Firms Left Behind: Emigration and Firm Productivity[a]

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Abstract

This paper establishes a causal link between the emigration of skilled workers and firm productivity. We create an innovative instrument for emigration by exploiting industry-level variation in the European labor mobility regulations between 2004 and 2017. Using a new self-assembled industry-level migration dataset and a large firm-level panel from eleven countries, we show that emigration reduces firm productivity in the short term. The negative effect concerns most firms along the initial productivity distribution, except for the most productive firms. At the industry level, firms' exit dynamics attenuates the negative effect. Additional evidence points to a loss of firm-specific human capital and reduced training due to increased worker turnover.

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1 Introduction

"In the Lithuanian town of Panevezys, a shiny new factory [...] sits alone in the local free economic zone. The factory is unable to fill 40 of its jobs, an eighth of the total. That is not because workers in Panevezys are too picky, but because there are fewer and fewer of them."

The Economist (19 January 2017)

The emigration of skilled workers poses a challenge for many countries, not only in the developing world. As workers leave their countries of origin to exploit opportunities abroad, policymakers and firm managers raise concerns about impeding skill shortages and brain drain. These concerns might translate into policies that discourage emigration, create barriers to cross-border labor mobility and hinder regional integration. However, whether there is a causal link between skilled emigration and deteriorating firm performance in countries of origin has not been established. The causality could be reversed with people leaving because of negative economic shocks in their country of origin, or other unobserved factors could trigger both lower firm performance and higher emigration. In addition, a scarcity of high-quality emigration and firm-level data has constrained the empirical analysis to date. Yet, identifying the economic consequences of emigration at the firm level is vital for understanding how firms respond to the outflow of workers, how aggregate growth is shaped, and for designing appropriate policies in countries of origin.

This paper investigates the causal economic effects of skilled emigration.[1] We exploit the unique institutional setting of the EU enlargements and build our analysis on harmonized firm-level data from eleven Central and Eastern European countries that experienced unprecedented emigration following their accession to the EU. Our main outcome of interest is firm productivity, measured by three different indicators: labor productivity, wage-adjusted labor productivity and total factor productivity (TFP). TFP, in particular, has been considered a strong predictor of firms' survival and growth (Bartelsman et al. 2013; Bloom and Sadun 2012).

We show that firms in industries exposed to higher emigration of skilled workers experience a drop in all three productivity measures. According to our preferred

[1] As "skilled", we denote individuals with either tertiary education or a professional qualification.

specification, a ten percent increase in labor emigration causes between four to five percent decrease in firm productivity during the same year. Effect magnitudes are similar across various productivity measures and are present only in the first year after emigration has increased. The negative effects on productivity are thus short-term, as both firms and workers adjust to free labor mobility. We find that, on average, firms adjust to emigration through substitution with other (lower-skilled) workers, rather than through substitution with capital. Our baseline results are robust to excluding micro- and macro-size firms, to controlling for changes in the sample composition, restricting the sample to certain time periods, and to using alternative specifications.

To identify causal effects, we construct a new instrument based on industry-level variation in the European labor mobility regulations, which were in place following the 2004, 2007 and 2013 EU Eastern enlargements. For a period of seven years after the official accession of new member states (NMS), the old EU member states could apply transitional provisions and restrict access to their labor markets for NMS workers. As a result, from 2004 to 2011 (for 2004 accession countries), 2007 to 2014 (for 2007 accession countries), 2013 to 2020 (for the 2013 accession country), labor mobility opportunities for NMS workers within the EU varied depending on their country of origin, destination, and the industry they worked in. We summarize these labor mobility regulations into a free labor mobility variable (FLM) that serves as an instrument for emigration. The instrument is plausibly exogenous to firm productivity because detailed industry-, year- and destination-specific regulatory changes were unlikely to be influenced by firms in countries of origin. These openings were not directed towards individual origin countries but towards all accession countries of a given accession year. Furthermore, they were uncorrelated with other immediate accession policy changes, such as the free movement of goods or capital. Using a new, self-assembled migration dataset, we show that these transitional provisions are relevant and have significant effects on labor emigration from NMS.

Firm-level panel data allow us to account for firm heterogeneity and to empirically explore the link between firms' characteristics and their sensitivity and adjustment to the emigration of workers. We find negative effects on productivity for most firms along the initial productivity distribution, except for the most productive ones. We also note that different firms adjust differently. The most productive firms (9-10th deciles) significantly increase their employee costs and seem to be able to retain workers and the quality of their workforce. As a result, these firms experience no negative effect on firm total factor productivity, nor on labor productivity, but a drop in wage-adjusted labor productivity. Firms in the upper productivity deciles (6-8th deciles) adjust by hiring new workers, but still face a moderate decline in all productivity measures. Even though these more productive firms manage to replace emigrated workers, the newly hired ones do not seem to be direct substitutes for those who left. We observe the strongest negative productivity effects among firms in lower productivity deciles whose workforce size shrinks; here we can attribute the drop in productivity measures to firms losing workers. We complement firm-level results with the analysis at the industry level, which shows that the adjustment to emigration also happens at the extensive margin - through the exit of the weakest firms.

We provide suggestive evidence for the mechanisms that can further explain our results. The fact that, besides labor productivity and wage-adjusted labor productivity, firms also experience a short-term drop in their TFP suggests that the emigrated workers generated positive externalities such as spillovers on other workers and firm-specific human capital. These externalities were not reflected in their wages. Even when firms replace emigrated workers, the new hires are not equally productive in the short term as it takes time to acquire necessary skills. We observe that firms in industries that experienced higher workforce emigration are more likely to report skill shortages. We also find that emigration increases worker turnover and reduces the share of employees receiving job-related training. Thus, one plausible channel behind the observed short-term drop in productivity measures is the loss of firm-specific skills and knowledge due to losing emigrated workers. The problem of missing human capital is further exacerbated by increased turnover and consequently expected shorter tenure due to better emigration opportunities. Firm-specific human capital can be acquired on the job through training or learning-by-doing. With a shorter expected tenure, both firms and individuals have fewer incentives to invest in firm-specific skill acquisition, thus slowing down the accumulation of necessary knowledge and skills among new hires.

This paper relates to several strands of the literature. Most importantly, we contribute to the literature studying the effects of emigration on countries of origin by providing firm-level evidence. The brain drain literature has traditionally focused on the negative effects on countries of origin through a loss of human capital (Docquier et al. 2007; Kapur and McHale 2005). However, further literature has also emphasized potential positive effects arising from higher incentives to invest in tertiary education as well as from incoming remittances and human capital gains of return migrants (Bollard et al. 2011; Docquier and Rapoport 2007).[2] Other studies on the economic effects of emigration and brain drain have focused on wages (Docquier et al. 2014; Dustmann et al. 2015; Hafner 2021), aggregated economic performance (Clemens 2013; Docquier and Rapoport 2012; Freeman 2006; Grossmann and Stadelmann 2011, 2013), and firm entry and entrepreneurship (Anelli et al. 2020).[3] We contribute with an innovative firm-level analysis that covers eleven origin countries and provides rich evidence on the dynamics of the effect, firm heterogeneity and potential mechanisms at play.[4]

While there is a growing migration literature that focuses on the firm as the unit of analysis, until now it has investigated the impact of *immigration*. Kerr et al. (2014), Kerr (2013), and Ottaviano and Peri (2013) encourage the firm-level approach, pointing out that it allows us to identify firm adjustment mechanisms and to address firm heterogeneity. Both are important for our understanding about how the economic effects of migration are being shaped. Kerr and Kerr (2013), Kerr et al. (2014), and Peri (2012) study the effects of immigration on firm-level outcomes in the US, and Mitaritonna et al. (2017), Ottaviano et al. (2018), and Paserman (2013) in France, the UK, and Israel respectively. They find that an increased supply of foreign-born workers positively affects firm productivity due to skill complementarities, faster accumulation of capital and the specialization of na-

[2]Especially highly skilled emigrants may send large amounts of remittances and thus spur growth (Hunt 2011, 2015).

[3]Bahar et al. (2019) study the effects of return migration on export behavior. However, in our setting, return migration remains at a low level (Atoyan et al. 2016).

[4]In a recent paper, Dicarlo (2022) studies the effects of emigration to Switzerland on firms in Italy.

tives in more complex tasks.[5] Our research complements this literature by focusing on the effects of *emigration*.

Some of the above-mentioned mechanisms can be transferred to the case of emigration. As illustrated by a vast body of literature, skilled workers contribute to firm TFP through education, experience, and managerial skills (Gennaioli et al. 2013; Lucas 1978; Murphy et al. 2012). The observed drop in firm productivity following the emigration of skilled workers could be linked to missing skill complementarities and thus lower productivity of stayers. We illustrate one more mechanism: the emigration of workers leads to the loss of firm-specific human capital that these workers had accumulated. This mechanism is in line with Jäger (2016) who observes a lack of substitutability between incumbent skilled workers and skilled workers outside the firm.

We contribute to the literature on the determinants of firm productivity (Bartelsman et al. 2013; Bloom and Sadun 2012; Bloom and Van Reenen 2007; Fox and Smeets 2011). While firm TFP is often treated as one of the core indicators of economic performance, it is also referred to as ”the measure of our ignorance” (Syverson 2011). We provide empirical evidence for the channel that links firm TFP to skilled emigration and thus emphasize the firm-specific human capital as an important determinant of TFP.

We are the first to exploit industry-level variation in the EU labor mobility regulations in order to causally evaluate the consequences of emigration. Moreover, we constructed a novel industry-specific migration dataset covering EU and EFTA member states. Beine et al. (2019), Grogger and Hanson (2011), and Ortega and Peri (2013) analyze how mobility regulations have affected migration patterns. Rojas-Romagosa and Bollen (2018) show that the general introduction of the free movement of people in the EU increased migration from new to old member states. Dustmann et al. (2017) and Beerli et al. (2018) show that granting labor market access for cross-border workers in Germany and Switzerland, respectively, increased cross-border workers' employment, while also affecting the native population's employment and wages.

[5] Further firm-level studies include Dustmann and Glitz (2015) for Germany, Peri et al. (2015) for the US, and Imbert et al. (2020) for China.

In addition, we supplement the literature on the consequences of free labor mobility in the context of the EU enlargement. Following their accession to the EU, Central and Eastern European countries have experienced particularly high emigration: in 2003, the number of Central and Eastern Europeans residing in other EU countries amounted to 2.5 million; by 2018 this number reached 9 million (OECD Migration Database, Figure 1). Mayr and Peri (2009) develop a model to study the consequences of European free labor mobility on human capital in the countries of origin. They differentiate between brain drain and brain gain due to return migration and increased incentives to invest in education. Dustmann et al. (2015) and Elsner (2013) estimate the effects of the post-enlargement emigration on wages in Poland and Lithuania and find that wages increase for stayers. Caliendo et al. (2017) jointly study the economic effects of trade and labor market integration in the EU and argue that NMS are the main winners of the EU enlargements. However, there have been growing concerns that the emigration of skilled workers has posed severe challenges for countries of origin (Kahanec 2013; OECD 2013; Zaiceva 2014). We supplement this literature by providing nuanced micro evidence: while firms in NMS, on average, experience a drop in productivity due to the emigration of workers, this effect is short-term. We also discuss policies that could help to mitigate the negative effects.

The paper is organized as follows. The next section presents our conceptual framework. Section 3 describes the institutional setting and the data, followed by Section 4 that presents the empirical specification. Section 5 discusses the results including heterogeneous effects. Section 6 sheds light on the mechanisms and Section 7 provides robustness checks. Section 8 concludes and outlines policy implications.

2 Conceptual Framework

Emigration can affect firm productivity through different channels. This section provides an overview of the links between emigration and firms' labor productivity, wage-adjusted labor productivity and TFP. While the focus of this paper is empirical, this section provides some theoretical considerations to navigate through the empirical analysis and to identify potential mechanisms.

As opportunities for emigration among the workforce increase, firms face a stronger competition in the labor market. Consequently, wages rise in the skill group of those workers likely to emigrate (Dustmann et al. 2015). Firms can respond by substituting emigrants with workers from a different skill group and thus by changing the within-firm skill intensity or by substituting labor with capital. If firms substitute emigrated workers with capital, labor productivity (measured as value added per employee) should not substantially drop or can even increase, as labor becomes relatively more productive. Wage-adjusted labor productivity (measured as value added over personnel costs) will behave similarly but will also reflect the consequences of increased wage levels due to more competition for scarce labor. If emigrants are positively selected and firms substitute them with less skilled workers, both labor and wage-adjusted labor productivity will fall. The effect on the wage-adjusted labor productivity might be attenuated as wages also reflect the quality of employees: when a firm substitutes a skilled worker with two unskilled workers, the personnel costs are unlikely to double.

These substitution effects, however, will not be reflected in firm TFP (obtained by dividing output by the weighted average of labor and capital input). There are several other channels through which emigration can influence all three productivity measures. For instance, more intense competition in the factor market might encourage firms to adopt better managerial practices to use scarce labor more efficiently. In this case, firm TFP will persistently increase (Bloom and Van Reenen 2007). Technology adoption will also positively influence labor and wage-adjusted labor productivity. On the contrary, if it is mainly skilled workers who emigrate, firms might reduce their investments in new technologies, if they complement skills. This will have persistent negative effects on TFP, as well as on the other two productivity measures. All three productivity measures will be also affected when workers generate positive externalities (such as spillovers on co-workers or accumulated firm-specific human capital), which are not reflected in their wages. Firm productivity measures will be negatively affected when such workers leave. Even if firms manage to hire new qualified workers, these might not be direct substitutes, at least in the short-term, due to the lack of firm-specific skills. Furthermore, better emigration opportunities lead to higher turnover and shorter expected tenure of employees, further exacerbating the problem of absent firm-specific human capital. First, employees have less time to accumulate this capital through learning-by-doing. Second, firms have fewer incentives to invest in firm-specific training.

When we look at productivity measures aggregated at the sector level, we need to consider additional composition effects due to firm exit and entry. Emigration might induce exits of less productive firms, thus resulting in a positive selection of survivors. Emigration can also lead to fewer entries of new firms (Anelli et al. 2020).

3 Institutional Setting and Data

3.1 Labor Mobility Regulations in the EU

This subsection shows how the gradual opening of EU labor markets created time, country, and industry-level variation in the emigration of NMS citizens. In 2004, ten Central, Eastern and Southern European countries joined the EU: Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia and Slovenia. While free movement of goods and capital was introduced by all countries either prior to or at the time of accession, free labor mobility was initially restricted by certain destination countries. Some EU15[6] countries feared an inflow of cheaper labor. Mainly motivated by political considerations, the old member states were therefore allowed to unilaterally limit access to their labor markets for a period of up to seven years. These transitional provisions were applied to all NMS in the same way, except Malta and Cyprus. In 2007, Bulgaria and Romania joined the European Union, and faced transitional provisions until 2014. In 2013, Croatia joined, experiencing labor market restrictions until 2020. Non-EU member states (Iceland, Liechtenstein, Norway, and Switzerland[7]), also applied transitional provisions to-

[6]EU15 denotes old EU member states: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom.

