on student flows (Abbott & Silles, 2016; Perkins & Neumayer, 2014).

Studies on labor migration often analyze migrants of a specific “skill” category. For example, Czaika and Parsons (2017) analyze the inflow of high-skilled migrants to OECD countries and find that destination unemployment rate and distance decrease inflows while higher wages in destination, bilateral stock, colonial ties, and common languages increase inflows. Gross and Schmitt (2012) analyze migration drivers for high-skilled, intermediate-skilled and low-skilled immigrants to France between 1983-2000. Their results indicate that for low and intermediate skilled migrants the bilateral migration stock is associated with increasing inflows, and the unemployment rate in France is associated with decreasing inflows. For all skill levels, higher origin country income levels in terms of GDP per capita is associated with decreasing inflows to France. In their analysis of the number of migrant worker permits issued in EU countries, Migali et al. (2018) find that distance and higher unemployment rate in destination countries is associated with a decreasing number of migrant workers while larger bilateral migration stocks are associated with an increase in migrant workers. On the other hand, origin country income levels do not have a statistically significant effect in their analysis.

The empirical literature on country level drivers of family migration is scant. Most of the literature focuses on individual and familial level characteristics. González-Ferrer (2007) analyzed the timing of migration (reunification) of wives to join their husbands in Germany. They found that higher female unemployment rate in Germany and higher origin country GDP growth delayed the migration process while higher origin country GDP growth accelerated the migration process. Higher origin country GDP also accelerated the migration process for children to join their parents in Germany. Viné (2021) analyzed family migration from Africa to Europe and find that costs of living in the destination country, greater distance, and shared language slow down the migration process. Origin country GDP per capita, colonial ties, and (surprisingly) more restrictive entry policies accelerated the migration process.

Migali and Natale’s (2017) results on the inflow of student, family, labor, and asylum migrants suggest there are differences in the direction and strength of migration drivers for different migration categories. Higher unemployment rates in destination country are associated with decreases in all categories, except for the student category in some specifications, but strongest for family and labor migration. On the origin country-side, higher unemployment rates are associated with more outmigration, particularly of family and asylum migrants.

Empirical analysis of the drivers of irregular migration are scarce in the context of irregular migration to Europe. Irregular migration is sometimes assessed with a focus on policy (deflection) effects (Czaika & Hobolth, 2016). Migration policy and border security are the heavily emphasized drivers because it is assumed that individuals would be more likely to migrate through regular as the difficulty of doing so decreases. Border security and enforcement policies is unique to the analysis of irregular migration because it often plays a role in the number of irregular migrants ultimately counted.

2.2 Migration policy effects

Since 1990 there have been two distinct trends in internal European-wide migration policymaking with border and return policies becoming increasingly restrictive while integration and entry (or, admission) policies have increasingly been liberalized (Czaika, Bohnet, & Zardo, 2021). Generally, more restrictive migration policies reduce inflows but the extent and the compositional effect on total inflows inconclusive (de Haas et al., 2019; Czaika & de Haas, 2013).

Migration policy changes may not only have an overall effect on total inflows, but also varying effects across specific migration categories. Several studies suggest that more restrictive migration policies make the ability to migrate to a particular destination country more difficult or less appealing for all categories of migrants with overall more restrictive immigration policies leading to a decline in overall immigration flows (Czaika & de Haas, 2017; Mayda, 2010; Ortega & Peri, 2013). Yet the effects of generally more restrictive migration policies on *individual* migration categories are not necessarily equal. Migali and Natale (2017), for instance, analyze the effect of migration and labor market policy, respectively, on the inflow of family and labor migrants. Their results indicate an association between less restrictive policies and increased migrant inflows of both categories. Finotelli and Sciortino (2013) find a negative effect of overall restrictive migration policies on asylum applications. Di Iasio and Wahba (forthcoming) analyze the effect of policies specific to asylum applicants' rights to social welfare and labor market access. They find that less restrictive policies of this kind are associated with an increase in asylum applications. Thus, we may assume that overall (or, average) trends towards migration policy restrictiveness is more relevant for asylum and irregular migrants than for other immigration categories also because of the trend over the last two decades of increasingly restrictive border and return policies which were concomitant with increasingly liberal integration and entry policies.

Visa policy as bilateral migration policy instrument has hereby some specific features. Torpey (1998) referred to visa travel restrictions as the “first line of defence” in controlling migration. Visa restrictions are often used to prevent the entry of potential asylum seekers and potential “visa overstayers” (Schoorl et al., 2000). As Migali and Natale (2017) point out that visa travel restrictions do not have a direct influence on the number of residence permits but might represent a cost for moving from a given origin country destination country. This cost could be in the form of an information cost where perspective migrants may prefer a location where they can travel to more easily to gather information before the migration or that their friends and relatives could visit more easily in case the individual does migrate to a destination country. Additionally, visas are thought to have a symbolic expression of power as it creates a highly visible prioritization of those who do not need a visa and those who do need one (who are then usually subject to more stringent checks) (Czaika, de Haas & Villares-Varela, 2018). Studies on the effects of visa policy have found that more restrictive policies reduce overall migration inflows (Czaika & de Haas, 2017), family, labor, and student migrants (Migali & Natale, 2017), asylum applicants and possibly also of irregular migrants (Czaika & Hobolth, 2016). We therefore hypothesize that the requirement of a visa for travel decreases migration inflows for all migration categories.

Besides the direct effect visa policy may have on total inflows we are interested in the impact on the composition of inflows. Liberal travel visa policies could be used as an entry point for irregular and asylum seekers (Czaika, Erdal & Talleraas, 2021). Therefore, we hypothesize that travel visa requirements change the composition of migration flows in such a way that the share of asylum and irregular migrants decreases, while the relative size of the other migration categories increase. Czaika, Erdall and Talleraas (2021) note that migration policies are embedded within larger and cross-scalar migration driver environments. They argue for more investigation into interaction effects between migration policy and other migration drivers. We hypothesize that visa policy restrictions are more binding in contexts where other migration facilitating factors (such as migration networks) are rather weak.

Migration policies may not only have direct effects on migration outcomes but may often also result in rather indirect and unintended effects, so-called substitution effects. De Haas (2011) identifies four types of substitution effects that can limit the effectiveness of immigration restrictions: (a) spatial substitution through the diversion of migration to other countries; (b) categorical substitution through a reorientation toward other legal or illegal channels of immigration; (c) inter-temporal substitution affecting the timing of migration, such as 'now or never migration' in the expectation of future tightening of policies; and (d) reverse flow substitution if immigration restrictions reduce not only inflows but also return migration, which can make the effects on net immigration rather ambiguous.

In the remainder of this study, we focus on categorical substitution effects, that is shifts in the composition of total migration flows directed to a particular destination. When past literature has focused on categorical substitution it is primarily about legal to irregular deflections or substitution of non-asylum by asylum inflows (Clemens & Gough, 2018; Czaika & Hobolth, 2016; Belmonte et al., 2019). Focusing on irregular flows to European countries, Czaika and Hobolth (2016) found that an increase in the asylum rejection rate raises the number of irregular migrants by 2-4 percent while increases in short-stay visa rejections led to a 4-7 percent increase in irregular migrants. Belmonte, McMahon, Scipioni, and Tintori (2019) looked at substitution effects from permits to asylum or irregular migration focusing on bilateral migration corridors including Morocco-Spain, Nigeria-Italy, Albania-Germany, and Pakistan-UK between 2008 and 2018. Their analysis concludes for Morocco-Spain and Albania-Germany corridors only minor categorical substitution effects of rising irregular migration or asylum applications because of less residence permits. Clemens and Gough (2018) conclude that regular pathways for migration from Mexico to the USA suppress irregular migration when combined with large border enforcement efforts and control of destination employer incentives.