[7]These four countries are denoted as +4.

wards new EU member states, and we thus include them in our analysis.[8]

The option to unilaterally restrict labor markets generated different labor mobility patterns within the EU. For example, for 2004 entrants, Ireland, Sweden, and the UK decided to open their labor markets immediately in 2004 without any restrictions, while other countries delayed or restricted the access to specific industries. Denmark, Greece, Spain, and Portugal, for instance, removed restrictions only in 2009. France, Belgium, the Netherlands, and Austria opened their labor markets gradually, allowing only workers in certain industries and introducing quotas. Germany virtually prohibited all access to the labor market until the expiration of the transitional provisions in 2011. Appendix Table A1 provides an overview of the precise opening dates for each destination (EU15+4) and origin (NMS) country.

One might argue that restricting a country's labor market is endogenous and related to local labor market conditions. Germany, for instance, experienced high unemployment rates during the mid-2000s and this was one of the reasons for its labor market restrictions. However, while the transitional provisions are endogenous to labor market conditions and firm productivity in the *destination* country, they are exogenous to firm outcomes in the countries of *origin*. Furthermore, restrictions needed to be the same for all NMS from a given accession year, so origin-specific exceptions were not possible.

We thus use the information on labor mobility regulations within the EU to construct an instrument for the emigration of workers to circumvent the endogeneity of emigration. We obtain the legal information from the Labor Reforms database (section on labor mobility) of the European Commission and complement it with information from national legislation.

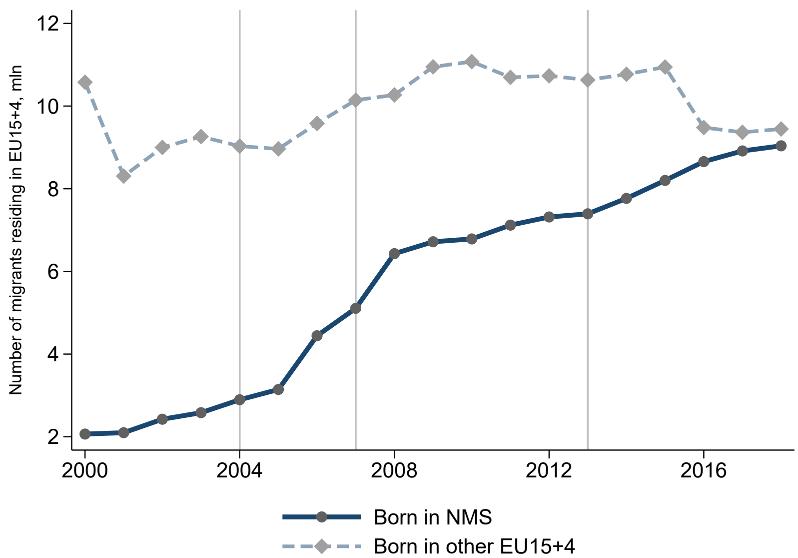
3.2 Migration Data and Descriptive Statistics

Our migration data is self-assembled industry-specific stock data from National Statistics offices of emigrants' destination countries (EU15+4).[9] For a few coun-

[8]EU15+4 denotes all countries that applied transitional provisions.

[9]In general, administrative data on immigration are of better quality compared to data on emigration. First, not all emigrants officially report their departure in origin countries. Second, even if they do report it, we are not likely to observe other characteristics, such as industry of work, before

Figure 1: **Stock of EU Migrants Residing in EU15+4 Countries Before and After EU Accession**



Notes: This figure shows the evolution of emigration from NMS to EU15+4 and the evolution of migration within EU15+4. The y-axis indicates the number of migrants in millions. The dark (light) line shows the number of migrants residing in the EU15+4 from the NMS (EU15+4). Vertical lines correspond to the EU enlargements of 2004, 2007 and 2013.
Source: OECD Migration (MIG) Database.

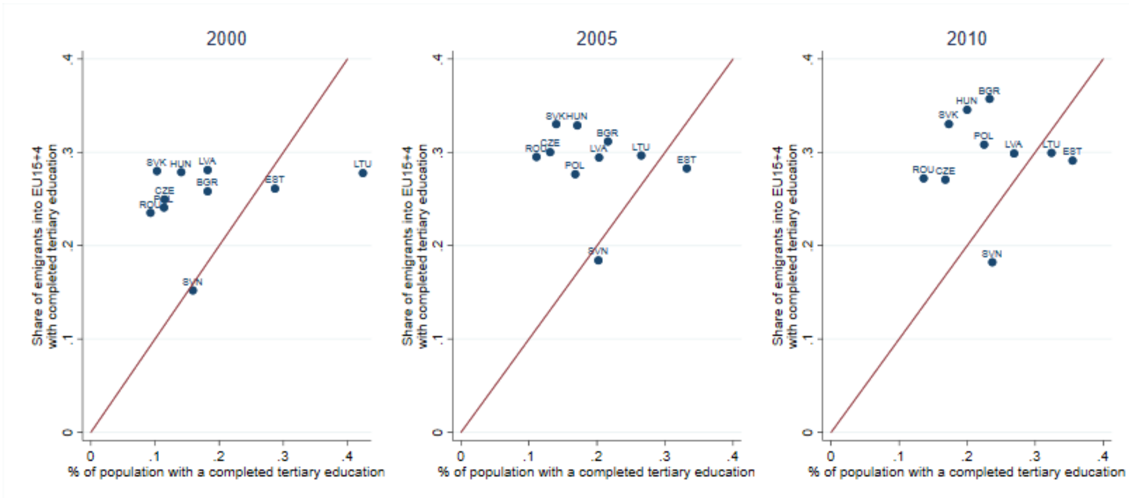
tries, it was not possible to obtain data from administrative sources, and hence we obtained the data from national labor force surveys or used other proxies (see Data Appendix A.4 for an overview of the precise data source by country).[10]

Figure 1 shows the stock of emigrants from NMS residing in EU15+4 countries (dark line). Emigration increased after the EU accession and subsequently remained at higher levels. For comparison, the light line shows the stock of emigrants from E15+4 residing in other EU15+4 countries, which remained stable throughout the time period of interest.

the departure.

[10]Other potential migration data sources could not be used as they do not include migration data at a two-digit sector level (Global bilateral migration stock databases from the UN and the World Bank, United Nations flow database), only provide observations every five or ten years or do not cover all the NMS (OECD DIOC). The Eurostat Labor Force Suvey aggregates all the relevant origin countries in two groups (NMS10 for 2004-entrants and NMS3 for Bulgaria, Romania, and Croatia). Moreover, as it is a survey of around five percent of the population some origin-destination-industry cells only have a few observations and are therefore unreliable.

Figure 2: **Education Level of NMS Emigrants as Compared to the NMS General Population**



Notes: This figure shows the share of tertiary educated emigrants in the emigrant stock of each of the NMS, contrasting it with the share of tertiary educated individuals in the respective origin country. For most NMS, the share of tertiary educated is higher among emigrants than in the general population.
Sources: IAB Brain Drain Dataset (Brücker et al. 2013), no data available after 2010. Eurostat for share of origin country population with tertiary education.

Kahanec et al. (2009), Constant (2011), and Kahanec (2013) provide descriptive evidence of increased EU migration flows following the enlargements. Using country-level data, they show that the transitional provisions influenced migration movements. The UK and Ireland, for example, became the main EU destination country for Polish, Slovakian and Latvian workers. Kahanec et al. (2016) apply a difference-in-differences analysis and confirm that emigration from NMS increased with the EU accession, but its full potential was hampered by the transitional provisions.

The self-selection of emigrants can be visualized by highlighting differences in skill levels between NMS emigrants and the NMS general population. Figure 2 uses the IAB Brain Drain Dataset developed by Brücker et al. (2013) and shows that on average highly skilled individuals are overrepresented in the stock of emigrants from NMS living in EU15+4 compared to the share in the remaining population of their origin countries. This indicates a loss of highly skilled human capital through emigration.

3.3 Firm Productivity Data and Descriptive Statistics

We obtain firm-level data from Bureau Van Dijk's ORBIS and Amadeus databases which provide standardized annual balance-sheet and profit information for European public and private companies of all sizes.[11] We work with an unbalanced panel of approximately 1.8 million firms located in NMS. The period covered ranges from 2000 to 2017, and there are about five annual observations for each firm on average. The sample includes companies in manufacturing, construction, retail trade and services. Besides financial reports, the dataset provides information on firms' patents, which we use in the heterogeneity analysis. Appendix A.4.3 provides a detailed description of the dataset.

Our sample comprises firms with at least one employee and with available data to estimate TFP. Having examined the histograms, we also noted that a few firms report unusually large figures for value added and number of employees, which is likely to be a reporting error. We therefore dropped these outliers in our baseline specifications (i.e. firms with value added equal to or above the 99th percentile and firms with over 100,000 workers). Our results are robust to keeping the outliers, but the estimated effects are noisier. Table 1 provides the summary statistics for firms in our sample and Table A2 in the Appendix provides the summary statistics for firms from the unrestricted sample.

We apply this firm-level data to calculate three measures of firm productivity: labor productivity, wage-adjusted labor productivity and TFP. The first measure is calculated as total value added over the number of employees. The second measure is calculated as total value added over personnel costs.[12] To obtain the third measure, we apply a semi-parametric approach as in Levinsohn and Petrin (2003) and Wooldridge (2009). This method enables us to overcome the simultaneity bias between firms' inputs and unobserved (to researchers) productivity shocks. For details, regarding the TFP calculation, we refer to the Appendix A.4.2. Other firm level outcomes are the number of employees, personnel costs per employee and the

[11] ORBIS and Amadeus databases overlap to some extent. In our baseline specifications we included firms available either in ORBIS or Amadeus. Further in the text, we will use *ORBIS* to denote this dataset.

[12] The personnel costs include wages, as well as other personnel-related expenditures, such as hiring and training costs.

Table 1: **Summary Statistics, Firm Data**

	Mean	SD	Min	Max	N
Firm age	8.904	7.097	0	403	8929421
Turnover, thousand EUR	788.165	4276.332	0	3375883.4	11392984
Value added, thousand EUR	309.689	922.121	0	10086	11398456
Total assets, thousand EUR	717.690	10841.654	0	9217911.6	11235964
Fixed assets, thousand EUR	376.353	12374.721	0	9795480	11398456
Number of employees	13.950	110.845	1	87282	11398456
Material costs, thousand EUR	483.198	19742.034	0	65207768	11326940
Personnel costs, per employee, EUR	5982.629	17233.088	0	21867552	11398456
Total assets/L, EUR	82402.870	1.98e+06	0	4.092e+09	11235964
Fixed assets/L, EUR	40647.584	1.48e+06	0	3.280e+09	11398456
Y/L, EUR	30670.831	1.15e+05	0	10077321	11398456
Y/(WL)	12.804	360.662	0	550754.31	11388091
TFP, Levinson-Petrin	4.249	1.410	-13	15.336807	11398456
TFP, Wooldridge	3.684	1.387	-14	15.339891	11398456

Notes: This table presents summary statistics for all firm-level variables from the ORBIS sample used in our regression analysis. Y denotes value added, L denotes number of employees, WL denotes total personnel costs. TFP is in natural logarithms. Firm age is calculated using the reported year of incorporation (eleven firms in the sample turned out to be more than 200 years old, the oldest firms belong to education and health sectors, as well as to several manufacturing industries). The number of observations slightly varies due to differences in the availability of variables.

capital-labor ratio.

In Appendix A.4.3 we provide details on the representativeness of ORBIS data by comparing country-year aggregates obtained with data from ORBIS and data from Eurostat Structural Business Statistics (described below). As Figure A7 shows, ORBIS coverage varies by country and over time. Because we use ORBIS data to study short-term within-firm effects of emigration, our results are less sensitive to the changes in firm coverage by ORBIS. We further check the robustness of our results by restricting our sample to those firms, which existed prior to the EU enlargement. However, ORBIS data is not well-suited to analyze entry and exit dynamics of firms. Therefore, for the industry-level analysis we resort to Eurostat that provides more complete data at the industry level.[13]

3.4 Additional Data

As additional covariates and for the analysis at the industry level, we use aggregated (two-digit NACE) industry-level data, which are available for all EU member

[13] To ensure that our firm-level results are not driven by data availability, we compare our industry-level results when using all available Eurostat data and when restricting the sample to those countries and industries, which are also well-covered in ORBIS.

states and are harmonized by Eurostat. The Eurostat Structural Business Statistics database contains annual indicators, such as value added, number of employees, and investment. We also use industry-level import data to control for competition that firms face. These data come from the UN Comtrade database.[14] Macroeconomic controls (GDP per capita and FDI) come from the World Bank statistical database.

We use additional data to illustrate the mechanisms. Industry-level data (two-digit NACE) on training and tenure comes from the EU Labor Force Survey, an annual survey conducted in all EU member states and compiled by Eurostat. We also adopt a measure of skill shortages from the EU Commission Business Survey, which is conducted in all EU member countries by the Directorate General for Economic and Financial Affairs (DG ECFIN). The survey addresses firms in the manufacturing, service, retail trade, and construction sector and enquires about their assessment and expectations of the business development. In addition to other questions, the survey's participants are asked to evaluate factors limiting their production (such as labor constraints or intense product-market competition). The EU Commission publishes information on a two-digit NACE industry level. Thus, the measure obtained is equal to the share of firms in each industry reporting constraints due to labor or competition. Table 2 provides summary statistics for all additional variables used in the estimations.

Table 2: **Summary Statistics, Independent Variables**

	Mean	SD	Min	Max	N
Emigrants (oit)	6101.947	21317.761	2.63	4.77e+05	15884
FLM (Free Labour Mobility) (oit)	0.080	0.122	0	1.000	15884
GDP per capita PPP, EUR (ot)	10361.370	3760.460	3010	20170.000	15884
FDI inflow mln, EUR (ot)	5032.438	9495.858	0	75107.773	15884
Value added in NMS, mln EUR (it)	6385.211	7462.687	.0395	59116.301	15048
Skill shortages in EU19, share of firms (it)	0.068	0.053	0	0.450	15884
Investment, mln EUR (oit)	186.941	365.721	0	7463.974	15048
Import share, to industry turnover (oit)	0.099	0.234	0	1.000	15048
Skill shortages in NMS, share of firms (oit)	0.121	0.146	0	1.000	8363
Product-market competition, share of firms (oit)	0.103	0.105	0	0.948	3136
Job-related training, share of workers (oit)	0.021	0.046	0	0.466	28364

Notes: The table presents summary statistics for the main independent variable (Emigrants), the baseline IV (FLM) and other covariates used in the regression analysis. We show the level of variation in parentheses: o-origin, i-industry, t-year.

[14] The data are available at the product level, which we convert to the industry level using the NACE Revision 1 - HS 1996 correspondence table.

4 Econometric Specification

Our baseline specification is a 2SLS regression of firm outcomes on emigration using the "Free Labor Mobility" (FLM) variable as an instrument for emigration levels in origin countries. This captures a local average treatment effect (LATE). The FLM variable, which we describe in Section 4.2 below, summarizes the EU labor mobility regulations and quantifies the exposure of NMS firms to their workforce emigrating. For comparison, we also run OLS regressions.

4.1 OLS Specification

We begin by estimating simple OLS regressions of firm outcomes on emigration. The regression equation we estimate is the following:

$$Y_{ft} = \alpha + \beta_1 Emigrants_{oit} + \beta_2 a_{ft} + \beta_3 a_{ft}^2 + \beta_4 I_{oit-1} + \tau_{ot} + \eta_{i't} + \nu_f + \varepsilon_{ft} \quad (1)$$

Y_{ft} are outcomes of a firm (f) in year (t). $Emigrants_{oit}$ denotes the number of emigrants from a given firm's origin (o), industry (i) and year (t). We use the contemporaneous value for the main independent variable, because by construction we observe emigrants once they are employed in the destination industry. β_1 captures the correlation between emigration and firm-level outcomes, controlling for a set of covariates and fixed effects.

Variables a_{ft} and a_{ft}^2 account for firm age. I_{oit-1} includes origin-specific industry controls such as total investment and import share. These variables account for variation in firm performance due to other shifters of labor demand within a particular origin's industry; for instance, technical change or higher competition on the product market. We include all origin-specific industry controls with a one year lag to limit the "bad control" problem, as the emigration of workers could have directly affected other demand shifters. τ_{ot} are origin-specific time dummies and $\eta_{i't}$ are industry-specific time dummies.[15]

[15] We employ i' here, because we use industries at a *one*-digit level with more detailed subdivision of the manufacturing sector. We provide details of this subdivision in the Data Appendix,

ν_f represent firm fixed effects, and ε_{ft} is the error term. Outcomes and most independent variables (except dummies and those in shares) are in natural logarithms, which is why the coefficients can be interpreted as elasticities.[16]

In the baseline empirical model, we consider only within-firm variation. Such a specification allows us to take account of firm unobserved time-invariant heterogeneity (as initial management ability or quality of business ideas) and other constant characteristics of a firm's location or industry-specific production technologies.

The main dependent variable is firm productivity. We then look at several other outcome variables and apply the same regression equation. We are particularly interested in the effects on total number of employees, the capital-labor ratio, and the average personnel costs.

With OLS, we encounter several endogeneity problems. First, we are likely to face reverse causality as people leave sectors experiencing negative productivity shocks. Second, there are likely to be omitted variables such as a change in firm management quality, which can drive both emigration and firm productivity alike. Third, the main independent variable may suffer from measurement error. In the next section, we therefore move to an instrumental variable approach .

4.2 2 Stage Least Squares Specification

Higher emigration of NMS workers was triggered by the opening of the EU15+4 labor markets. We capture these changes in EU labor mobility regulations by constructing the Free Labor Mobility (FLM) variable, which we use as an instrument for emigration in the 2SLS empirical specification. The first stage has the form:

$$Emigrants_{oit} = \alpha + \gamma_1 FLM_{oit} + \gamma_2 I_{oit-1} + \tau_{ot} + \eta_{i't} + \nu_{oi} + \phi_{oit} \tag{2}$$

Variables are denoted as above in Equation 1. We then estimate the 2SLS re-

Section A.4.4. As Table A3 in the Appendix shows, employing industry-2-digit-specific time dummies results in low unexplained variation of our instrument. To account for remaining unobserved industry-2-digit time-varying shocks, we control for value added with one-year lag at this level.

[16]We applied an alternative transformation using inverse hyperbolic sine function, however, as we do not have negative values, nor many zeroes, the results are very close.

gressions at the firm- or industry-level in one step. Note that when we perform the analysis at the firm level, the first stage is adjusted to the firm level. In the results section, therefore, we provide first-stage results at both firm- and industry-level.

We construct the instrument as follows. First, for each origin-industry-year observation we obtain a set of 19 dummies D_{doit}, with each dummy corresponding to one of the EU15+4 destination countries, d. A dummy takes the value of one, if according to an old EU member state's regulation, a specific industry i is open to labor migrants from a given origin country o in year t. For example, the UK completely opened its labor market for the NMS (2004-entry) group in 2004. Therefore, UK dummies for all industries for all origin countries from this accession year equal one starting from 2004. In contrast, France retained the transitional provisions for the 2004-entrants until 2008. Prior to 2008, the French government applied a special job scheme, which authorized free labor market access only in construction, tourism, and catering. France dummies for NMS industries take a value of zero until 2008, except for the three mentioned sectors.

One of the limitations of the legislation dummies is rather low explicit industry-level variation. Austria, Germany, Italy, and the Netherlands, for instance, did not specify which industries are open to labor migrants from new member states. Instead, they allowed for special job schemes in sectors that experienced skill shortages. In addition, the legislation dummies do not capture different capacities of EU15+4 markets to absorb immigrants. To account for this, we multiply the legislation dummies D_{doit} by a measure of skill shortages in each industry of a EU15+4 destination. For this, we use the share of firms (in destination industries) reporting to be constrained in production by the factor labor. These data come from the EU Commission Business Survey. This modification controls for implicit regulatory changes and for differences in labor market conditions across and within industries in the destination.[17] A possible concern with such a modification is that skill shortages in the old EU member states might be endogenous to firm productivity in NMS countries, due to common technology or demand shocks, for example. We

[17]This allows to capture, for example, a decrease in demand for foreign workers during and after the economic crisis between 2008 and 2009. At this time, many labor markets were already open for NMS citizens, but effective job possibilities were limited. De-jure, only Spain reacted to the worsening of economic conditions by reintroducing restrictions for Romanian citizens in 2011.

control for this by including industry-time fixed effects, which capture common shocks across all NMS industries and by controlling for industry-origin specific investment. Another concern is that labor demand (and thus reported skill shortages) could increase in EU15+4 industries, which had become more competitive relative to their NMS rivals following the EU enlargements. In this case, however, one would already expect to see negative tendencies in NMS firm performance prior to the emigration of workers. Moreover, we can account for higher product-market competition by controlling for the import share. In addition, we run a placebo test showing that our instrument is not correlated with the perceived product-market competition in NMS.

To summarize the set of 19 dummies into a single variable, we apply proximity weights reflecting how strongly the opening of a particular EU15+4 labor market affects the citizens of a respective new member state. We apply bilateral distances between the two largest cities of each origin and destination country as a measure of proximity: the shorter the distance, the larger the weight for a corresponding EU15+4 labor market. This assumes that labor migrants, for example, from Estonia were more sensitive to the opening of the Finnish labor market than the Portuguese one. This assumption is commonly confirmed in gravity equations for migration flows.[18]

The instrument is described by the equation:

$$FLM_{oit} = \sum_{d=1}^{19} w_{d,o} \cdot D_{doit} \tag{3}$$

FLM_{oit} is the value for one observation (origin-industry-year). D_{doit} denotes the openness level of the labor market in a destination d industry i for the citizens of a given origin o in a given year.[19] $w_{d,o}$ denotes the proximity weight. To ensure the comparability of different versions of FLM variables, we standardize the instrument to be in the range [0,1], where zero corresponds to a closed labor market and one to

[18]As an alternative to bilateral distances between the countries, we can calculate the proximity weights by using the distribution of migrants as of 2000. The results are similar. We selected bilateral distances, as they generate a higher F-statistics in the first-stage regression.

[19]In our baseline specification, D_{doit} represents an interaction between a legal dummy and a share of firms in the destination reporting skill shortages. D_{doit} is thus a value between 0 and 1.

the largest exposure to emigration in our sample.

For the instrument to be valid, we need it to be relevant and to satisfy the exclusion restriction. The results for the first-stage regression are presented in the Appendix and confirm the instrument's relevance. Table A4 shows that our first-stage results are robust to using different proximity factors for constructing the FLM variable. The distance-weighted version of FLM generates the largest F-Statistics and is therefore used in our baseline specification. Moreover, this table demonstrates that the results are robust to using pure legal dummies (without multiplying them by skill shortages in the destination), the F-statistics is, as expected, lower.

Because the FLM variable varies at industry, origin, and year level, Table A4 illustrates how our instrument works with the industry-level data that covers all available industries in all NMS. When we conduct the analysis at the firm-level, the first stage is re-estimated at the firm level, with the same fixed effects and controls as in the second stage. For completeness, we report the corresponding F-statistics, as well as the first-stage FLM coefficient and standard error under every 2SLS specification below.

Appendix Figures A1 and A2 illustrate the variation in the FLM variable across time, industries and countries. Figure A4 plots migration stocks against the FLM variable (after partialling-out controls and fixed effects) to show that our variation is not driven by outliers.

We argue that the instrument meets the exclusion restriction, since detailed industry-, year- and destination-specific regulatory changes could not have been influenced by firms in origin countries and were uncorrelated with other immediate accession policy changes, such as the free movement of goods or capital. Given that destination countries had to apply the same industry openings to all NMS from the same accession year, it is unlikely that a single firm (or even an industry from a certain origin) could have exerted any influence on them.

Another important assumption for our identification is that emigrated workers stay in the same industry. The industry exemptions in the transitional provisions were quite broad (often defined at a two-digit industry level), so that we consider it plausible that most skilled migrants stay in the same industry. If there were much industry switching, this would bias our estimates towards zero. While there is evidence that skilled immigrants are typically overqualified in the destination country (Chiswick and Miller 2008, 2009; Drinkwater et al. 2009; Johnston et al. 2015; Lindley 2009; Nielsen 2011; Visintin et al. 2015), they are still more likely to stay within the same sector. For instance, Kuhnen and Oyer (2016) show that firms try to reduce uncertainty regarding workers' future productivity and prefer to make offers to candidates with experience in the firm's industry. To provide some evidence, we use EU LFS data where for a subset of NMS respondents we can observe both their industry of work in the country of origin and their current industry of work.[20] As Figure A3 in the Appendix shows, about 75 percent of NMS migrants are staying in the same industry. This share is slightly higher among NMS migrants with lower or upper secondary degrees (close to 80 percent) and somewhat lower for NMS migrants with a tertiary degree who are also more likely to be overqualified (just below 70 percent).

5 Results

This section presents and discusses the empirical results. Regressions in Subsection 5.1, 5.2 and 5.3 include firm fixed effects and thus capture within-firm variation in outcomes as a response to the emigration of workers. Subsection 5.4 focuses on industry dynamics and thus takes into account the effects stemming from the exit and entry of firms.

5.1 Productivity Results

Table 3 presents our main results in Columns 4 - 6: we regress total factor productivity (Column 4), labor productivity (Column 5) and wage-adjusted labor productivity (Column 6) on emigration, instrumented by the Free Labor Mobility (FLM) variable.[21] Columns 1-3 show respective OLS results for comparison. All outcomes and the main independent variable are in natural logarithms. Thus the coefficients may be interpreted as elasticities.

[20] Because of data restrictions, we can observe only 1-digit industry classification.

[21] Our first stage estimates differ from those presented in Table A4, because the latter was estimated using origin-industry-year data for all industries for which we have migration data.

Table 3: **The Effect of Emigration on Firm productivity (OLS and 2SLS)**

VARIABLES	(1) OLS TFP LP	(2) OLS Y/L	(3) OLS Y/(WL)	(4) 2SLS TFP LP	(5) 2SLS Y/L	(6) 2SLS Y/(WL)
$Emigrants_{oit}$	-0.030**	-0.036***	-0.022**	-0.418**	-0.485**	-0.446***
	(0.013)	(0.014)	(0.010)	(0.192)	(0.201)	(0.170)
Age_{ft}	0.280***	0.781***	-0.129***	0.279***	0.780***	-0.130***
	(0.013)	(0.014)	(0.010)	(0.013)	(0.014)	(0.011)
Age^2_{ft}	-0.109***	-0.349***	0.012**	-0.110***	-0.350***	0.010**
	(0.007)	(0.008)	(0.005)	(0.007)	(0.008)	(0.005)
$Value\ added_{it-1}$	0.035***	0.037***	0.023**	0.069***	0.077***	0.061***
	(0.013)	(0.013)	(0.010)	(0.023)	(0.024)	(0.020)
$Investment_{oit-1}$	-0.017*	-0.013	-0.009	-0.032**	-0.031**	-0.026**
	(0.009)	(0.008)	(0.007)	(0.013)	(0.013)	(0.011)
$Import\ share_{oit-1}$	-0.001	0.036	-0.004	0.010	0.048	0.008
	(0.039)	(0.042)	(0.031)	(0.056)	(0.063)	(0.053)
Observations	8,413,561	8,413,561	8,413,561	8,413,561	8,413,561	8,413,561
R-squared	0.571	0.671	0.659			
Clusters	11132	11132	11132	11132	11132	11132
First stage F-stat				13.78	13.78	13.78
FLM coefficient				0.546	0.546	0.546
FLM se				0.147	0.147	0.147

Notes: The table presents OLS (Columns 1-3) and 2SLS (Columns 4-6) effects of emigration on three measures of firm productivity. Columns 1 and 4 show the effect of emigration on TFP (estimated according to the Levinson Petrin method). Columns 2 and 5 show results for labor productivity (value added/employees) and Columns 3 and 6 show wage-adjusted labor productivity (value added/employee costs). All specifications are estimated with firm fixed effects, industry-specific time dummies and origin-specific time dummies. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

For an average firm in our sample, the causal effect of emigration on three different measures of productivity is negative.[22] In the main specification, an increase in emigration of 10 percent causes between four to five percent decrease in firm productivity in that same year. A median annual increase in emigration of 7.86 percent as in our sample, would then lead to a 3-4 percent decrease in firm productivity.

There could be several reasons why our IV estimates are stronger than the OLS results. First, OLS estimates are likely to be biased toward zero due to measurement error in the migration variable. Second, we proxy the stock of emigrants by the number of NMS-born workers employed in a respective industry of an EU15+4 country. This number may increase due to the emigration of workers, but also due

[22] As Table A5 shows, the result for total factor productivity is robust to alternative ways of computing TFP.

to other reasons: for instance, previously unemployed NMS migrants (from earlier emigration cohorts) or family migrants could become employed or former NMS students who had already studied in EU15+4 could enter the labor market there. While the emigration of workers is important for firms in origin countries as they are losing workers, the other reasons should not fundamentally affect firms in origin countries. When we use our IV to predict emigration, by construction we are more likely to capture an increase due to labor emigration, since the identifying variation is generated by changes in labor mobility regulations.

Our results are corroborated by looking at the reduced-form estimations (see Appendix Table A6). The reduced form abstracts from a measurement error that could arise in the migration data and shows how firm productivity changes with higher *exposure* to emigration. A median annual increase in the FLM variable of 0.12 would result in a $\simeq$ 2.7 percent decrease in firm productivity. Given that our reduced-form estimates lead to the same qualitative conclusions as the 2SLS, for some additional analyses below, we report results from the reduced-form estimations.

Table A7 explores the dynamics of the emigration effect. We focus on the reduced form specification and firm TFP as an outcome (the results for other productivity measures are similar). We subsequently add first, second, and third lags of the FLM variable to our regression and check how the coefficient for contemporaneous FLM_{oit} changes. If the change in productivity happens with a delay but the shocks are correlated, we would expect that the coefficient becomes weaker when we add the relevant lags. However, the magnitude of the FLM_{oit} coefficient remains statistically intact, which confirms that there is a short-term drop in TFP in the year of the emigration shock. Table A7 also shows that the coefficient of interest is stable to changes in the sample composition, as some firms drop out from the sample when we add more lags.

5.2 Other Firm-level Outcomes

To shed light on how firms adjust to emigration, we look at other firm-level outcomes: personnel costs, capital-labor ratio and number of employees. The elasticity of personnel costs to emigration is positive, but imprecisely estimated. We find a statistically significant increase in the number of employees (a 10 percent increase in emigration results in a 1.6 percent increase in the number of employees) and consequently a decrease in the capital-labor ratio. This might seem counter-intuitive at fist if one expects that firms increase wages or replace workers with capital in response to emigration.