Based on a large N dataset on bilateral migration flows of multiple categories to 28 EU destinations, Czaika, Bohnet and Soto-Nishimura (2021) find evidence that migration flows of various legal categories are not only spatially dependent across destination countries but are also categorically dependent within destination countries. For instance, they find that especially family migration is a cross-cutting legal category that is structurally connected to flows of the other legal pathways. Yet also education and labor migration flows, as well as asylum and family migration, are found to be categorically interconnected. These hypotheses are put to test in the following analysis.

3 Empirical strategy: data and method

3.1 Migration flows across categories: data and patterns

Our analysis is based on data capturing annual migration inflows by legal category as well as multiple migration policy indicators and a comprehensive set of structural drivers. For measuring inflows, we use annual EU first residence permit data, asylum applications, and a proxy indicator for the number of irregular entries in the period 2008-2019. The following analysis provides a brief sketch of the categorical patterns of migration inflows across 32 European destination countries during this period. For this analysis we use bilateral migration flow data of different legal entry and residence categories of migration into the EU28 and four EFTA countries. The migration categories of education, family, and labor come from the Eurostat first permits dataset (Eurostat 2022a)[1]. First time asylum applications primarily come from Eurostat asylum dataset (Eurostat 2022b)[2]. In cases where first time applications data was missing in the Eurostat dataset, UNHCR asylum application data is used instead. As a proxy of irregular migration, we use data on third country nationals refused entry at the external border (Eurostat 2022c)[3]. Besides an analysis of these five specific migration categories separately, we also analyze the aggregated total inflow of third-country nationals across the five categories. For comparability reasons, we count total flows as missing if there is missing data in one of the five individual flow categories.[4]

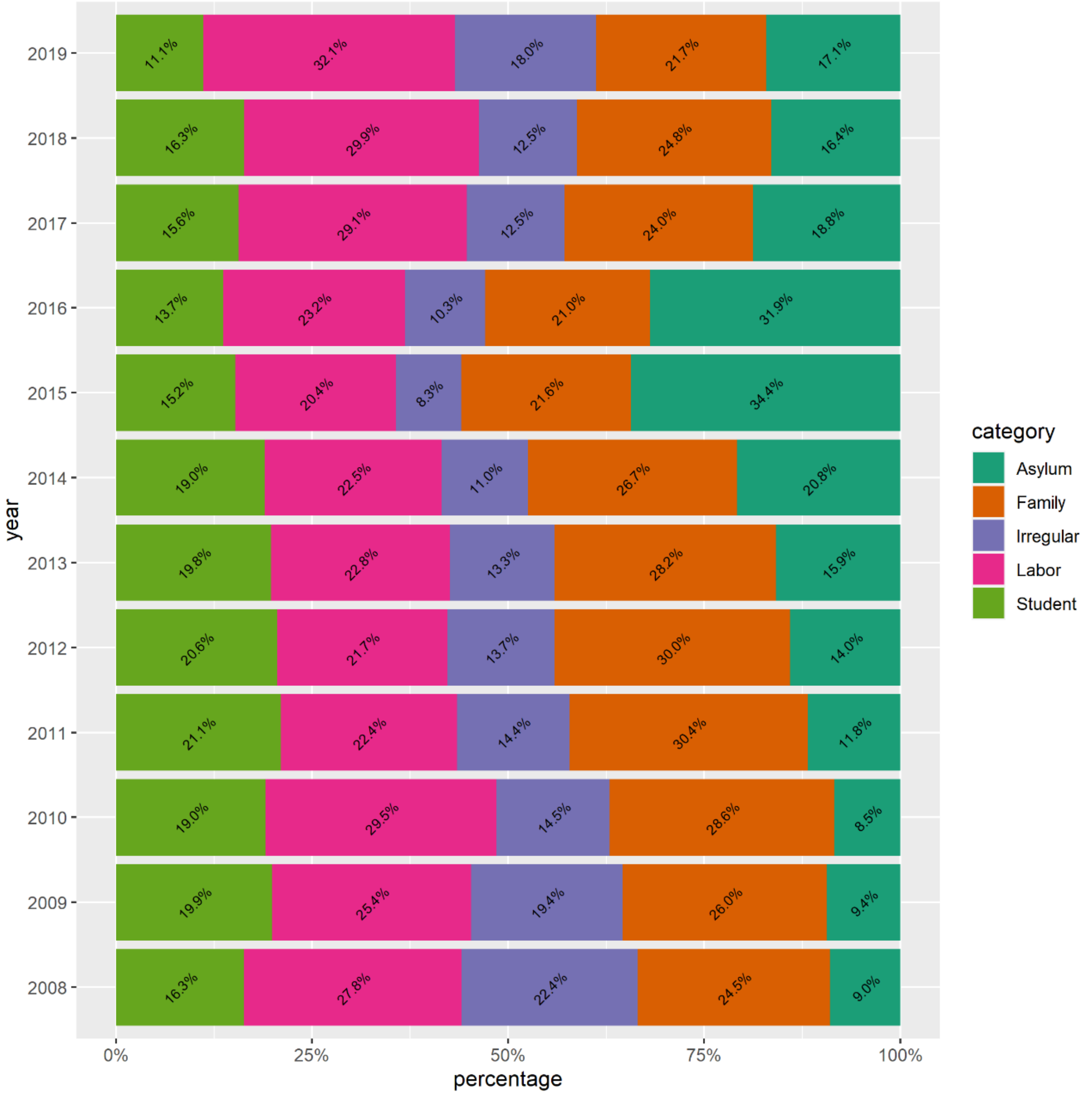
[1] Data source: https://ec.europa.eu/eurostat/databrowser/view/MIGR_RESFIRST
First permit data is a proxy for flow data as it does include renewed permits. To be considered as first, the validity of the new permit has to start at least six months after the cessation of the validity of the old permit Eurostat (2015).
[2] Data source: http://appsso.eurostat.ec.europa.eu/nui/show.do?wai=true&dataset=migr_asyappctza.
This variable captures first asylum applications and excludes appeals.
[3] Eurostat (2022): https://ec.europa.eu/eurostat/web/products-datasets/-/migr_eirfs
[4] This primarily concerns destination countries which were always missing data from one of the datasets for a specific year. Luxembourg in 2008 is missing permit data, Croatia is missing permit and irregular data from 2008-2012, Switzerland is missing permit data from 2008-2011, The UK is missing permit data in 2019, and Liechtenstein is missing permit data from 2008-2012.

The five migration categories that we consider in this analysis include first permits for family formation or reunification. This primarily concerns the spouses, children and other family members of EU-citizens or third country nationals (Eurostat, 2015). The labor category includes high-skilled workers, EU-Blue cards, researchers, seasonal and other migrants who are authorized to work in the EU. The education category consists of students admitted to full-time higher education courses, unremunerated trainees, volunteers, and school pupils. The asylum category includes first time asylum applicants. Data on irregular migrants is proxied by the number of apprehensions at border, which is de facto an underestimated number of the actual but unknown entry of irregular migrants as their number depends on the amount, quality and effectiveness of government resources dedicated to detecting irregular migrants (see discussion in Czaika and Hobolth 2016).[5]

Figure 1a shows how the composition of total inflows has changed over time for all 32 European destination countries. A significant trend is that labor permits have made up an increasing percentage of the total composition since reaching its low in 2015. This seems to primarily be due to the surge and then fall in asylum applications in 2015 and 2016. Student permits reached its lowest share in 2019 which may be because in that year data from the UK is missing. In general, migration composition of inflows into Europe is relatively stable, and to some extent even well-balanced between the different legal entry categories. This, however, is only true on aggregate, yet across individual European destinations, variation between migrant categories is substantive (Figure 1b). Categorical variation across destinations is significant, often reflected by the fact dominant entry categories vary significantly across European destination countries. One example is the case of Ireland where nearly 59 percent of the migration flow is made of students while in the case of Greece student migrants comprises less than 2 percent of the migration flow. Assessing the underlying drivers of these compositional patterns is the objective of the subsequent analysis.

[5] The first permit dataset does include an "other" category that we exclude from this analysis. Some examples of people who fall into the other category include pensioners, people in international protection, people in the intermediate stages of a "regularization" process, and specific statuses that only exist under national legislation (Residence permits - statistics on first permits issued during the year, 2021). We decided to exclude this category because of the vast variety of reasons why migrants fall into this category. Additionally, there might be significant overlap with the asylum application category. Results from analyses where we use the other category instead of the asylum application category are available upon request.

Figure 1a: Overall migrant categorical flows total sample



Source: Own elaboration based on data provided by Eurostat (2021 a,b,c).

Figure 1b: Total overall migration flow composition, by country 2008-2019

Source: Own elaboration based on data provided by Eurostat (2021 a,b,c).

Table 1 presents the total number of observations, mean, standard deviation, minimum and maximum for each legal migrant category and the total overall flow (the sum of the categories). Of the legal migrant categories, the labor category has the highest mean, standard deviation, and maximum. Interestingly, the irregular category has the lowest mean but the second highest standard deviation. To add some context to maximum numbers, the country pair with the highest total flow is Ukraine-Poland in 2019, for asylum it is Syria-Germany in 2016, for irregular it is Morocco-Spain in 2008, for student China-UK in 2018, for family it is Morocco-Spain in 2019, and for labor it is Ukraine-Poland in 2019.

Table 1: Descriptive statistics of bilateral migration flow data per legal category

Variable	Obs	Mean	SD	Min	Max
Total	60455	587.7	7541,1	0	626524
Asylum	64259	107.3	1646.1	0	266250
Irregular	62411	80.3	4029.4	0	496435
Student	61254	97.9	1114.1	0	91215
Family	61254	146.3	985.3	0	39750
Labor	61254	150.9	4575.1	0	551109

3.2 Migration driver and policy data

The selection of the driver indicators is based on their theoretical relevance, ubiquity in the literature and data coverage. Czaika and Reinprecht (2022) distinguish nine broad migration driver dimensions, those being demographic, economic, environmental, human development, politico-institutional, security, socio-cultural, supranational, and migration policy (Table 2). We have aimed to identify at least one control variable for each of the nine driver dimensions covered by the analysis. The variables that we have selected include many of the most common variables in large N studies of international migration (Soto Nishimura, 2022).

Table 2: Migration driver dimensions

Driver dimension	Variable	Source	Obs	Mean	SD
Demographic	Total population in thousands- *Population_o*	CEPII Gravity dataset	74784	36707.8	142451.1
	Total population in thousands- *Population_d*	CEPII Gravity dataset	89856	16298.7	22072.8
	Population 18-35/total population- *Pop18-35_o*	UN population prospects, population by age dataset	81952	.287	.048
Economic	GDPPP- *GDPP_o*	CEPII Gravity dataset	63392	14.8	19.4
	GDPPP- *GDPP_d*	CEPII Gravity dataset	87048	502.8	2939.9
	GDP per capita growth- *GDPCGR_o*	World Development Indicators via Quality of Governance dataset	65024	1.999	5.362
	GDP per capita growth- *GDPCGR_d*	World Development Indicators via Quality of Governance dataset	87696	1.42	3.58
	Gini inequality index- *Gini_o*	Standardized World Income Inequality Database	63296	41.30	7.10
	Gini inequality index- *Gini_d*	Standardized World Income Inequality Database	87048	29.37	3.44
	Urbanization- *Urban_o*	United Nations World Urbanization Prospects	81952	57.79	25.68
	Urbanization- *Urban_d*	United Nations World Urbanization Prospects	89856	71.91	16.16
	Unemployment rate- *Unemploy_o*	World Development Indicators via Quality of Governance dataset	61024	7.51	5.93
	Unemployment rate- *Unemploy_d*	World Development Indicators via Quality of Governance dataset	87048	8.24	4.47
Environmental	People affected by natural disasters- *Disaster_o*	Emergency events database	89856	856420	9377191
Human Development	Education expenditure (% of GDP)- *EduExpend_o*	World Bank	65824	4.41	2.605
	Education expenditure (% of GDP)- *EduExpend_d*	World Bank	87048	3.87	1.26
	Physicians per 1000 people- *Doctors_o*	World Bank	63808	1.396	1.583
	Physicians per 1000 people- *Docotrs_d*	World Bank	89856	5.11	1.26
Politico-Institutional	Public corruption- *PubCorrup_o*	(Varieties of democracy dataset)	59776	.565	.271

	Public corruption-*PubCorrup_d*	(Varieties of democracy dataset)	87048	.119	.137
Security	Political terror index-*Terror_o*	Political terror scale-Amnesty International variable	55808	2.74	1.12
	Freedom of movement index- *FreeMove_o*	Varieties of democracy dataset	59776	.937	1.18
Socio-Cultural	Bilateral migrant stock- *MigStckBilat*	International migrant stock 2019 United Nations Population Division	81952	5319.0	41496.3
	Muslim population % of total population– *Muslim _o*	https://datahub.io/sagargg/world-religion-projections#r	82368	25.66	37.374
	Muslim population % of total population-*Muslim_d*	https://datahub.io/sagargg/world-religion-projections#r	89856	4.17	4.731
	Female to male labor gap- *LaborGap_o*	World Bank	63648	69.49	20.59
	Female to male labor gap- *LaborGap_d*	World Bank	87048	79.95	6.91
Supranational	Shared language- *Language*	CEPII Gravity dataset	77119	.07	.255
	Shared border- *Contiguous*	CEPII Gravity dataset	77119	.004	.062
	Bilateral trade flow- *TradeBilat*	CEPII Gravity dataset	70756	374400	2532952
	Distance - *Distance*	CEPII Gravity dataset	78273	7473.9	3956.4
	Colonial ties- *Colonial*	CEPII Gravity dataset	86539	.026	.16
Migration policy	Border policy- *Border* (destination countries)	DEMIG-Quantmig policy dataset	87048	4.307	5.18
	Admission policy- *Admission* (destination countries)	DEMIG-Quantmig policy dataset	87048	-5.55	5.11
	Integration policy- *Integrate* (destination countries)	DEMIG-Quantmig policy dataset	87048	-2.3	4.66
	Return policy- *Return* (destination countries)	DEMIG-Quantmig policy dataset	87048	2.256	4.574
	Overall migration policy- *MigPolicy* (destination countries)	DEMIG-Quantmig policy dataset	87048	-16.42	29.04
	Visa policy- *Visa*	DEMIG visa dataset	79540	.61	.488

Note: Variable names are in italics. The _o and _d at the end of variable signifies an origin county variable and destination country variable respectively. Data for Romania for total population and GDPPP comes from the World Bank.

The included independent control variables, proxying the nine fundamental driver dimensions are listed in Table 1 and include variables both on the origin and destination side. Political terror *(Terror)*, freedom of movement index (*FreeMove)*, the number of people affected by natural disasters (*Disasters*), and the young population cohort (age 18-

35) divided by total population (*Pop18-35*) only appear as origin controls. We have little reason to believe that these variables would be relevant as destination country controls. Political terror and freedom of movement represent forms of insecurity and repression. We would expect higher values (more terror, less freedom) to be associated with higher migration outflows. However, it is possible that both simultaneously decrease people's capacity to migrate (de Haas, 2011). People affected by natural disasters represent a displacing force, so we expect higher values to be associated with higher migration outflows. It is well established that young adults are more likely to migrate than older adults (Plane, 1993). Hence, we expect higher values for *Pop18-35_o* to be associated with higher migration outflows. For the origin country economic control variables, we expect worse economic conditions (higher unemployment rate and Gini inequality index) to be associated with higher migration outflows, and better economic conditions (higher GDPPP, urbanization, and GDP per capita growth) to be associated with lower migration outflows (Fitzgerald, 2014). We reverse these expectations for the destination country economic control variables where better economic conditions should be associated with higher migration inflows and worse economic conditions associated with lower migration inflows. GDPPP squared (GDPPP_osq), not listed in table 1, is an additional control variable that only appears as an origin control as it could be the case that very poor and very high economic conditions reduce migration outflows.