There could be two explanations for these effects. Either, different firms react differently to emigration and the average results we find are driven by a certain type of firms. Or, the outcome, for instance, personnel costs per employee captures different reactions within a firm, which cancel each other out. One could imagine that, on average, wages increase as labor becomes scarcer. Simultaneously, firms can replace more experienced and therefore also more expensive workers with new (less experienced and less skilled) hires that have lower wages. This could be in line with the weak effect on personnel costs per employee and a positive effect on the number of employees. We dig deeper into the firm adjustment by looking at firm heterogeneity in the next section.

Table 4: **The Effect of Emigration on Other Firm Outcomes (OLS and 2SLS)**

VARIABLES	(1) OLS Costs per employee	(2) OLS Assets/L	(3) OLS N employees	(4) 2SLS Costs per employee	(5) 2SLS Assets/L	(6) 2SLS N employees
$Emigrants_{oit}$	-0.002	-0.017***	0.010***	0.062	-0.208**	0.162***
	(0.003)	(0.005)	(0.003)	(0.054)	(0.087)	(0.052)
Age_{ft}	0.852***	0.442***	0.234***	0.852***	0.442***	0.234***
	(0.012)	(0.011)	(0.006)	(0.012)	(0.010)	(0.006)
Age^2_{ft}	-0.330***	-0.170***	0.039***	-0.330***	-0.170***	0.040***
	(0.006)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)
$Value\ added_{it-1}$	0.005	0.014**	-0.004	-0.000	0.030***	-0.018***
	(0.004)	(0.007)	(0.003)	(0.007)	(0.010)	(0.007)
$Investment_{oit-1}$	0.000	0.009***	-0.004***	0.003	0.001	0.002
	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)	(0.003)
$Import\ share_{oit-1}$	0.051***	0.040**	-0.009	0.050***	0.045*	-0.013
	(0.017)	(0.020)	(0.014)	(0.018)	(0.027)	(0.020)
Observations	8,413,561	8,413,561	8,413,561	8,413,561	8,413,561	8,413,561
R-squared	0.818	0.833	0.882			
Clusters	11132	11132	11132	11132	11132	11132
First stage F-stat				13.78	13.78	13.78
FLM coefficient				0.546	0.546	0.546
FLM se				0.147	0.147	0.147

Notes: The table presents OLS (Columns 1-3) and 2SLS (Columns 4-6) effects of emigration on various firm outcomes. Columns 1 and 4 show results for costs per employee. This includes wages and other labor costs. Columns 2 and 5 show results for assets over the number of employees, which we use to measure the capital-labor ratio. Columns 3 and 6 show results for the number of employees. All specifications are estimated with firm fixed effects, industry-specific time dummies and origin-specific time dummies. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** p<0.01, ** p<0.05, * p<0.1

5.3 Heterogeneity

In the main specification, we analyze the effect of higher within-EU labor mobility for the full sample of NMS firms. To examine heterogeneous effects, we repeat the estimations for different sub-samples of firms: 1) incumbents, 2) firms with different initial productivities, and 3) innovating firms.

We first look at incumbents, which are defined as firms existing prior to the first EU enlargement in 2004. The advantage of focusing on these firms is that their productivity is neither affected by endogenous entry decisions nor by changes in data availability over time. Yet, as Table 5 shows, the overall results for incumbents do not differ significantly from the baseline results.

Once we estimate the effects for incumbent firms along different deciles of their initial productivity distribution, interesting patterns emerge. This exercise allows us to study whether initially more productive firms behave differently compared to initially less productive ones.

Table 5: **The Effect of Emigration on Firm Outcomes, Incumbent Firms (2SLS)**

VARIABLES	(1) 2SLS TFP LP	(2) 2SLS Y/L	(3) 2SLS Y/(WL)	(4) 2SLS Costs per employee	(5) 2SLS Assets/L	(6) 2SLS N employees
$Emigrants_{oit}$	-0.521***	-0.577***	-0.488***	0.030	-0.220***	0.127***
	(0.166)	(0.170)	(0.142)	(0.038)	(0.061)	(0.035)
Age_{ft}	0.097***	0.492***	-0.228***	0.698***	0.249***	0.215***
	(0.019)	(0.036)	(0.023)	(0.048)	(0.018)	(0.018)
Age^2_{ft}	-0.056***	-0.229***	0.018**	-0.226***	-0.120***	0.046***
	(0.009)	(0.016)	(0.008)	(0.016)	(0.007)	(0.008)
$Value\ added_{it-1}$	0.085***	0.091***	0.066***	0.007	0.022**	-0.015***
	(0.021)	(0.022)	(0.018)	(0.006)	(0.009)	(0.006)
$Investment_{oit-1}$	-0.038***	-0.037***	-0.029**	0.001	0.004	-0.002
	(0.014)	(0.014)	(0.012)	(0.004)	(0.005)	(0.003)
$Import\ share_{oit-1}$	0.006	0.041	-0.018	0.066***	0.029	-0.001
	(0.066)	(0.071)	(0.059)	(0.020)	(0.031)	(0.020)
Observations	3,563,031	3,563,031	3,563,031	3,563,031	3,563,031	3,563,031
Clusters	9908	9908	9908	9908	9908	9908
First stage F-stat	28.65	28.65	28.65	28.65	28.65	28.65
FLM coefficient	0.815	0.815	0.815	0.815	0.815	0.815
FLM se	0.152	0.152	0.152	0.152	0.152	0.152

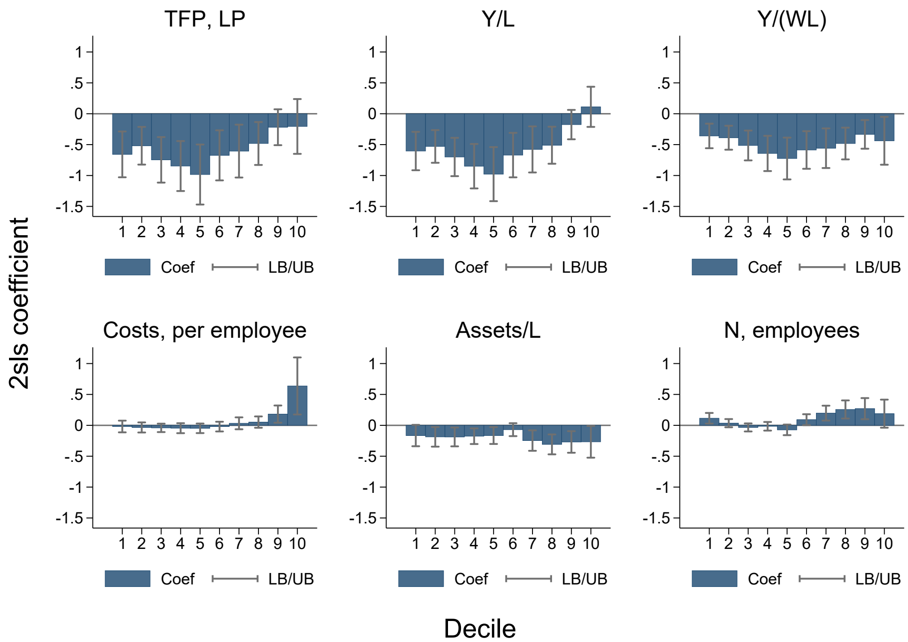
Notes: The table presents 2SLS effects of emigration on different firm outcomes for incumbent firms: three measures of firm productivity (Column 1-3) and other firm outcomes. Column 1 shows the effect of emigration on TFP (estimated according to the Levinson Petrin method). Column 2 shows the result for labor productivity (value added/employees) and Column 3 - for wage-adjusted labor productivity (value added/employee costs). Column 4 shows the result for costs per employee, Column 5 - for the capital-labor ratio and Column 6 - for the number of employees. All specifications are estimated with firm fixed effects, industry-specific time dummies and origin-specific time dummies. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** p<0.01, ** p<0.05, * p<0.1

Figure 3 shows the contemporaneous effect of emigration on firm productivity and other outcomes along the initial productivity distribution. To estimate the coefficients shown in this figure, the sample was split into deciles depending on a firm's total factor productivity prior to the first labor market opening.[23]

Reduction in total factor and labor productivity is experienced by all firms along the productivity distribution with the exception of the most productive firms from the 9th and 10th deciles. It appears that these most productive firms manage to adjust to emigration by increasing wages to retain their workers or by increasing their

[23] We consider the average productivity of firms between 2000 and 2003.

Figure 3: **Results Along the Productivity Distribution**



Notes: This figure presents regression results for our main outcomes for incumbent firms along different productivity deciles. The sample only includes firms that existed prior to 2004 as firms are divided into productivity deciles based on their average productivity between 2000 and 2003. On the x-axes we indicate firm productivity deciles and on the y-axes we indicate the estimated coefficients from a 2sls regression with the respective outcome indicated at the top of each graph. The blue bars show the estimated coefficients for instrumented migration and the black lines show the upper and lower bounds of the 95 percent confidence interval.

hiring efforts to replace those who emigrate with equally qualified ones. Adjustment through wages is also reflected in the drop of wage-adjusted labor productivity for these firms.

Firms in the upper productivity deciles (6th – 8th) increase the number of employees. It seems that these productive, but not most productive firms adjust by replacing emigrated workers with more new hires. The fact that productivity still falls and the personnel costs are not increasing suggests that the new hires are not direct substitutes for those who left.

Firms experiencing the strongest drop in productivity are those whose workforce becomes significantly lower. We can thus attribute the drop in their productivity to the inability to replace emigrated workers. There is a somewhat puzzling effect on the productivity and number of workers for firms in the lowest three deciles. We can hypothesize that this is driven by higher selection to survival for these firms:

low-productivity firms are more likely to exit the market, and the fact that we still observe some of these firms in our sample several years later means that they have managed to move up and behave similarly to firms in the 6th-8th deciles.

Table 6 shows the results for innovating firms. We define innovating firms as firms holding at least one patent. On the one hand, these firms are especially likely to suffer from brain drain as their highly skilled workers could be in high demand abroad. On the other hand, innovating firms belong to the more productive firms. As we can see, the estimated effect of emigration on firm TFP is not statistically significant and is no longer negative. These firms may be able to provide an interesting work environment, as well as having retention initiatives to keep their essential staff. While we focus on short-term effects, there is also evidence that innovating firms benefit from reverse knowledge flows and increased research networks through their former employees over the longer term (Braunerhjelm et al. 2015; Fackler et al. 2020; Kaiser et al. 2015; Kerr 2008; Peri 2004).

Another relevant heterogeneity dimension to explore is the skill level of emigrating workers. We would expect that firms exposed to emigration of more skilled workers should be more strongly affected than those facing less skilled emigration. While we have no firm-level or detailed industry-level data on the level of emigrants' education or skill, we can use insights from the Roy-Borjas model (Borjas 1987) as a tool to determine self-selection patters of migrants between different origin-destination pairs in our sample. We can thus distinguish the effect of exposure to positively self-selected emigration from the effect of exposure to negatively self-selected emigration. Section A.3 in the Appendix describes our approach and presents the results, which show that negative effects on productivity measures are stronger in case of positive self-selection.

Table 6: **The Effect of Free Labor Mobility of Workers on Firm Productivity (Firms with Patents)**

VARIABLES	(1) 2SLS TFP LP	(2) 2SLS Y/L	(3) 2SLS Y/(WL)	(4) 2SLS Costs per employee	(5) 2SLS Assets/L	(6) 2SLS N employees
$Emigrants_{oit}$	0.466	0.062	0.007	-0.103	-0.256	0.980**
	(0.335)	(0.273)	(0.147)	(0.158)	(0.283)	(0.385)
Age_{ft}	0.398***	0.492***	-0.073	0.400***	-0.059	0.415***
	(0.111)	(0.107)	(0.064)	(0.066)	(0.085)	(0.083)
Age^2_{ft}	-0.084*	-0.173***	-0.002	-0.124***	0.057*	0.087**
	(0.044)	(0.044)	(0.026)	(0.026)	(0.034)	(0.035)
$Value\ added_{it-1}$	-0.138	-0.016	-0.044	0.073	0.057	-0.246*
	(0.118)	(0.094)	(0.052)	(0.055)	(0.099)	(0.137)
$Investment_{oit-1}$	0.003	0.009	0.013*	-0.011	0.031***	-0.027*
	(0.015)	(0.012)	(0.007)	(0.007)	(0.011)	(0.015)
$Import\ share_{oit-1}$	-0.059	0.014	0.031	-0.007	0.125*	-0.137
	(0.125)	(0.100)	(0.043)	(0.044)	(0.068)	(0.103)
Observations	31,920	31,920	31,920	31,920	31,920	31,920
Clusters	3908	3908	3908	3908	3908	3908
First stage F-stat	7.419	7.419	7.419	7.419	7.419	7.419
FLM coefficient	0.423	0.423	0.423	0.423	0.423	0.423
FLM se	0.155	0.155	0.155	0.155	0.155	0.155

Notes: The table presents 2SLS effects of emigration on different firm outcomes for innovating firms: three measures of firm productivity (Column 1-3) and other firm outcomes. Column 1 shows the effect of emigration on TFP (estimated according to the Levinson Petrin method). Column 2 shows the result for labor productivity (value added/employees) and Column 3 - for wage-adjusted labor productivity (value added/employee costs). Column 4 shows the result for costs per employee, Column 5 - for the capital-labor ratio and Column 6 - for the number of employees. All specifications are estimated with firm fixed effects, industry-specific time dummies and origin-specific time dummies. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

5.4 Industry-level Results

We complement the firm-level analysis with results at the industry level. Thus we can analyze the effect of emigration on aggregate productivity in the presence of firm entry and exit dynamics. Additionally, because we are using more complete Eurostat data, we can check whether the results differ when we use all available origin countries and industries and when we restrict our data to origins and industries, which are covered by ORBIS.

Table A8 shows that industry-level results are qualitatively similar to our firm-level estimates. However, we obtain several noteworthy additional insights. First, the effect of emigration on productivity at the industry level is negative and statistically significant, but its magnitude is smaller compared to firm-level estimates.

The firm-level regressions treated every firm (independent of its size) with the same weight, while the industry-level aggregate outcomes give a larger weight to larger (and more productive) firms, which in line with our heterogeneity finding experience a weaker effect of emigration. Furthermore, the least productive firms may exit following an emigration shock and no longer appear in the data. The latter is confirmed by the results in Columns 5 and 6 of Table A8: emigration exerts a negative effect on the number of firms and increases the number of exits.

Second, we can observe that the first-stage F-statistics is much higher at the industry level. This stems from more complete coverage of the industry-level data by Eurostat compared to the firm-level data by ORBIS.[24] In addition, we are exploiting within-industry rather than (aggregated at the industry level) within-firm variation in the instrument.

Third, industry-level results hold when we restrict the sample to only those industries and origin countries, for which we have good ORBIS coverage. This alleviates the concerns that our firm-level results are not representative for NMS in general.

In a similar way to the firm-level analysis in Table A7, we study the dynamics of the emigration effect at the industry level. Tables A9 and A10 show how the FLM coefficient in the reduced form specification changes when we add first, second, and third lags. While the contamporaneous FLM_{oit} coefficient is robust for productivity, we note that firm exits happen with a 1-2 year delay.

[24]For example, in ORBIS we have only few observations from Latvia, Lithuania and Poland who were strongly affected by emigration.