In the case of very poor economic conditions, it may be difficult to gather resources for a costly migration journey, and in the case of very good economic conditions it may be less desirable to take on the journey as the potential for economic gain is reduced (Clemens, 2014). We expect at both the origin and destination side that higher levels of human development to be associated with higher migration flows. On the origin side increased human development may increase people's life aspirations and awareness of opportunities elsewhere and on the destination side it represents opportunity for better life conditions (de Haas, 2011). We expect more public corruption in origin countries to be associated with higher migration outflows as it represents worse societal conditions and opportunities, and we expect the opposite effect for destination countries where more public corruption is associated with decreased migration inflows (Dimant, Krieger, & Meierrieks, 2013). Both bilateral migrant stock and bilateral trade flow are dyadic variables where increased values represent stronger ties between the two countries and should therefore be associated with higher migration flows (de Haas, 2011; Campaniello, 2014). The female to male labor gap represents gender equality where we expect higher values (more equality) for both the origin and destination side to be associated with higher migration outflows for similar reasons discussed regarding human capital (Belot & Ederveen, 2012). Regarding the Muslim population micro-level studies have found that at least in the case of Muslims in Africa they are less likely to migrate to Europe than non-Muslims (Black et al., 2013; Kirwin & Anderson, 2018). Therefore, on the origin side we would expect higher a Muslim population to be associated with less migration outflow. On the destination side it is unclear what role a larger Muslim population should have.

The main independent variables of interest are the migration policy variables taken from the DEMIG-Quantmig policy dataset which codes changes in migration policy restrictiveness. Migration policy changes are coded as major, mid-level, minor, or fine tuning. We have aggregated individual policy changes within years to create an overall score of whether as a whole migration policy for a particular country in a particular year has become more or less restrictive. Naturally, major changes are given the most weight (factor 4) and fine-tuning the least weight (factor 1) in calculating an overall annual score. For more details on the coding process see (de Haas, Natter, & Vezzoli, 2014; de Haas, Natter, & Vezzoli, 2015). Thus, the DEMIG-Quantmig policy indicator is about changes in policy and not an absolute indicator as is common in other migration policy datasets[6]. However, besides the overall policy indicator (*Migpolicy*), we also use disaggregated indicators per policy area capturing polices on integration (*Integrate*), border enforcement and land control (*Border*), legal entry and stay (*Admission*), and exit and return (*Return*). In our analysis we use cumulative score of these policy indicators starting in the year 2007, meaning that the policy score per country used in 2008 is the change in the policy indicator of 2007, and the policy score used in 2009 is the sum of changes in 2007 and 2008, etc. As another policy indicator and dyadic control, we use visa policy (*Visa*) which comes from the DEMIG visa dataset. It indicates whether individuals from country A need a visa to visit country B or do not need a visa to visit[7] (DEMIG, 2015). The dataset was created from information contained in the monthly IATA travel information manuals, which track the requirements of entry visas. The original visa variable covered the period until 2013 and has been extended by the authors for the period 2014-2019.

We include time invariant variables in regressions when country or dyadic fixed effects were not possible to use. That is, we include geographical distance between most populated cities (*Distance*), or when origin and destination countries share a common language (*Language*), border (*Contiguous*), or colonial history (*Colonial*). Multilateral resistance, which essentially means the influence of alternative destinations, is controlled for when destination-time *and* origin-time fixed effects are used (Bertoli & Moraga 2013; Fally, 2015). Country-pair (dyad) fixed effects help reduce endogeneity bias at the dyad level (Baier & Bergstrand 2007). To lessen the amount of missing data the following variables for both origin and destination were linearly interpolated urbanization, Muslim population, bilateral migration stock, trade flow, doctors, Gini inequality index, and education expenditure. For political terror the missing values were filled by the closest value in a future year. All control variables, except binary variables, are z-standardized, i.e., transformed to z scores with a mean of zero and standard deviation of one. The variables GDPPP, total population, bilateral migration stock, and people affected by natural disasters were first log-transformed, and then z-standardized.

[6] An absolute indicator would be for example Mipex (Solano & Huddleston, 2020).
[7] The Visa policy dataset has a different value for countries that are blacklisted but we recoded these to the same value as countries that need a visa as there are few countries that are blacklisted.

3.3 Analytical strategy

Formally, we estimate the following model:

$$M_{ijt}^{a} = \beta_0 + \beta_1 D_{ijt}^{a} + \beta_2 P_{ijt}^{a} + \gamma_{ij}^{a} + \mu_{it}^{a} + \rho_{jt}^{a} + \varepsilon_{ijt}^{a}, \qquad (1)$$

where M_{ijt}^{a} is the natural log of migration flows of type $a \in \{labor, family, education, asylum, irregular\}$ from country of origin i to European destination country j in time period t; D_{ijt}^{a} is the vector of driving factors which includes a set of factors common to all flow categories a and some category-specific factors, while P_{ijt}^{a} is a vector of migration policy indicators applied to all five migration categories. To control for unobserved spatial heterogeneity and spatial clustering, we include origin-time μ_{it}^{a} and destination-time fixed effects ρ_{jt}^{a}, as well as ixj dyad-specific fixed effects γ_{ij}^{a} to capture any form of unobserved heterogeneity across dyads. ε_{ijt}^{a} represents the idiosyncratic error term in the model of migration flow of type. Standard errors are clustered at the country-pair level.

We employ two methods of analysis, first, a gravity model implemented by a pseudo-poisson maximum likelihood estimator (PPML) estimating absolute flows M. And second, a fractional multinomial logit regression (fmlogit) estimating proportions of the five flow categories. Both approaches have their strengths and weaknesses. PPML has the advantage of allowing for fixed effects and it can be more easily compared to results from past studies that used a gravity model. The disadvantage is with multiple dependent variables, the PPML regression is run on the dependent variables (DV) separately. However, Model (1) represents five migration equations for which assume that flows of different categories are interdependent and therefore, error terms ε_{ijt}^{a} across the equations are correlated. Fmlogit requires all dependent variables to be in one equation, but computational limitations make the inclusion of fixed effects difficult.

3.3.1 Pseudo Poisson

We prefer pseudo poisson maximum likelihood (PPML) over the commonly used log OLS regression for several reasons. Log transformations of the DV are often done because the distribution of the DV is positively skewed. The presence of zeros, as we have in our data, in the dependent variable makes a log transformation unfeasible. Therefore, researchers have adopted the approach of adding some value, often one, to the variable before the log transformation (Motta, 2019). Another downside of the log OLS approach is in the presence of heteroskedasticity the estimates are biased (Silva & Tenreyro, 2006). PPML with fixed effects is better at controlling multilateral resistance than OLS (Fally, 2015). We implemented the PPML regression with the Stata command PPMLHDFE.
The strengths of PPML are that it is suited for the type of data, can deal with zero values, robust in the presence of heteroskedasticity, there is no need to specify a distribution for the dependent variable, and it is easy to implement fixed effects (Correia, Guimarães, & Zylkin, 2020). In addition, we include various fixed effects to control for the presence of unobserved heterogeneity.

3.3.2 Fractional multinomial logit

The inflows of migrants by each of the five migrant categories can be thought of as components of one total inflow which means that each category makes up a part of that total. Each flow category forms a fraction (or, proportion) of the total inflow hence the fractional part of a fractional multinomial logit regression (fmlogit). Fmlogit estimates fractional responses by modelling the five dependent variables as fractions using multinomial logits (Xi, 2019). Fmlogit provides a natural option to account for all DVs at once unlike PPML regression where separate regressions for each DV are run. Fmlogit is a multivariate generalization of the fractional model of Papke and Wooldridge (1996) where they proposed a quasi-maximum likelihood estimator for fractional responses. Fmlogit assumes that the conditional means have a multinomial logit functional form (Buis, N.D). The fractional multinomial logit does not model variances and covariances of proportions which limits it in a way that it can answer questions about the conditional means but not other aspects of the distribution. As mentioned before, a downside of this approach is the difficulty in including fixed effects due to computational limitations. This prevents us from mirroring the same approach used in the PPML regressions. The inability to use destination-year, origin-year, and dyadic fixed effects required a different strategy than what was used in the PPML regressions. In the Fmlogit regression we include time invariant dyadic variables and year dummies. Lastly, there is the assumption of independence from irrelevant alternatives (IIA). The IIA assumption is that given a choice among a set of alternatives, the odds of choosing migration category A over B does not depend on whether some other alternative C is present or absent. In the context of this analysis, it would mean that a person migrating via a student permit instead of migrating via asylum, labor, family, or irregular means does not depend on whether there is another option, not included in the regression, such as permit for self-funded retirees. Despite its limitations fmlogit still provides insight where PPML cannot. It can better show how the composition of the migration flow should change. Fmlogit shows how a variable affects a DV relative to other DVs. In other words, when an independent variable changes how does the ratio of, for example, labor migrants to student migrants change. Thus, in terms of investigating categorical substitution effects it provides more insight than PPML. We used the Stata command FMLOGIT. To facilitate interpretation of coefficients, we report the average marginal effects.

4 Results

In the following analyses of model (1), we disaggregate the comprehensive, three-dimensional set of origin, destination and dyadic drivers by focusing on one dimension at a time while controlling for the other two dimensions through the most rigorous sets of fixed effects.

Table 3: PPML regression: origin-side drivers

VARIABLES	(1) Total	(2) Student	(3) Family	(4) Labor	(5) Asylum	(6) Irregular
Gini_o	0.498***	-0.013	0.534***	0.947***	0.060	0.661***
	(0.093)	(0.115)	(0.080)	(0.134)	(0.169)	(0.175)
GDPCGR_o	0.028	-0.083***	0.036***	0.034	-0.003	0.016
	(0.020)	(0.032)	(0.012)	(0.027)	(0.030)	(0.032)
GDPPP_o	-0.376	-1.260***	0.481***	0.711**	-0.594	1.640***
	(0.230)	(0.327)	(0.176)	(0.301)	(0.483)	(0.478)
GDPPP_osq	0.627**	1.806***	-0.522***	-1.908***	0.918*	-1.381**
	(0.256)	(0.325)	(0.180)	(0.279)	(0.537)	(0.572)
Unemploy_o	0.060	-0.131**	0.016	-0.207***	0.321***	0.113
	(0.046)	(0.062)	(0.029)	(0.056)	(0.089)	(0.082)
Urban_o	0.751***	1.769***	0.044	-0.145	1.813***	0.978*
	(0.224)	(0.282)	(0.157)	(0.285)	(0.381)	(0.548)
Pop18-35	0.330***	0.033	0.111***	0.044	0.765***	0.469***
	(0.053)	(0.058)	(0.036)	(0.083)	(0.097)	(0.111)
Population_o	1.389***	3.531***	0.082	-1.854**	-1.583*	-2.909***
	(0.516)	(0.506)	(0.385)	(0.753)	(0.834)	(1.122)
Doctors_o	-0.137***	-0.127***	-0.051**	-0.049	-0.043	-0.360***
	(0.030)	(0.031)	(0.023)	(0.041)	(0.064)	(0.058)
EduExpend_o	-0.026	0.002	0.000	0.069	-0.022	-0.138
	(0.037)	(0.047)	(0.025)	(0.060)	(0.068)	(0.089)
FreeMove_o	0.003	0.004	-0.042*	-0.043	0.055	0.198***
	(0.031)	(0.040)	(0.023)	(0.042)	(0.064)	(0.070)
PubCorrup_o	-0.086**	-0.010	-0.047*	-0.143**	-0.020	0.050
	(0.040)	(0.056)	(0.027)	(0.058)	(0.073)	(0.085)
Muslim_o	-2.520*	-3.313**	2.716**	8.726***	-9.501***	2.779
	(1.474)	(1.650)	(1.333)	(2.226)	(3.106)	(3.301)
LaborGap_o	0.205**	-0.081	0.006	0.284**	0.026	0.366**
	(0.091)	(0.179)	(0.072)	(0.142)	(0.183)	(0.176)
Terror_o	0.045**	0.097***	0.010	0.008	0.302***	-0.049
	(0.020)	(0.028)	(0.012)	(0.026)	(0.055)	(0.038)
Disaster_o	-0.002	0.028*	0.026***	0.018	0.011	0.028
	(0.016)	(0.014)	(0.007)	(0.016)	(0.030)	(0.022)
Constant	9.500***	2.380***	6.529***	14.790***	19.327***	9.437*
	(0.818)	(0.728)	(0.631)	(1.049)	(3.486)	(4.962)
Observations	36,790	33,932	34,996	33,056	23,765	21,943
Dest-year FE	YES	YES	YES	YES	YES	YES
Dyad FE	YES	YES	YES	YES	YES	YES
Pseudo R-sq	0.979	0.974	0.983	0.987	0.927	0.991

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dest-year means destination-year

Table 3 explicitly reports the statistical significance of origin-side factors along the comprehensive set of the nine driver dimensions based on PPML regressions using destination-year and dyad fixed effects in addition to origin-side control variables only. Effect sizes can be compared across migration flow categories due to the z-standardization of all variables. Interpretation of estimates therefore refers changes in standard deviations in the driving factors. The first column captures the per-year aggregation of the overall (total) dyadic migration flows of regular and irregular migrants. As migration policy is exclusively employed as a destination side variable it only implicitly (captured by time-variant destination-side fixed effects) part of this analysis. Except of the logged variables, the coefficients are semi-elasticities and can be converted to percentage changes. Thus, a one standard deviation increase in the Gini inequality index would be associated with a (exp(0.498)-1)*100 = 64.54 percent increase in total flows, holding all variables in the model constant. That is, greater economic inequality enhances total outflows of migrants, particularly for the family, labor and irregular migration categories.

We further identify a demographic push effect, in particular when measured by the size of the young age cohort, but also for origin countries characterized by relatively high urban populations. High urbanization seems predominantly a facilitating factor for internationally mobile students but is also associated with the outflow of asylum seekers and irregular migrants. A factor that is rather holding back migrants is the quality of health services as proxied by doctors per capita, which has the strongest migration-reducing effect for the category of irregular migrants. Most of the other control variables have mixed effects across the categories. Testing the well-established migration transition hypothesis (cf. Zelinsky, 1971), income levels (GDPPP) show a non-linear, yet inconsistent pattern: while for family, labor, and irregular migration categories the migratory pattern shows the expected inverted U-shape with rising numbers of outmigrants for lower income levels, outbound international student migration shows the opposite, namely a decrease in the outmigration of students from countries low but increasing income levels. At the same time, higher education expenditures, suggesting better domestic opportunities in particular for students, does not show a significant effect.

Unemployment does not show significance on total outflows, but only for asylum migrants, and is even associated with less out migration of labor migrants and students. More gender equality, as measured by the female to male labor participation gap, has a migration-inducing effect, in particular for labor and irregular migration, respectively.

Political terror and instability are associated with an increase in total outflows but affects predominantly outbound student migration and asylum migration. Emigration, which may potentially be driven by environmental change but is imperfectly proxied by our natural disaster variable, shows statistical significance, yet small sized effects for student and family migration category.