Table 7: **Industry-level Effects, Eurostat Data (all available industries)**

VARIABLES	(1) 2SLS Y/L Eurostat derived	(2) 2SLS Y/(WL) Eurostat derived	(3) 2SLS Costs per employee Eurostat	(4) 2SLS N employees Eurostat	(5) 2SLS N firms Eurostat	(6) 2SLS Exits
$Emigrants_{oit}$	-0.177***	-0.166***	0.049**	0.609***	-0.352***	0.867***
	(0.044)	(0.031)	(0.021)	(0.083)	(0.098)	(0.156)
$Value\ added_{it-1}$	0.121***	0.065***	0.028***	0.274***	0.409***	0.029
	(0.016)	(0.011)	(0.006)	(0.025)	(0.030)	(0.023)
$Investment_{oit-1}$	0.068***	0.032***	0.020***	0.249***	0.184***	0.052***
	(0.008)	(0.005)	(0.003)	(0.013)	(0.014)	(0.016)
$Import\ share_{oit-1}$	0.006	-0.044*	0.052***	-0.552***	-0.472***	-0.148*
	(0.037)	(0.025)	(0.018)	(0.078)	(0.086)	(0.083)
Observations	10,601	10,626	10,618	10,762	11,044	12,990
Clusters	10601	10626	10618	10762	11044	12990
First stage F-stat	175.2	176.1	177.2	194	212	208.5
FLM coefficient	1.138	1.142	1.144	1.188	1.242	1.192
FLM se	0.0860	0.0861	0.0859	0.0853	0.0853	0.0825

Notes: The table presents 2SLS regressions of different industry-level outcomes on emigration. The main outcomes are labor productivity (Column 1) and wage-adjusted labor productivity (Column 2), calculated respectively as a ratio between industry-level value added and number of employees and between value added and personnel costs. Other industry level outcomes are average costs per employee (Column 3), the total number of employees (Column 4), the number of firms (Column 5), and the number of firm exits (Column 6) in a given industry, origin and year cell. All specifications are estimated with origin-industry fixed effects, industry-specific and origin-specific time dummies. Standard errors (in parentheses) are clustered at the origin-industry-year level.

*** p<0.01, ** p<0.05, * p<0.1

6 The Mechanisms

We provide additional evidence to shed more light on the mechanisms behind our main result: all three firm productivity measures drop in the short term. This cannot be exclusively explained by the substitution with lower skilled workers or by wage adjustment, as these should affect (wage-adjusted) labor productivity, but not necessarily firm TFP. The complementarity between technology investments and skilled workers is also an unlikely channel, because it would have led to a more persistent decrease in TFP. One plausible mechanism is the temporary loss of firm-specific human capital caused by emigration. This problem is further exacerbated by firms' lower incentives to invest in training of new hires, which slows down the accumulation of firm-specific human capital.

Column 1 in Table 8 shows that firms experiencing an increase in emigration, are more likely to report skill shortages. A 10 percent increase in emigration leads to a 1.9 percentage point increase in the share of firms reporting skill shortages. From Table 2, this corresponds to about 15 percent increase in reported skill shortages. Economists are often sceptical when hearing firms' concerns about skill shortages, as they can be alleviated by paying higher wages to attract workers.[25] In our setting, however, the reported skill shortages also reflect the fact that even when firms manage to replace emigrated workers with new workers, those new workers are less productive. This could be due to the lack of firm-specific knowledge and skills, which are not accounted for in wages.

Firm-specific human capital can be accumulated either through learning by doing or through firm-specific training. Enhanced emigration opportunities increase worker turnover and, thus, reduce expected tenure. Column 2 in Table 8 confirms that increasing emigration reduces tenure, which is measured as the share of workers who stay in the firm for more than one year.

As a result, firms, which now face higher turnover, have lower incentives to invest in training of new hires. Column 3 in Table 8 indeed shows that firms invest less in training: a 10 percent increase in emigration leads to a 0.17 percentage point decrease in the share of employees who receive job-related training. From Table 2,

[25] If only the wage increase were the case, we would not have observed the drop in firm TFP.

this corresponds approximately to an eight percent decrease in the share of trained workers. Thus, the loss of firm-specific human capital is exacerbated by the lack of firm-specific training. Instead, new workers learn by doing, which takes more time. This is also in line with our dynamic results, which demonstrate how the negative effect only persists in the short term and then fades away.

Table 8: **Effect on Skill Shortages, Tenure and Training**

	(1)	(2)	(3)
	2SLS	2SLS	2SLS
VARIABLES	Skill shortages	Tenure $\geq$ 1 year	Job-related training
$Emigrants_{oit}$	0.196***	-0.045*	-0.018**
	(0.024)	(0.026)	(0.008)
$Value\ added_{it-1}$	-0.003	0.007***	0.003***
	(0.004)	(0.002)	(0.001)
$Investment_{oit-1}$	0.007***	-0.006***	-0.000
	(0.003)	(0.001)	(0.000)
$Import\ share_{oit-1}$	0.045**	-0.023*	0.003
	(0.018)	(0.013)	(0.003)
Observations	8,238	6,499	9,896
First stage F-stat	147.8	53.63	50.27
FLM coefficient	1.070	0.649	0.561
FLM se	0.0880	0.0886	0.0791

Notes: Columns 1,2 and 3 present industry-level 2SLS regressions of skills shortages, tenure and job-related training on instrumented emigration. The variable skill shortages measures the percentage of firms in a given industry, country and year that indicates being constrained in production by a lack of skilled workers. The tenure variable measures the percentage of employees that have a tenure above one year. The variable job-related training measures the percentage of employees that receive job-related training. All specifications are estimated with origin country·time and industry·time fixed effects. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** p<0.01, ** p<0.05, * p<0.1

While the above results are plausible, we treat them as suggestive evidence. We do not have the perfect data to disentangle the mechanisms in play. Therefore, better data (such as measures for firm-specific human capital, better proxies for the skill level and self-selection of emigrants, detailed migration data by industry and skill level, or detailed training and tenure data at the firm level) and further research are necessary to analyze the mechanisms with more precision.

7 Robustness

7.1 Changes in the Sample Composition

The results are robust to excluding certain observations. First, we exclude very small and very large firms to show that results are not driven by outliers in terms of firm size. Appendix Table A11 shows the main results when the sample of firms is restricted to firms with 5 - 250 employees, i.e. to small and medium sized enterprises. While the sample size drops from eight firm-year million observations to less than four million, all our main results still hold. This enables us to conclude that the results are not driven by very small or very large firms behaving differently.

The results are also robust to restricting the sample to the years before the financial crisis (before 2009). Emigration has been particularly strong in the early years of the opening, and firms were hit harder during the earlier years as demand and economic opportunities in EU15+4 were stronger. During the financial crisis, which hit most destinations in our sample in 2009, labor demand decreased and therefore firms did not experience skill shortages as strongly as during an economic boom. This is consistent with our data. For the sample that restricts the observations to the years before 2009, we find stronger negative productivity results. All productivity indicators are negative and significant as shown in Appendix Table A12.

7.2 Changes in the Empirical Specification

In our baseline specification, in addition to firm fixed effects (or origin-industry fixed effects for the industry-level regressions), we include origin-year and industry-year fixed effects. On the one hand, we ensure that our results are not driven by time-varying shocks across different NMS or across different industries. On the other hand, we limit the identifying variation of the FLM (see Table A3 in the Appendix). Table A13 presents the results of a less restrictive specification with firm and year fixed effects and lagged controls at the origin-year and industry-year level. While all results are qualitatively similar to our baseline, the estimated elasticities for productivity measures are almost double in magnitude (-0.8, -0.85 with a less restrictive model vs -0.4 -0.5 in the baseline). The elasticities in Table A13 can be, thus, interpreted as an upper bound of the effect size.

In the baseline regressions, we cluster standard errors at the origin-industry-year level - the level of variation in the FLM variable. The assumption is that conditional on fixed effects and controls employed in the empirical models, the remaining errors are uncorrelated between origin-industry-year clusters. To alleviate concerns that fixed effects and controls do not completely control for error correlation (for example, due to serial correlation), in Tables A14 and A15, we re-estimate the baseline firm-level and industry-level regressions using more conservative clustering at the origin-industry level. Most coefficients of interest remain statistically significant. At the firm level, only the emigration effect on TFP becomes borderline imprecise, with a p-value of 0.14. At the industry level, the effect on personnel costs is no longer significant with a p-value of 0.21.

7.3 Robustness of the Instrument

In Table A16, we check the baseline first- and second-stage results at the firm level by using alternative definitions of the instrument. In Column 1, we provide the 2sls coefficient and the first-stage statistics for the baseline instrument as a benchmark. In Column 2, we use an alternative FLM variable, which was constructed only based on industry-specific legal dummies (without skill shortages in the destination) and bilateral distances. We note that the F-statistics drops below 5, even though the first-stage coefficient remains positive and statistically significant. As we discussed earlier, legal dummies alone have a limited ability to describe different capacities of the destination industries to absorb migrants.

In Columns 3 and 4, we employ an alternative method to construct the instrument. Instead of using equation 3 to construct the FLM variable (as a weighted sum of legal dummies interacted with skill shortages) and use it as an instrument for emigration at the *origin*-industry-year level, we first model emigration at the *destination-origin*-industry-year level using components of the FLM variable and then aggregate the obtained predictions at the origin-industry-year level to construct an alternative instrument. The advantage of this method is that we can use flexible non-parametric methods (e.g. a random forest) to allow for various interactions and non-linearities in how the inputs (legal dummies, skill shortages, and bilateral distances) shape emigration. We provide technical details on this method under Table A16 in the Appendix. Column 3 presents the results with an IV constructed using legal dummies, skill shortages and bilateral distances as inputs, while Column 4 uses only legal dummies and bilateral distances. Reassuringly, the first-stage and the second-stage results are qualitatively similar to our baseline estimations.

Finally Column 5 uses a placebo instrument. To construct it, we reshuffled legal dummies across our destination-origin-industry-year observations, but kept skill shortages and proximity weights as in the baseline. First-stage coefficient changes sign and becomes statistically insignificant, which points to the importance of legal dummies in the construction of the FLM variable.

7.4 Placebo Test

The placebo test uses an outcome that should not be affected by changes in the FLM, but also varies at the origin-industry-year level and would capture economic changes: firms' perception of the product-market competition. In the EU Business Survey, besides skill shortages, firms also report on business challenges due to strong competition. Appendix Table A17 presents first-stage regression results with competition as the dependent variable. While for emigration all IV modifications returned statistically significant coefficients with high F-statistics, none of them is correlated with reported competition. This result reassures us that the constructed IV captures labor supply shrinking, which is due to emigration as opposed to other contemporaneous shocks.

Another placebo test regresses firms' productivity measures on future labor market openings. Appendix Table A18 demonstrates that future labor market openings do not predict the productivity of firms today, which is what we would expect if the instrument is valid.

7.5 Event Study

Another option to show dynamic results and to confirm that there are no pre-trends is to conduct an event study. We show the results in Appendix Figure A5. We can see that there are no pre-trends, and that the effect on firm productivity takes effect in year zero. This is defined as the year of the largest increase in the FLM value, i.e. the largest labor market opening for firms in a respective industry. For this robustness check, we restrict our data to the period between 2000 and 2008 because in later years the variation in FLM becomes more gradual, making it difficult to define a single large event. Moreover, the interpretation of the effect's dynamics becomes less clear: for example, the coefficient at x = +1 captures the lasting effect of the largest increase at x = 0 *and* the effect of a subsequent opening at x = +1. Due to these limitations in the event study design, this is not our preferred specification and we only present it as a robustness check to argue for the absence of pre-trends before the first big increase in exposure to emigration.

8 Conclusion and Policy Implications

Countries in Central and Eastern Europe have experienced a large emigration wave, especially among young and skilled workers. Emigration has accelerated with the accession to the EU and remained at a high level. While emigration has economically benefited the individual migrants and the destination countries in most cases, the effects on the origin are more contentious.

This paper uses firm- and industry-level panel data to illustrate a negative causal effect of emigration on firm productivity. To overcome the endogeneity problem, we exploit the natural experiment of EU enlargements and show how the gradual and industry-specific opening of the EU15+4 labor markets has created exogenous variation in emigration experienced by NMS. We show that the emigration of workers results in lower productivity for NMS firms in the short term. This effect can be observed for most firms along the initial productivity distribution, except for the most productive ones. These firms have been more successful in circumventing the loss in productivity by increasing their personnel costs.

Our results are important both for firms and policymakers. Being aware of the challenge helps firms react in a timely and adequate way. Firms may benefit from investing in automation technology or active human resource strategies, focusing, for instance, on providing training and retention measures. For policymakers, the effects of emigration "are not a matter of fate, [but] to a large extent, they depend on the public policies adopted in the destination and origin countries".[26] We see three areas of policy interventions.

First, policymakers should enhance their efforts to increase the labor force participation of the existing population through investments in education and the encouragement of women. The prevalence of skill shortages justifies the need to invest in the skills of the local labor force and to mitigate search frictions. A skill upgrading of the local labor force can be addressed in the short-term by providing specific training courses, which the state could subsidize to alleviate the burden on firms. Over the long term, the education system should be better adjusted to labor market needs. Knowing that those skilled people are needed, may justify the investment. An increase in local human capital might also happen over the long term due to increased incentives to invest in education, which rise with the prospect to emigrate (Beine et al. 2001). While a small fraction of the population will in fact emigrate, a significant fraction of well-educated workers typically remains and can help to develop the country. An further leeway is to encourage more women to participate in the labor force by improving access and quality of childcare, and abolishing disincentives to work for the second earner (Atoyan et al. 2016).

Second, policymakers could encourage return migration and immigration to increase the skilled workforce. Return migration may have various benefits for the origin country. Bahar et al. (2019) show that the former Yugoslavia has benefited from return migration to boost their exports. Even if return migration is low, firms could benefit from knowledge transfers, if firms and policymakers succeed in maintaining close ties with the diaspora (Fackler et al. 2020). A few countries such as Poland and Lithuania have already recognized this potential and introduced incentives to encourage return migration. Another opportunity is to attract immigrants from other Eastern European countries such as Belarus or Ukraine, by facilitating

[26] Docquier and Rapoport (2012).

labor market access. Since 2015, Poland, for instance, has provided more than half a million work and residence permits each year for workers from Ukraine and Belarus following recent political turmoil in these countries.

Third, the fact that certain European countries benefit, and others lose out from free labor mobility provides a justification for EU structural and cohesion funds to be channeled to countries that bore the brunt of emigrants' education expenses, while not benefiting from them.