For testing robustness, we have re-run these models with harmonized samples to address a possible sample selection bias due to dissimilar sample sizes for the different legal categories. Unequal sample sizes come for two reasons. First, some of the DVs come from different datasets and have therefore different coverage. Second, during the regression analysis observations are automatically dropped because of the problem of statistical separation[8] and singletons. The number of observations reported in Tables 1 and 2 do therefore not reflect the actual observations used in each regression. To address possible

[8] See Correia, Guimarães, & Zylkin (2019) for an explanation of statistical separation and Correia (2015) for singletons.

sample selection biases in our estimates, we ran additional analyses using only country-year observations that are available for all six flow categories (including total). That is, we re-run the analysis from Table 3 using observations that appeared in all six regressions for Table 3. The observations that are used for the results of the destination-side and dyadic driver analysis of Tables 4 and 5 are not considered. The same procedure however is applied for those analyses. Results from these harmonized 'same sample regressions' do not differ substantially and are available upon request.[9]

Table 4 present the results of the PPML regression with only destination side drivers in addition to origin-year and dyad fixed effects. Models 1 and 2 capture the overall annual bilateral migration flow across all five migration categories. In the first column, we estimate the effect of the overall migration policy change index *Migpolicy*, a composite index of the four migration policy areas which are separately assessed models (2) to (7). A one standard deviation increase (i.e., towards more restrictiveness) in the overall migration policy restrictiveness is hereby associated with a ((exp(-.147)-1)*100) = 13.7 percent decline in total inflows, holding all other drivers constant. Or, a one standard deviation increase in border policy restrictiveness is associated with a ((exp(-.140)-1)*100) = 13.1 percent reduction in total migration inflows, holding all other drivers and policies constant. For the most part, the migration policy indicators are in the expected direction where more restrictive (liberal) policies are associated with significant decreases (increases) in total and most category-specific immigration flows. This is the case for admission and integration policy changes towards more restrictive (liberal) regulations which seem to reduce (increase) inflows across all categories except for labor immigration in the case of admission policies, and student inflows in the case of integration policies. Interestingly, more restrictive return policies have a positive effect on all categories (except on student immigration) which implies that deterrence of immigrants do work to some extent for three out of four policy areas, i.e., not for return policies.

Besides migration policies, the estimates for unemployment indicate that migrants across all entry categories (except irregular migrants) do consider economic cycles and respond to economic downturns. On the other hand, economic opportunities, measured by income levels, is a strong and statistically significant factor for attracting migrants of most but not all legal categories (surprisingly not for labor migrants). A factor that functions as a driver of enhanced immigration flows is the quality of the health sector; inflows in all migrant categories increase with medical coverage (doctors per capita), but also with enhanced expenditures on education indicating better educational opportunities for migrants and their children. The Gini index as a measure of inequality shows a mixed outcome. An overall negative effect of inequality on total inflows is hampered by a positive effect on the inflow of students and family members.

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[9] The descriptive statistics for the observations that actually compose each regression are available upon request.

Table 4 PPML regression: Destination-side drivers

VARIABLES	(1) Total	(2) Total	(3) Student	(4) Family	(5) Labor	(6) Asylum	(7) Irregular
Migpolicy	-0.147***						
	(0.013)						
Border		-0.140***	0.202***	0.004	-0.206***	-0.170***	-0.345***
		(0.022)	(0.024)	(0.015)	(0.046)	(0.064)	(0.037)
Admission		-0.108***	-0.145***	-0.076***	0.162***	-0.277***	-0.217***
		(0.021)	(0.025)	(0.015)	(0.047)	(0.055)	(0.038)
Integrate		-0.110***	0.039*	-0.014	-0.141***	-0.226***	-0.031
		(0.018)	(0.021)	(0.012)	(0.046)	(0.039)	(0.032)
Return		0.160***	-0.072***	0.105***	0.179***	0.288***	0.015
		(0.020)	(0.022)	(0.013)	(0.046)	(0.061)	(0.041)
Gini_d	-0.021	-0.214***	0.219***	0.368***	-0.203*	-0.494***	-0.083
	(0.055)	(0.056)	(0.068)	(0.050)	(0.118)	(0.134)	(0.073)
GDPCGR_d	-0.063***	-0.030	-0.023	-0.015	-0.147***	0.159***	-0.040*
	(0.019)	(0.019)	(0.023)	(0.015)	(0.047)	(0.046)	(0.022)
GDPPP_d	0.070***	0.029*	0.055***	0.126***	0.014	-0.183***	0.068***
	(0.018)	(0.018)	(0.015)	(0.016)	(0.041)	(0.047)	(0.023)
Unemploy_d	-0.332***	-0.294***	-0.235***	-0.187***	-0.619***	-0.528***	0.078*
	(0.020)	(0.021)	(0.025)	(0.017)	(0.050)	(0.045)	(0.045)
Urban_d	-1.813***	-0.252	-1.076***	-0.908***	-1.849***	2.663***	1.680***
	(0.272)	(0.295)	(0.287)	(0.207)	(0.664)	(0.519)	(0.450)
Population_d	-1.356*	0.129	0.771	-0.552	5.258***	-2.560	2.862***
	(0.734)	(0.708)	(0.786)	(0.633)	(1.403)	(1.994)	(1.109)
Doctors_d	0.187***	0.143***	0.169***	0.102***	0.449***	-0.141	0.183***
	(0.033)	(0.034)	(0.034)	(0.026)	(0.061)	(0.096)	(0.061)
EduExpend_d	0.076**	0.040	0.059**	0.145***	0.151*	-0.567***	-0.075
	(0.033)	(0.031)	(0.029)	(0.021)	(0.078)	(0.110)	(0.050)
PubCorrup_d	-0.093	-0.160**	-0.056	-0.285***	0.365**	-0.250	0.013
	(0.073)	(0.068)	(0.078)	(0.067)	(0.164)	(0.164)	(0.083)
LaborGap_d	0.139**	0.153***	0.263***	0.056	-0.048	0.276**	-0.198**
	(0.058)	(0.056)	(0.066)	(0.045)	(0.123)	(0.110)	(0.099)
Muslim_d	-2.683***	-2.372***	-3.854***	-1.527***	-6.575***	2.565***	-0.119

	(0.265)	(0.265)	(0.260)	(0.177)	(0.612)	(0.627)	(0.426)
Constant	11.303***	9.427***	7.600***	8.521***	2.691*	8.341***	6.931***
	(0.752)	(0.729)	(0.851)	(0.652)	(1.416)	(2.121)	(1.249)
Observations	53,209	53,209	47,689	48,880	46,134	31,236	29,317
Origin-year FE	YES	YES	YES	YES	YES	YES	YES
Dyad FE	YES	YES	YES	YES	YES	YES	YES
Pseudo R-squared	0.978	0.979	0.976	0.981	0.973	0.933	0.990

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

Table 5 present the results of the PPML regression with a focus on dyadic drivers, supplemented by the most rigorous set of origin-year, destination-year and dyad fixed effects. Restrictive visa policy, measured by the presence of a visa requirement to visit a destination country, is associated with an on average (exp(-0.544)-1)*100 = 42.0 percent reduction in total bilateral flows, holding all variables in the model constant. This strong negative visa effect on overall inflows supported by existing evidence (cf. Czaika & de Haas, 2017), but now also supported by similar estimates for student, family and labor migration categories, yet not for asylum and irregular migration. Comparing the effect sizes of these visa policy estimates, knowing that these may suffer minor bias due to different sample sizes, it is shown that international student and labor mobility are most affected by visa constraints, followed by family migration flows.

Table 5 PPML regression: Dyadic drivers

VARIABLES	(1) Total	(3) Student	(4) Family	(5) Labor	(6) Asylum	(7) Irregular
TradeBilat	0.064***	0.063***	-0.015	0.026**	0.008	-0.032*
	(0.013)	(0.016)	(0.010)	(0.011)	(0.025)	(0.018)
Visa	-0.544***	-0.423***	-0.369***	-0.457***	-0.068	-0.106
	(0.132)	(0.140)	(0.080)	(0.133)	(0.295)	(0.137)
MigstckBilat	1.333***	0.393*	2.349***	1.195***	0.901***	0.396*
	(0.166)	(0.203)	(0.139)	(0.218)	(0.240)	(0.239)
Visa x MigstckBilat	0.202***	-0.071	0.234***	0.066	-0.007	-0.103
	(0.060)	(0.052)	(0.034)	(0.061)	(0.129)	(0.066)
constant	6.474***	6.984***	2.349***	6.833***	6.511***	9.864***
	(0.370)	(0.439)	(0.312)	(0.494)	(0.479)	(0.614)
Observations	48,693	43,933	45,307	42,514	29,529	28,634
Origin-year FE	YES	YES	YES	YES	YES	YES
Dest-year FE	YES	YES	YES	YES	YES	YES
Dyad FE	YES	YES	YES	YES	YES	YES
Pseudo R-squared	0.985	0.981	0.987	0.990	0.962	0.993

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dest-year means destination-year

It is a well-established and evidence-based fact that migrant networks facilitate and often self-perpetuate international migration flows (cf. Haug, 2008; Beine & Salomone, 2013). Our results on total flows confirm this finding, yet again, effect sizes vary significantly between the different migrant categories. While networks seem to play the strongest role in facilitating labor, family and asylum migration, the effect is much smaller and only significant at the 10 percent level for student and irregular migration. By interacting visa policy restrictions and migrant networks, we hypothesize that networks are even more relevant as migration-facilitating factor when institutional barriers such as visa requirements hamper mobility. Our results indicate that while this mechanism is statistically significant for total migration flows, it seems primarily relevant in the context of family migration. Our only time-variant dyadic control is the bilateral trade volume which proxies economic openness and ties between origin and destination countries. Even though positively associated with total migration flows, pre-established economic ties are mainly linked to the flow of labor migrants and students.

Turning to the analysis of shifts in the composition of total flows that are associated with changes in the configuration of drivers and migration policies, regressions are based on a fractional multinomial logit model by quasi-maximum likelihood, i.e., a model that estimates simultaneously all five types of migration as proportion of the total inflow. Computational limitations prevent the inclusion of the respective time-variant fixed effects used in the previous PPML regressions, but we instead run the full model including all time variant and invariant variables at origin, destination, and dyadic levels in addition to overall year dummies.

Table 6 reports average marginal effects (which are easier to interpret than point estimates[10]) from two separate fmlogit regressions. Marginal effects add up to zero, save for rounding error, for each row so the predicated proportions do add up to one.

The results for all variables above the *Panel B* row come from a regression (*Panel A*) where the overall migration policy (migPolicy) indicator was included in the regression. The variables under the row *Panel B* come from a regression with all the same variables as *Panel A* except the overall migration policy indicator is replaced by the four separate migration policy indicators (Border, Admission, Integrate, Return). The results from Table 6 indicate that an increase in one standard deviation of the overall migration policy variable (*MigPolicy*) towards a more restrictive level would not only affect (decrease) the total inflow of migrants as shown in Table 4 but would also change its composition by decreasing the *share* of labor, asylum, and irregular migrants and increasing the *share* of students and of family migrants in the total number of immigrants. Specifically, a one standard deviation change in the overall level of migration policy restrictiveness would increase the share of student migrants among the total inflow of migrants by 0.2 percentage points, family by 0.9 percentage points, but decrease the share of asylum and irregular migration by 0.3 and labor migration by 0.05 percentage points. More restrictive border policy increases the share of student migrants and decreases the share of all other categories. Interestingly, for all migration policy indicators, including the overall policy indicator, more restrictive policy decreases the share of labor migrants. With exception of integration policy this is also the case for irregular migrants. In the PPML regression integration policy did not have a statistically significant effect on irregular migration.

The results reported here and for the PPML regression may occur because irregular migrants by their irregular status may feel unencumbered by whatever integration requirements a destination country sets. The introduction of a travel visa requirement significantly decreases the share of student and irregular migrants by on average 4.1 percentage points less students and 2.7 percentage points fewer irregular migrants, shifting the overall composition of inflows mainly towards family migration. The PPML regression has confirmed that well-established migrant networks, proxied by bilateral migration stocks, generally facilitate international migration across all migrant categories.

[10] The results for the point estimate coefficients are in Table A-1 in the appendix.

Table 6 Fmlogit regression: Compositional shifts in migration flows

	Student	Family	Labor	Asylum	Irregular
Dyadic drivers					
TradeBilat	0.008	-0.001	0.001	-0.006	-0.001
Distance	0.032	0.075	0.027	-0.106	-0.028
Colonial	0.072	0.000	0.019	-0.077	-0.014
Language	-0.002	-0.040	0.007	0.006	0.028
Contiguous	-0.066	-0.048	0.071	-0.044	0.088
Visa	-0.042	0.042	0.003	0.024	-0.027
MigStckBilat	-0.056	0.067	-0.001	-0.004	-0.005
Origin-side drivers					
Gini_o	0.011	0.006	-0.017	-0.010	0.010
GDPCGR_o	-0.013	-0.000	0.001	0.009	0.003
GDPPP_o	-0.070	0.017	0.029	-0.027	0.051
GDPPP_osq	0.102	-0.021	0.020	-0.058	-0.044
Unemploy_o	-0.020	-0.002	0.011	0.012	-0.001
Urban_o	-0.019	0.049	-0.034	-0.000	0.004
Pop18-35	0.031	-0.022	-0.003	-0.012	0.006
Population_o	0.059	-0.053	0.047	-0.033	-0.019
Doctors_o	0.021	-0.017	0.002	-0.008	0.002
EduExpend_o	-0.001	0.019	0.020	-0.045	0.007
FreeMove_o	-0.015	-0.004	0.014	-0.001	0.007
PubCorrup_o	-0.012	0.008	-0.009	-0.001	0.014
Muslim_o	0.004	0.000	-0.019	0.013	0.002
LaborGap_o	0.014	-0.007	-0.001	-0.009	0.003
Terror_o	-0.023	-0.009	-0.007	0.041	-0.001
Disaster_o	-0.009	-0.003	-0.000	0.005	0.007
Destination-side drivers					
MigPolicy	0.002	0.009	-0.005	-0.003	-0.003
Gini_d	0.009	0.008	0.003	-0.038	0.018
GDPCGR_d	0.011	0.001	-0.001	-0.011	-0.000
GDPPP_d	-0.006	-0.004	-0.009	0.023	-0.004
Unemploy_d	-0.025	0.014	0.002	0.003	0.006
Urban_d	0.004	0.026	-0.041	0.035	-0.023
Population_d	0.037	-0.027	-0.006	-0.006	0.002
Doctors_d	-0.006	-0.011	-0.015	0.041	-0.009
EduExpend_d	0.003	0.011	0.035	-0.038	-0.011
PubCorrup_d	-0.030	0.055	-0.000	-0.034	0.009
Muslim_d	-0.015	-0.024	0.002	0.037	0.001
laborGap_d	-0.002	0.003	-0.004	0.001	0.002
Migration Policy					
Panel A					
MigPolicy	0.002	0.009	-0.005	-0.003	-0.003
Panel B					
Border	0.016	-0.006	-0.002	-0.006	-0.002
Admission	-0.027	0.033	-0.002	0.004	-0.007
Integrate	0.011	-0.003	-0.007	-0.026	0.0024
Return	-0.014	0.017	-0.005	0.017	-0.015
Observations	29,228	29,228	29,228	29,228	29,228

Note: dy/dx for factor levels is the discrete change from the base level. A unit increase in dx reflects for continuous variables one standard deviation, and for dummy variables a 0-1 change. Year dummies are included but not reported.

However, the ‘pull in’ effect of a well-established diaspora is strongest for subsequent inflows of family migrants, similar to the results from the PPML regression, so that growing migrant populations of the same origin changes the composition of migration flows predominately towards higher proportions of family migrants.

Destination unemployment decreases the share of student migrants while increasing the share (but not the absolute number!) of all other migrant groups. Political terror increases the share and number of asylum migrants among the total bilateral flow of migrants yet decreasing shares of all other migrant categories.