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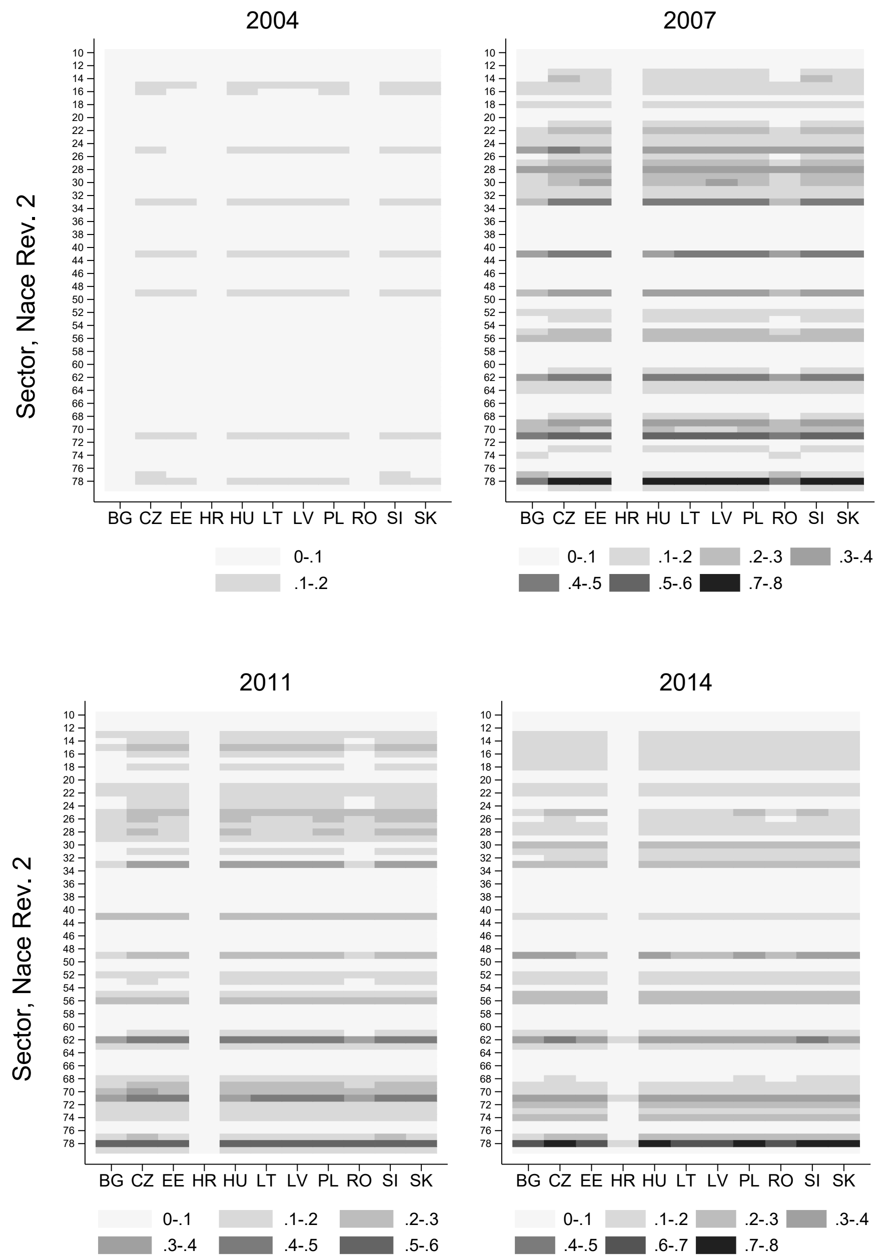
A Appendix (For Online Publication)

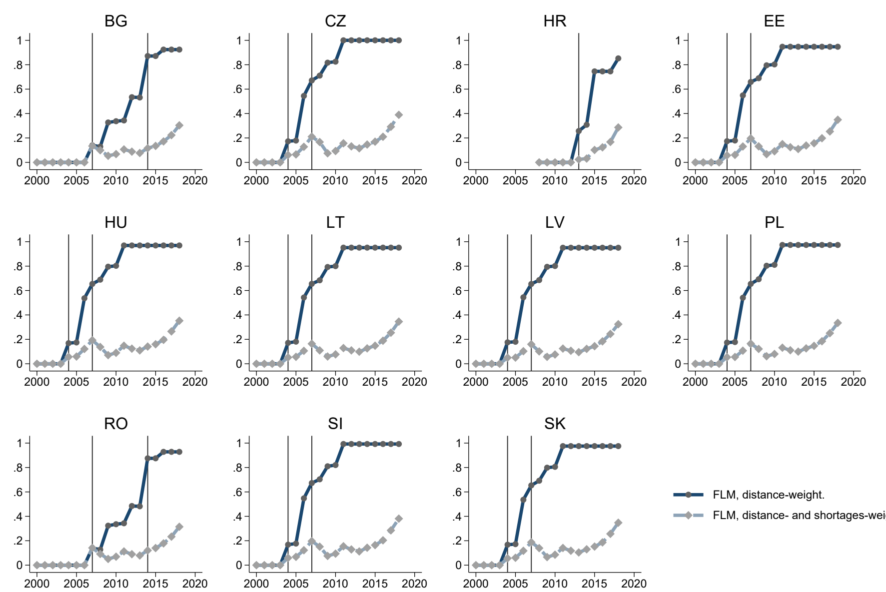
A.1 Additional Figures

Figure A1: **Variation in the Free Labor Mobility Variable**



Notes: This graph shows the variation in the FLM variable (weighted by bilateral distances and skill shortages in destination industries). We compare different industries (y-Axis) in different countries (x-Axis) in 2004, 2007, 2011, and 2014. The darker the shading, the stronger a specific industry in a specific country in a given year has been exposed to emigration of workers. The shading reflects a number between 0 and 1, where 0 means that emigration opportunities were very restricted and 1 means that emigration opportunities were the strongest in our sample. One can see, for instance, that Croatia, Bulgaria and Romania are completely in white in 2004 because those countries had not yet joined the EU and therefore emigration opportunities were restricted. In 2007, however, Romania and Bulgaria joined the EU and certain sectors in certain destination countries were open for migrants, therefore creating better emigration opportunities. Our FLM variable is weighted by skill shortages in destination industries. Because they were more prevalent for some industries in 2007 than in 2011 or 2014, the exposure to emigration for these industries appears larger in this year.

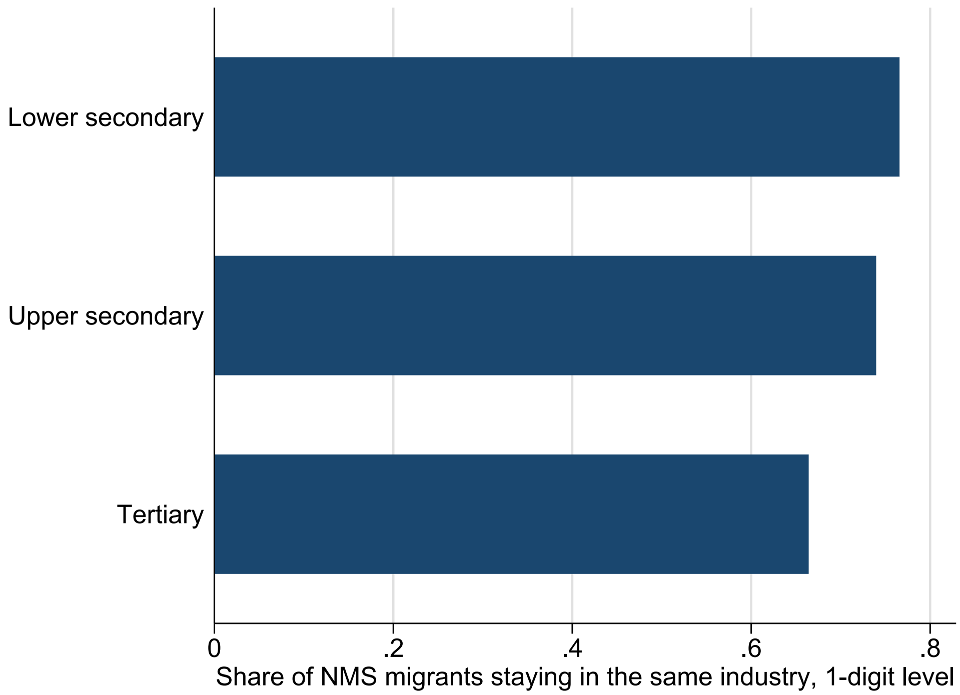
Figure A2: **Variation in the Free Labor Mobility across Countries**



Average country-level FLM, weighted by employment in origin industries.

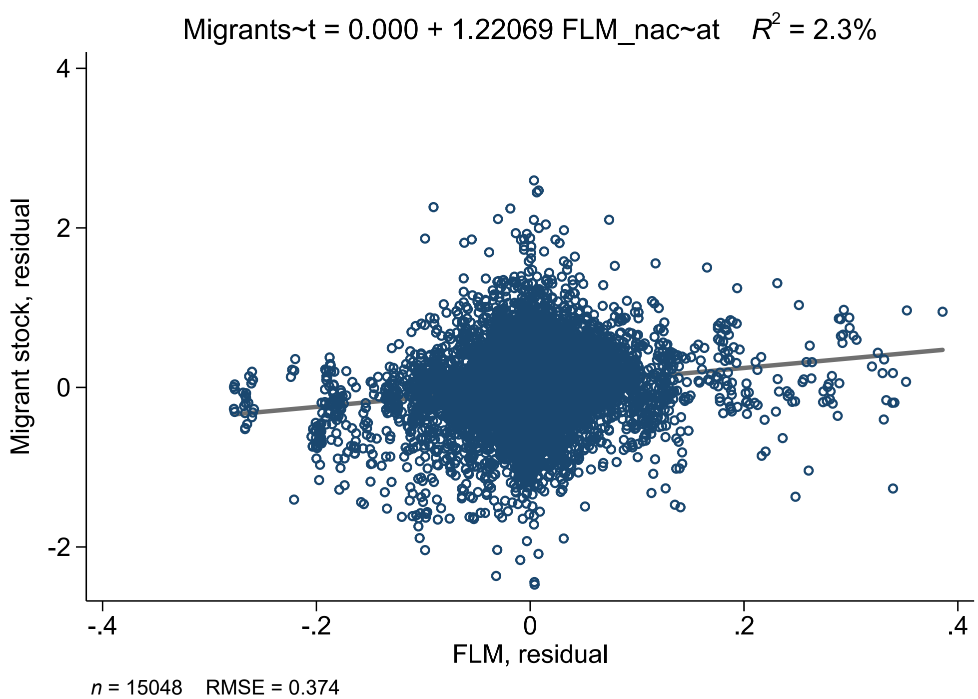
Notes: This graph compares the variation generated by two types of FLM variable: weighted only by distances (solid line) and weighted by distances and skill shortages (dash line). Country-level aggregates are obtained by calculating an average FLM across industries (weighted by employment) for a given year and country of origin.

Figure A3: **Do NMS Migrants Stay in the Same Industry in Destination Countries?**



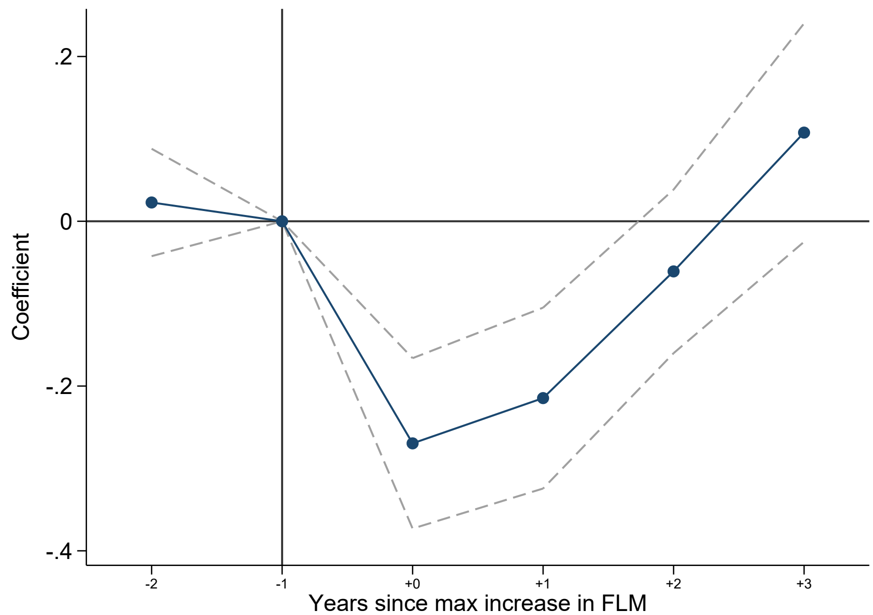
Source: EU LFS 2005-19. *Notes:* The sample includes migrants from NMS countries between 20-64 years old, who moved to another EU Member State in the year of the survey and who worked both in the previous and the current countries of residence.

Figure A4: **First Stage Illustration**



Notes: The scatter plot shows the correlation between the residuals of the number of emigrants and the FLM variable after partialling out origin-industry, origin-year specific and industry-year specific fixed effects and the control variables (lagged value added, investment, and import share).

Figure A5: **Event Study, 2000-2008**



Notes: This figure shows the results from an event study design. As the event we define the year with the largest increase in FLM value, i.e. the largest labor market opening. We only use the time period between 2000 and 2008 because in later years the variation in FLM is more gradual and it is difficult to define a single event. This is also a limitation in this graph because it is possible that there has been a large opening in 2004 and another large opening in 2005, explaining the continuing drop also in subsequent years. The dash line represents the 95 percent confidence interval.

A.2 Additional Tables

Table A1: **Overview of the Gradual Opening of the EU15+4 Labor Markets**

Country	NMS10 (2004 entry)	NMS3 (2007 entry: Bulgaria, Romania)	NMS3 (2013 entry: Croatia)	Sectoral Exceptions
Austria	2011	2014	2020	NMS10 (2007-2010), NMS3 (2007-2013): Construction, Manufacturing of Electronics and Metals, Food and beverage services (restaurant business), other sectors with labor shortages
Belgium	2009	2014	2015	-
Denmark	2009	2009	2013	-
Finland	2006	2007	2013	-
France	2008	2014	2015	NMS10 (2005-2007), NMS3 (2007-2013): Agriculture, Construction, Accommodation and food services (tourism and catering), other sectors with labor shortages
Germany	2011	2014	2015	NMS10 (2004-2010), NMS3 (2007-2013): sectors with labor shortages
Greece	2006	2009	2015	-
Iceland	2006	2012	2015	-
Ireland	2004	2012	2013	-
Italy	2006	2012	2015	NMS10 (2004-2005): sectors with labor shortages; NMS3 (2007-2011): Agriculture, Construction, Engineering, Accommodation and food services (tourism and catering), Domestic work and care services, other sectors with labor shortages; Occupations: Managerial and professional occupations
Luxembourg	2008	2014	2015	NMS3 (2007 - 2013): Agriculture, Viticulture, Accommodation and food services (tourism and catering)
Netherlands	2007	2014	2018	NMS10 (2004-2006), NMS3 (2007-2013): International transport, Inland shipping, Health, Slaugther-house/meat-packaging, other sectors with labor shortages
Norway	2009	2012	2014	NMS10 (2004-2008), NMS3 (2007-2011): sectors with labor shortages
Portugal	2006	2009	2013	-
Spain	2006	2009	2015	Reintroduction of restrictions for Romanians: 11/08/2011 - 31/12/2013
Sweden	2004	2007	2013	-
Switzerland	2011	2016	2024 (tbc)	-
United Kingdom	2004	2014	2018	NMS3 (2007-2013): Agriculture, Food manufacturing

Notes: Column 2 shows the year of the labor market opening of the respective country for NMS8 countries, column 3 shows the year of the labor market opening of the respective country for Bulgaria and Romania and column 4 for Croatia. Column 5 shows, which industries were exempt from restrictions before the transitional provisions for the entire labor market.
Source: Compiled by the authors using the LABREF database (European Commission) and national legislations.