5 Conclusion

This paper sets out to explore the role of structural drivers and migration policies in migration processes across different legal categories as well as their compositional effects on total migration flows. We find strong evidence for category-specific driver configurations distinguishing between five alternative modes of entry. This provides support to conceptualise structural factors as either fundamental for all types and forms of migration, or rather as supplemental for some specific modes of migration. Broader configurations of ever-changing driving factors are associated with sometimes fundamental compositional shifts in international migration flows. All European destinations receive migrants across all legal categories and (ir-)regular pathways from a large mostly global range of sending countries. However, what is unclear, and which is mostly an empirical question, is the relative importance of certain migration forms in some particular migration corridors and the variation in the overall composition in international migration flows. Our analysis shows that so-called categorical substitution effects exist not only as a consequence of changes in migration policy regulations (Czaika & de Haas, 2013), but also when other structural migration drivers change with often unequal effects on migration forms and modes. Thus, changing configurations of migration drivers and policies are not only affecting overall numbers of migrants but ultimately leading to changing compositions of both emigrant and immigrant populations.

Our analysis comes not without limitations. There exist potential issues of reverse (feedback) effects between migration and some drivers. For instance, trade flows between countries may not only be a determinant of migration but also, at least partially, the consequences of (prior) migration. Also, computational limitations prevented us from including the same fixed effects specifications in the fmlogit regressions as were used in the PPML regressions which is why estimates of both techniques are not fully consistent. Nevertheless, we consider the fractural multinomial regression model a useful tool for tackling simultaneous estimation of interdependent migration flow categories.

In spite these limitations, our results have some bearing for policymaking. Our results indicate that stabilising origin countries either politically or economically would not only affect (decrease) total overall outflows but would increase the 'labor intensity' of these flows. Improving conditions at origin, e.g., by reducing political terror, or by improving economic prospects, have not only an impact on the total numbers but also on the composition, or the character, of migration flows. Our analysis surfaces also complexities and trade-offs that are hard to resolve. For instance, restrictive migration policy interventions including visa policy restrictions have – as expected- a largely deterrent effect on overall flows. While more restrictive migration policies lower the share of asylum seekers and irregular migrants, they – often unwantedly – also lower the share of labor migrants among the total immigrant population. Similarly, bilateral visa policy interventions help reducing the share of unwanted irregular migration but do also reduce the number and share of (mostly wanted) student migrants. These results provide evidence for fundamental policy trade-offs in the context of intended and unintended consequences of migration policy interventions.

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Appendix

Table A-1: Fmlogit results point estimates

	(1)	(2)	(3)	(4)
VARIABLES	Family	Labor	Asylum	Irregular
Dyadic drivers				
TradeBilat	-0.036**	-0.027**	-0.086**	-0.048*
	(0.014)	(0.013)	(0.042)	(0.026)
Distance	0.075**	0.025	-1.025***	-0.569***
	(0.031)	(0.037)	(0.067)	(0.071)
Colonial	-0.310**	-0.179	-0.947***	-0.528**
	(0.128)	(0.172)	(0.251)	(0.226)
Language	-0.112	0.048	0.056	0.424**
	(0.099)	(0.133)	(0.150)	(0.175)
Contiguous	0.125	0.669**	-0.096	1.576***
	(0.341)	(0.338)	(0.720)	(0.410)
Visa	0.307***	0.185**	0.381***	-0.223*
	(0.061)	(0.072)	(0.119)	(0.130)
MigStckBilat	0.437***	0.223***	0.206***	0.168**
	(0.046)	(0.051)	(0.063)	(0.073)
Origin-side drivers				
Gini_o	-0.026	-0.138***	-0.127***	0.107**
	(0.028)	(0.033)	(0.046)	(0.048)
GDPCGR_o	0.054**	0.055**	0.132***	0.098***
	(0.021)	(0.026)	(0.027)	(0.033)
GDPPP_o	0.344***	0.455***	0.072	1.048***
	(0.125)	(0.150)	(0.215)	(0.245)
GDPPP_osq	-0.501***	-0.304**	-0.926***	-1.100***
	(0.124)	(0.145)	(0.237)	(0.253)
Unemploy_o	0.079**	0.139***	0.184***	0.074
	(0.032)	(0.037)	(0.052)	(0.053)
Urban_o	0.231***	-0.110**	0.088	0.146**
	(0.045)	(0.052)	(0.078)	(0.074)
Pop18-35	-0.197***	-0.144***	-0.235***	-0.047
	(0.034)	(0.044)	(0.065)	(0.066)
Population_o	-0.414***	0.015	-0.545***	-0.546***
	(0.051)	(0.059)	(0.084)	(0.086)
Doctors_o	-0.143***	-0.076**	-0.158**	-0.069
	(0.032)	(0.032)	(0.063)	(0.051)
EduExpend_o	0.055	0.116***	-0.371***	0.106
	(0.035)	(0.041)	(0.054)	(0.068)
FreeMove_o	0.050	0.141***	0.053	0.163***
	(0.032)	(0.035)	(0.047)	(0.053)
PubCorrup_o	0.077**	0.002	0.051	0.263***
	(0.031)	(0.034)	(0.049)	(0.052)
Muslim_o	-0.015	-0.125***	0.092**	0.014
	(0.029)	(0.035)	(0.045)	(0.055)
LaborGap_o	-0.084***	-0.065**	-0.137***	-0.014
	(0.028)	(0.032)	(0.049)	(0.050)
Terror_o	0.073***	0.049*	0.438***	0.089**
	(0.023)	(0.025)	(0.036)	(0.041)
Disaster_o	0.030**	0.037**	0.082***	0.147***

	(0.015)	(0.018)	(0.022)	(0.026)
Destination-side drivers				
Gini_d	-0.016	-0.017	-0.351***	0.215***
	(0.029)	(0.031)	(0.046)	(0.043)
GDPCGR_d	-0.043***	-0.052***	-0.135***	-0.053**
	(0.016)	(0.017)	(0.025)	(0.025)
GDPPP_d	0.017	-0.029	0.220***	-0.037
	(0.023)	(0.025)	(0.038)	(0.032)
Unemploy_d	0.149***	0.116***	0.131***	0.194***
	(0.021)	(0.026)	(0.036)	(0.034)
Urban_d	0.068*	-0.244***	0.280***	-0.355***
	(0.035)	(0.037)	(0.060)	(0.068)
Population_d	-0.239***	-0.182***	-0.211***	-0.128*
	(0.039)	(0.044)	(0.060)	(0.067)
Doctors_d	-0.003	-0.065**	0.372***	-0.095**
	(0.025)	(0.029)	(0.040)	(0.043)
EduExpend_d	0.013	0.183***	-0.336***	-0.179***
	(0.030)	(0.032)	(0.051)	(0.056)
PubCorrup_d	0.290***	0.127***	-0.151**	0.253***
	(0.037)	(0.037)	(0.068)	(0.053)
Muslim_d	-0.005	0.071**	0.367***	0.081*
	(0.032)	(0.033)	(0.042)	(0.042)
laborGap_d	0.019***	-0.014***	0.022***	0.041***
	(0.004)	(0.004)	(0.008)	(0.008)
Migration Policy				
Panel A				
MigPolicy	0.019	-0.035*	-0.033	-0.055
	(0.017)	(0.020)	(0.026)	(0.042)
Panel B				
Border	-0.087***	-0.074**	-0.117**	-0.099
	(0.032)	(0.036)	(0,048)	(0.055)
Admission	0.213***	0.099***	0.153***	0.008
	(0.023)	(0.027)	(0.037)	(0.044)
Integrate	-0.058***	-0.083***	-0.260***	0.315***
	(0.020)	(0.022)	(0.034)	(0.047)
Return	0.115***	0.028	.204***	-0.161***
	(0.019)	(0.023)	(0.027)	(0.038)
Constant	-1.136***	0.936***	-3.543***	-4.026***
	(0.324)	(0.335)	(0.607)	(0.613)
Observations	29,228	29,228	29,228	29,228

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