Table A2: **Summary Statistics, Unrestricted Firm Data**

	Mean	SD	Min	Max	N
Firm age	7.694	6.754	0	652	39942622
Turnover, thousand EUR	1335.461	1.95e+05	0	9.452e+08	24572914
Value added, thousand EUR	805.557	1.40e+05	0	5.159e+08	13970786
Total assets, thousand EUR	1595.088	2.71e+05	0	1.199e+09	20461502
Fixed assets, thousand EUR	926.599	1.25e+05	0	5.336e+08	20667258
Number of employees	13.079	230.719	0	401427	32162784
Material costs, thousand EUR	970.942	1.17e+05	0	4.294e+08	14611593
Personnel costs, per employee, EUR	6216.815	2.37e+05	0	8.099e+08	14557943
Total assets/L, EUR	1.23e+05	1.96e+07	0	7.187e+10	16251358
Fixed assets/L, EUR	66392.303	7.25e+06	0	1.712e+10	16440313
Y/L, EUR	39108.917	6.91e+06	0	2.377e+10	12083682
Y/(WL)	14.133	569.566	0	1126350	12339550

Notes: The table presents summary statistics for all firm-level variables from the ORBIS sample that is not restricted by the availability of TFP data and that does not drop outliers based on the reported value added.

Table A3: **Explained Variation in Firm Productivity and FLM Variable**

	(1)	(2)	(3)	(4)	(5)	(6)
	TFP	TFP	TFP	FLM	FLM	FLM
Fixed Effects	firm year	firm	firm	firm year	firm	firm
		year#o year#nace1d+	year#o year#nace2		year#o year#nace1d+	year#o year#nace2
Age_{ft}	0.285***	0.280***	0.285***	0.006***	0.000	0.000
	(0.016)	(0.013)	(0.012)	(0.002)	(0.001)	(0.000)
Age^2_{ft}	-0.122***	-0.109***	-0.108***	0.002	0.000	0.000*
	(0.010)	(0.007)	(0.006)	(0.001)	(0.000)	(0.000)
$Investment_{oit-1}$	0.030*	-0.016*	-0.021***	0.004	0.006***	0.004**
	(0.016)	(0.009)	(0.007)	(0.004)	(0.002)	(0.002)
$Import\ share_{oit-1}$	0.048	-0.002	-0.053	0.017	0.017	0.015
	(0.061)	(0.039)	(0.037)	(0.026)	(0.013)	(0.011)
$Value\ added_{it-1}$	0.026*	0.032**		0.020***	-0.001	
	(0.015)	(0.013)		(0.005)	(0.003)	
$GDPpercap,\ PPP_{ot-1}$	-0.360			0.067*		
	(0.231)			(0.036)		
$FDI\ inflow_{ot-1}$	0.015***			0.001		
	(0.003)			(0.001)		
Observations	8,413,568	8,413,561	8,413,552	8,413,568	8,413,561	8,413,552
R-squared	0.555	0.571	0.573	0.815	0.935	0.974
Clusters	11139	11132	11123	11139	11132	11123

Notes: The table shows explained variation in the firm-level outcome - TFP (Columns 1-3) and in the FLM (Columns 4-6) under different sets of fixed effects: firm and year (Columns 1 and 4), firm, origin*year, industry-1-digit+*year (baseline, Columns 2 and 5) and firm, origin*year, industry-2-digit*year (Columns 3 and 6). Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** p<0.01, ** p<0.05, * p<0.1

Table A4: **First Stage Regressions with Instrument Variations**

VARIABLES	(1) Legal dummies Distance	(2) Legal dummies&Shortages Distance	(3) Legal dummies Diaspora/Pop	(4) Legal dummies&Shortages Diaspora/Pop
FLM_{oit}	0.566***	1.221***	0.451***	1.441***
	(0.045)	(0.082)	(0.104)	(0.285)
$Value\ added_{it-1}$	0.064***	0.061***	0.065***	0.064***
	(0.008)	(0.008)	(0.008)	(0.008)
$Investment_{oit-1}$	-0.005	-0.004	0.001	0.003
	(0.006)	(0.006)	(0.006)	(0.006)
$Import\ share_{oit-1}$	-0.118**	-0.129***	-0.124**	-0.116**
	(0.047)	(0.047)	(0.048)	(0.048)
Observations	15,048	15,048	15,048	15,048
R-squared	0.959	0.960	0.959	0.959
F-stat	158.8	224	18.87	25.52

Notes: The table presents the effect of higher within-EU labor mobility on emigration from NMS. Dependent variable: Number of emigrants (log). The columns compare first stage results for different variations of the FLM. As the proximity factor, we use either inverse bilateral distances (Columns 1-2) or previous distribution of emigrants across destinations (Columns 3-4). In columns 2 and 4 we interact FLM dummies with skill shortages in a destination industry to better capture labor demand. All specifications control for origin-industry, origin-year, and industry-year fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table A5: **Alternative TFP Measures**

VARIABLES	(1) 2SLS TFP LP	(2) 2SLS TFP WDG	(3) 2SLS TFP (nace) LP
$Emigrants_{oit}$	-0.418**	-0.432**	-0.387**
	(0.192)	(0.194)	(0.186)
Age_{ft}	0.279***	0.209***	0.315***
	(0.013)	(0.013)	(0.012)
Age^2_{ft}	-0.110***	-0.093***	-0.118***
	(0.007)	(0.007)	(0.006)
$Value\ added_{it-1}$	0.069***	0.070***	0.065***
	(0.023)	(0.023)	(0.022)
$Investment_{oit-1}$	-0.032**	-0.033**	-0.028**
	(0.013)	(0.013)	(0.012)
$Import\ share_{oit-1}$	0.010	0.007	0.013
	(0.056)	(0.057)	(0.054)
Observations	8,413,561	8,413,561	8,413,561
Clusters	11132	11132	11132
First stage F-stat	13.78	13.78	13.78
FLM coefficient	0.546	0.546	0.546
FLM se	0.147	0.147	0.147

Notes: The table presents the effect of higher emigration on different measures of firm TFP. Column 1 presents the baseline TFP (calculated according to the Levinson and Petrin method) as a benchmark, Column 2 uses a modification suggested by Wooldridge (as described in Mollisi and Rovigatti 2017), Column 3 shows the results when TFP was calculated using industry-specific coefficients in the estimated production function. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** p<0.01, ** p<0.05, * p<0.1

Table A6: **Reduced Form Results**

VARIABLES	(1) TFP LP	(2) Y/L	(3) Y/(WL)	(4) Costs per employee	(5) Assets/L	(6) N employees
FLM_{oit}	-0.228**	-0.265***	-0.244***	0.034	-0.113***	0.089***
	(0.092)	(0.091)	(0.074)	(0.028)	(0.033)	(0.018)
Age_{ft}	0.280***	0.781***	-0.129***	0.852***	0.442***	0.234***
	(0.013)	(0.014)	(0.010)	(0.012)	(0.011)	(0.006)
Age^2_{ft}	-0.109***	-0.348***	0.012**	-0.330***	-0.170***	0.039***
	(0.007)	(0.008)	(0.005)	(0.006)	(0.004)	(0.004)
$Value\ added_{it-1}$	0.032**	0.033**	0.021**	0.005	0.012*	-0.003
	(0.013)	(0.013)	(0.010)	(0.004)	(0.007)	(0.003)
$Investment_{oit-1}$	-0.015*	-0.010	-0.007	0.000	0.010***	-0.005***
	(0.009)	(0.008)	(0.007)	(0.003)	(0.003)	(0.002)
$Import\ share_{oit-1}$	0.002	0.040	-0.000	0.051***	0.041**	-0.010
	(0.040)	(0.042)	(0.031)	(0.017)	(0.020)	(0.014)
Observations	8,413,561	8,413,561	8,413,561	8,413,561	8,413,561	8,413,561
R-squared	0.571	0.671	0.659	0.818	0.833	0.882
Clusters	11132	11132	11132	11132	11132	11132

Notes: The table presents reduced form effects of higher within-EU labor mobility on various firm outcomes. The columns show the results for the following outcomes: firm TFP, labor productivity, wage-adjusted labor productivity, costs per employee, capital-labor ratio and the number of employees. All specifications are estimated with firm fixed effects, industry-specific and origin-specific time dummies. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** p<0.01, ** p<0.05, * p<0.1

Table A7: **Firm TFP: Various Lags of the Free labor Mobility Variable**

VARIABLES	(1) TFP LP	(2) TFP LP	(3) TFP LP	(4) TFP LP
FLM_{oit}	-0.228**	-0.359***	-0.295**	-0.299**
	(0.092)	(0.113)	(0.118)	(0.121)
FLM_{oit-1}		0.284**	0.113	0.099
		(0.135)	(0.167)	(0.176)
FLM_{oit-2}			0.310**	0.326**
			(0.131)	(0.150)
FLM_{oit-3}				-0.041
				(0.097)
Age_{ft}	0.280***	0.279***	0.285***	0.291***
	(0.013)	(0.013)	(0.013)	(0.014)
Age^2_{ft}	-0.109***	-0.109***	-0.109***	-0.109***
	(0.007)	(0.007)	(0.007)	(0.007)
$Value\ added_{it-1}$	0.032**	0.032**	0.034**	0.021
	(0.013)	(0.013)	(0.014)	(0.013)
$Investment_{oit-1}$	-0.015*	-0.016*	-0.018*	-0.014
	(0.009)	(0.009)	(0.009)	(0.010)
$Import\ share_{oit-1}$	0.002	-0.005	-0.022	-0.041
	(0.040)	(0.041)	(0.042)	(0.045)
Observations	8,413,561	8,413,561	8,205,941	7,973,202
R-squared	0.571	0.571	0.573	0.575
Clusters	11132	11132	10595	9966

Notes: The table presents the reduced form of our main TFP result (Column 1) and consecutively adds various lags of the FLM variable. All specifications are estimated with firm fixed effects, industry-specific and origin-specific time dummies. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** p<0.01, ** p<0.05, * p<0.1

Table A8: **Industry-level Effects, Eurostat Data (only industries with good Orbis coverage)**

VARIABLES	(1) 2SLS Y/L Eurostat derived	(2) 2SLS Y/(WL) Eurostat derived	(3) 2SLS Costs per employee Eurostat	(4) 2SLS N employees Eurostat	(5) 2SLS N firms Eurostat	(6) 2SLS Exits
$Emigrants_{oit}$	-0.162***	-0.136***	0.023	0.756***	-0.191	1.144***
	(0.059)	(0.038)	(0.030)	(0.115)	(0.122)	(0.203)
$Value\ added_{it-1}$	0.076***	0.033***	0.020***	0.316***	0.468***	0.077***
	(0.016)	(0.011)	(0.007)	(0.031)	(0.035)	(0.029)
$Investment_{oit-1}$	0.073***	0.036***	0.023***	0.185***	0.145***	0.043**
	(0.009)	(0.006)	(0.004)	(0.016)	(0.015)	(0.022)
$Import\ share_{oit-1}$	0.104***	-0.044	0.134***	-0.747***	-0.718***	-0.311**
	(0.039)	(0.027)	(0.022)	(0.113)	(0.124)	(0.126)
Observations	6,561	6,582	6,574	6,651	6,876	8,163
Clusters	6561	6582	6574	6651	6876	8163
First stage F-stat	80.03	81.43	82.55	95.68	109.3	107.1
FLM coefficient	1.019	1.026	1.034	1.107	1.193	1.130
FLM se	0.114	0.114	0.114	0.113	0.114	0.109

Notes: The table presents 2SLS regressions of industry-level outcomes on emigration. The sample is limited to industry-origin-year observations, which are not missing in the Orbis data. In addition, countries with very few observations per industry (Hungary, Lithuania, Latvia, Poland) are dropped. The main outcomes are labor productivity (Column 1) and wage-adjusted labor productivity (Column 2). Other industry level outcomes are average costs per employee (Column 3), the total number of employees (Column 4), the number of firms (Column 5), and the number of firm exits (Column 6) in a given industry, country and year cell. All specifications are estimated with industry-origin fixed effects, industry-specific and origin-specific time dummies. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** p<0.01, ** p<0.05, * p<0.1

Table A9: **Industry-level Labor Productivity, Various Lags of the Free Labor Mobility Variable**

VARIABLES	(1) Y/L Eurostat derived	(2) Y/L Eurostat derived	(3) Y/L Eurostat derived	(4) Y/L Eurostat derived
FLM_{oit}	-0.202***	-0.209***	-0.211***	-0.205***
	(0.049)	(0.064)	(0.065)	(0.066)
FLM_{oit-1}		0.012	0.033	0.013
		(0.069)	(0.085)	(0.089)
FLM_{oit-2}			-0.023	0.015
			(0.066)	(0.090)
FLM_{oit-3}				-0.058
				(0.074)
$Value\ added_{it-1}$	0.105***	0.105***	0.099***	0.107***
	(0.014)	(0.014)	(0.015)	(0.016)
$Investment_{oit-1}$	0.068***	0.068***	0.070***	0.063***
	(0.008)	(0.008)	(0.009)	(0.009)
$Import\ share_{oit-1}$	0.022	0.022	0.028	0.008
	(0.036)	(0.036)	(0.038)	(0.040)
Observations	10,601	10,601	10,103	9,598
R-squared	0.890	0.890	0.891	0.890
Clusters	10601	10601	10103	9598

Notes: The table presents the reduced form effect of emigration on industry-level labor productivity (Column 1) and consecutively adds various lags of the FLM variable. All specifications are estimated with industry·origin, industry·time and origin·time fixed effects. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** p<0.01, ** p<0.05, * p<0.1

Table A10: **Firm Exits, Various Lags of the Free Labor Mobility Variable**

VARIABLES	(1) Exits	(2) Exits	(3) Exits	(4) Exits
FLM_{oit}	1.033***	-0.204	-0.119	-0.452**
	(0.180)	(0.225)	(0.223)	(0.229)
FLM_{oit-1}		1.928***	0.564**	0.969***
		(0.226)	(0.257)	(0.264)
FLM_{oit-2}			1.864***	0.671***
			(0.223)	(0.252)
FLM_{oit-3}				1.575***
				(0.207)
$Value\ added_{it-1}$	0.083***	0.076***	0.060***	0.034
	(0.019)	(0.019)	(0.020)	(0.022)
$Investment_{oit-1}$	0.054***	0.053***	0.055***	0.059***
	(0.016)	(0.015)	(0.016)	(0.017)
$Import\ share_{oit-1}$	-0.271***	-0.281***	-0.308***	-0.339***
	(0.071)	(0.070)	(0.074)	(0.079)
Observations	12,990	12,990	12,374	11,751
R-squared	0.896	0.897	0.900	0.906
Clusters	12990	12990	12374	11751

Notes: The table presents the reduced form effect of emigration on firm exits (Column 1) and consecutively adds various lags of the FLM variable. All specifications are estimated with industry·origin, industry·time and origin·time fixed effects. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** p<0.01, ** p<0.05, * p<0.1

Table A11: **Regression Restricted to Firms with 5-250 employees**

VARIABLES	(1) 2SLS TFP LP	(2) 2SLS Y/L	(3) 2SLS Y/(WL)	(4) 2SLS Costs per employee	(5) 2SLS Assets/L	(6) 2SLS N employees
$Emigrants_{oit}$	-0.423**	-0.466**	-0.443***	0.080*	-0.164***	0.194***
	(0.195)	(0.200)	(0.169)	(0.041)	(0.063)	(0.053)
Age_{ft}	0.338***	0.731***	0.020***	0.629***	0.394***	0.172***
	(0.011)	(0.012)	(0.007)	(0.010)	(0.010)	(0.009)
Age^2_{ft}	-0.107***	-0.286***	-0.030***	-0.222***	-0.136***	0.060***
	(0.005)	(0.006)	(0.004)	(0.004)	(0.005)	(0.004)
$Value\ added_{it-1}$	0.074***	0.086***	0.063***	0.005	0.037***	-0.018**
	(0.025)	(0.026)	(0.021)	(0.006)	(0.009)	(0.008)
$Investment_{oit-1}$	-0.017*	-0.015	-0.014	0.003	0.010***	0.003
	(0.010)	(0.010)	(0.009)	(0.002)	(0.004)	(0.003)
$Import\ share_{oit-1}$	-0.026	0.011	-0.014	0.038**	0.066**	-0.010
	(0.060)	(0.064)	(0.055)	(0.017)	(0.026)	(0.024)
Observations	3,974,476	3,974,476	3,974,476	3,974,476	3,974,476	3,974,476
Clusters	10975	10975	10975	10975	10975	10975
First stage F-stat	18.13	18.13	18.13	18.13	18.13	18.13
FLM coefficient	0.530	0.530	0.530	0.530	0.530	0.530
FLM se	0.124	0.124	0.124	0.124	0.124	0.124

Notes: The table presents 2SLS effects of emigration on various firm outcomes. The sample excludes micro firms (less than 5 employees) and macro firms (more than 250 employees). The columns show the results for the following outcomes: firm TFP, labor productivity, wage-adjusted labor productivity, costs per employee, capital-labor ratio and the number of employees. All specifications are estimated with firm fixed effects, industry-specific time fixed effects and origin-specific time fixed effects. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** p<0.01, ** p<0.05, * p<0.1

Table A12: **Regression Restricted to Before 2009**

VARIABLES	(1) 2SLS TFP LP	(2) 2SLS Y/L	(3) 2SLS Y/(WL)	(4) 2SLS Costs per employee	(5) 2SLS Assets/L	(6) 2SLS N employees
$Emigrants_{oit}$	-1.166**	-1.118**	-1.076***	0.184**	0.064	0.155**
	(0.466)	(0.450)	(0.410)	(0.082)	(0.071)	(0.061)
Age_{ft}	0.240***	0.851***	-0.256***	1.045***	0.383***	0.240***
	(0.027)	(0.031)	(0.020)	(0.024)	(0.019)	(0.009)
Age^2_{ft}	-0.177***	-0.508***	0.020**	-0.473***	-0.187***	0.065***
	(0.014)	(0.019)	(0.010)	(0.019)	(0.010)	(0.007)
$Value\ added_{it-1}$	0.096	0.098	0.083	-0.001	-0.014	-0.014
	(0.064)	(0.061)	(0.060)	(0.016)	(0.019)	(0.009)
$Investment_{oit-1}$	-0.085**	-0.080**	-0.076**	0.013*	0.013**	0.004
	(0.039)	(0.038)	(0.035)	(0.007)	(0.005)	(0.005)
$Import\ share_{oit-1}$	-0.193	-0.142	-0.201	0.095**	0.115***	0.012
	(0.267)	(0.261)	(0.240)	(0.041)	(0.033)	(0.032)
Observations	3,011,765	3,011,765	3,011,765	3,011,765	3,011,765	3,011,765
Clusters	5231	5231	5231	5231	5231	5231
First stage F-stat	7.950	7.950	7.950	7.950	7.950	7.950
FLM coefficient	0.646	0.646	0.646	0.646	0.646	0.646
FLM se	0.229	0.229	0.229	0.229	0.229	0.229

Notes: The table presents 2SLS effects of emigration on various firm outcomes. The sample is restricted to the years before 2009. The columns show the results for the following outcomes: firm TFP, labor productivity, wage-adjusted labor productivity, costs per employee, capital-labor ratio and the number of employees. All specifications are estimated with firm fixed effects, industry-specific time fixed effects and origin-specific time fixed effects. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** p<0.01, ** p<0.05, * p<0.1

Table A13: **Specification with Firm and Year Fixed Effects**

VARIABLES	(1) 2SLS TFP LP	(2) 2SLS Y/L	(3) 2SLS Y/(WL)	(4) 2SLS Costs per employee	(5) 2SLS Assets/L	(6) 2SLS N employees
$Emigrants_{oit}$	-0.848**	-0.853**	-0.793***	0.100	-0.013	0.104***
	(0.332)	(0.356)	(0.259)	(0.067)	(0.078)	(0.033)
Age_{ft}	0.289***	0.810***	-0.131***	0.884***	0.468***	0.233***
	(0.017)	(0.018)	(0.013)	(0.013)	(0.012)	(0.006)
Age^2_{ft}	-0.114***	-0.362***	0.013*	-0.344***	-0.179***	0.036***
	(0.010)	(0.012)	(0.008)	(0.006)	(0.005)	(0.004)
$GDPpercap,\ PPP_{ot-1}$	1.589**	2.734***	1.121*	1.519***	1.376***	-0.396***
	(0.796)	(0.850)	(0.608)	(0.175)	(0.188)	(0.088)
$FDI\ inflow_{ot-1}$	0.018***	0.023***	0.012***	0.007***	0.004***	-0.000
	(0.004)	(0.005)	(0.003)	(0.001)	(0.001)	(0.001)
$Value\ added_{it-1}$	0.062	0.057	0.045	-0.005	0.010	-0.005
	(0.039)	(0.041)	(0.034)	(0.008)	(0.010)	(0.005)
$Investment_{oit-1}$	0.025	0.046**	0.027	0.014**	0.049***	-0.006**
	(0.021)	(0.023)	(0.018)	(0.005)	(0.006)	(0.003)
$Import\ share_{oit-1}$	0.004	0.066	0.038	0.028	0.137***	-0.037*
	(0.107)	(0.111)	(0.094)	(0.026)	(0.030)	(0.021)
Observations	8,413,568	8,413,568	8,413,568	8,413,568	8,413,568	8,413,568
Clusters	11139	11139	11139	11139	11139	11139
First stage F-stat	36.31	36.31	36.31	36.31	36.31	36.31
FLM coefficient	0.883	0.883	0.883	0.883	0.883	0.883
FLM se	0.147	0.147	0.147	0.147	0.147	0.147
FE	firm year	firm year	firm year	firm year	firm year	firm year

Notes: The table presents our baseline results but uses less restrictive fixed effects: only firm and year fixed effects. Instead of origin- and industry-specific time dummies, we add controls at the country-year and industry-year level. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** p<0.01, ** p<0.05, * p<0.1

Table A14: **More Conservative Clustering, Firm Level**

VARIABLES	(1) 2SLS TFP LP	(2) 2SLS Y/L	(3) 2SLS Y/(WL)	(4) 2SLS Costs per employee	(5) 2SLS Assets/L	(6) 2SLS N employees
$Emigrants_{oit}$	-0.418	-0.485*	-0.446*	0.062	-0.208*	0.162**
	(0.295)	(0.288)	(0.249)	(0.075)	(0.116)	(0.071)
Age_{ft}	0.279***	0.780***	-0.130***	0.852***	0.442***	0.234***
	(0.034)	(0.035)	(0.026)	(0.024)	(0.027)	(0.017)
Age^2_{ft}	-0.110***	-0.350***	0.010	-0.330***	-0.170***	0.040***
	(0.019)	(0.020)	(0.013)	(0.010)	(0.010)	(0.008)
$Value\ added_{it-1}$	0.069*	0.077*	0.061*	-0.000	0.030**	-0.018*
	(0.040)	(0.041)	(0.033)	(0.010)	(0.015)	(0.011)
$Investment_{oit-1}$	-0.032*	-0.031*	-0.026*	0.003	0.001	0.002
	(0.018)	(0.018)	(0.015)	(0.005)	(0.008)	(0.004)
$Import\ share_{oit-1}$	0.010	0.048	0.008	0.050**	0.045	-0.013
	(0.111)	(0.120)	(0.098)	(0.020)	(0.046)	(0.030)
Observations	8,413,561	8,413,561	8,413,561	8,413,561	8,413,561	8,413,561
Clusters	750	750	750	750	750	750
First stage F-stat	11.26	11.26	11.26	11.26	11.26	11.26
FLM coefficient	0.546	0.546	0.546	0.546	0.546	0.546
FLM se	0.163	0.163	0.163	0.163	0.163	0.163

Notes: The table presents our baseline results at the firm level, but uses more conservative clustering of standard errors at the origin-industry level.
*** p<0.01, ** p<0.05, * p<0.1

Table A15: **More Conservative Clustering, Industry Level**

VARIABLES	(1) 2SLS Y/L Eurostat derived	(2) 2SLS Y/(WL) Eurostat derived	(3) 2SLS Costs per employee Eurostat	(4) 2SLS N employees Eurostat	(5) 2SLS N firms Eurostat	(6) 2SLS Exits
$Emigrants_{oit}$	-0.177**	-0.166***	0.049	0.609***	-0.352*	0.867***
	(0.074)	(0.050)	(0.039)	(0.151)	(0.181)	(0.257)
$Value\ added_{it-1}$	0.121***	0.065***	0.028*	0.274***	0.409***	0.029
	(0.031)	(0.018)	(0.014)	(0.054)	(0.068)	(0.053)
$Investment_{oit-1}$	0.068***	0.032***	0.020***	0.249***	0.184***	0.052
	(0.016)	(0.010)	(0.007)	(0.029)	(0.033)	(0.035)
$Import\ share_{oit-1}$	0.006	-0.044	0.052	-0.552***	-0.472**	-0.148
	(0.073)	(0.042)	(0.042)	(0.161)	(0.189)	(0.151)
Observations	10,601	10,626	10,618	10,762	11,044	12,990
Clusters	675	675	675	676	680	792
First stage F-stat	57.04	57.43	57.97	63.53	67.74	67.71
FLM coefficient	1.138	1.142	1.144	1.188	1.242	1.192
FLM se	0.151	0.151	0.150	0.149	0.151	0.145

Notes: The table presents our baseline results at the industry level, but uses more conservative clustering of standard errors at the origin-industry level.
*** p<0.01, ** p<0.05, * p<0.1

Table A16: **Robustness of 2sls Results to Alternative Instruments**

VARIABLES	(1) TFP Baseline FLM	(2) TFP FLM w/t shortages	(3) TFP Random-forest FLM 1	(4) TFP Random-forest FLM 2	(5) TFP Placebo FLM
$Emigrants_{oit}$	-0.418**	-0.824*	-0.503*	-0.187*	-1.225
	(0.192)	(0.464)	(0.263)	(0.103)	(0.817)
Observations	8,413,561	8,413,561	8,413,561	8,413,561	8,413,561
Clusters	11132	11132	11132	11132	11132
First stage F-stat	13.78	4.788	10.58	43.69	2.697
FLM coefficient	0.546	1.025	0.146	0.284	-0.190
FLM se	0.147	0.468	0.0448	0.0429	0.115

Notes: The table presents 2sls estimations for firm TFP with alternative instruments. Column 1 repeats the baseline estimation from Column 4 in Table 3. Column 2 uses a version of an FLM variable that contains only legal dummies and distance proximity weights. Column 3 uses an alternative instrument constructed using a random forest with legal dummies, skill shortages and bilateral distance as inputs. Column 4 uses the same method, but limits the inputs to legal dummies and distance. Column (5) uses a placebo instrument, where legal dummies are randomly shuffled across observations while distance weights and skill shortages remain. All specifications are estimated with the same controls and fixed effects as our baseline specification in Table 3. Standard errors (in parentheses) are clustered at the origin-industry-year level in Columns 1, 2, and 5. Bootstrap standard errors in Columns 3 and 4.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes on the alternative instrument: The instruments used in the estimations presented in Columns 3 and 4 were constructed as follows. We started-off with a bilateral migration dataset at the destination-origin-industry-year level. These data characterize the stock of emigrants from origin o working in destination d, industry i in year t.

First, we partialled-out destination-origin-industry and year fixed effects.

Second, we used components of our FLM variable to model residualized bilateral migration. We included legal dummies, skill shortages, and distances for an IV in Column 3 and legal dummies and distances for an IV in Column 4. We used a non-parametric model - random forest - to model the data. We also tried a linear specification, but the fit was substantially worse. The model fit ($R-squared$) constituted 0.403 in-sample and 0.133 out-of-sample* for the full model and 0.163 in-sample and 0.142 out-of-sample* for the model containing only legal dummies and distances.

We then obtain an in-sample and out-of-sample* prediction for each observation (a flexible combination of FLM components) and aggregate the obtained data at the origin-industry-year level. We use the results as alternative instruments.

There are at least two challenges associated with this approach. First, if we simply use the aggregated predictions as an IV, the standard errors will be wrong. We thus use bootstrap standard errors. Second, our flexible data-driven models might be biased due to overfitting. Hence for a robustness check (available upon request), we use out-of-sample* (instead of in-sample) predictions. The results become less precise, but the coefficients of interest remain qualitatively similar.

*Out-of-sample fit in a random-forest model was proxied with an out-of-bag score. This method exploits the fact that only a subset of observations is used in the estimation of each tree within a forest. Hence, one can construct a prediction for each observation by averaging predictions from only those trees, which do not contain this observation when estimating the model.

Table A17: **First Stage with Competition**

VARIABLES	(1) Legal dummies Distance	(2) Legal dummies&Shortages Distance	(3) Legal dummies Diaspora/Pop	(4) Legal dummies&Shortages Diaspora/Pop
FLM_{oit}	-0.058	-0.033	0.107	0.082
	(0.056)	(0.052)	(0.082)	(0.155)
$Value\ added_{it-1}$	-0.008	-0.008	-0.007	-0.009
	(0.008)	(0.008)	(0.008)	(0.008)
$Investment_{oit-1}$	-0.002	-0.002	-0.002	-0.002
	(0.005)	(0.005)	(0.005)	(0.005)
$Import\ share_{oit-1}$	-0.010	-0.008	-0.003	-0.007
	(0.024)	(0.024)	(0.024)	(0.024)
Observations	3,117	3,117	3,117	3,117
R-squared	0.457	0.457	0.458	0.457
F-stat	1.104	0.410	1.693	0.278
Level	Industry	Industry	Industry	Industry

Notes: This table presents the first stage of an alternative dependent variable - the share of firms reporting intense product-market competition as an obstacle to doing business. The columns compare first stage results for different variations of the FLM. As the proximity factor, we use either inverse bilateral distances (Columns 1-2) or previous distribution of emigrants (Columns 3-4). As the pull factor, we use either skill shortages (Columns 1 and 3) or employment growth (Columns 2 and 4) in destination industries. All specifications control for origin-industry, origin-year, and industry-year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Table A18: **Firm Productivity and Forward of the Free labor Mobility Variable**

VARIABLES	(1) TFP LP	(2) Y/L	(3) Y/(WL)
FLM_{oit+1}	0.038	-0.036	0.007
	(0.089)	(0.088)	(0.073)
FLM_{oit}	-0.247**	-0.247**	-0.247***
	(0.109)	(0.107)	(0.090)
Age_{ft}	0.280***	0.781***	-0.129***
	(0.013)	(0.014)	(0.010)
Age^2_{ft}	-0.109***	-0.348***	0.012**
	(0.007)	(0.008)	(0.005)
$Value\ added_{it-1}$	0.032**	0.033**	0.021**
	(0.013)	(0.013)	(0.010)
$Investment_{oit-1}$	-0.015*	-0.010	-0.007
	(0.009)	(0.008)	(0.007)
$Import\ share_{oit-1}$	0.003	0.039	0.000
	(0.040)	(0.042)	(0.032)
Observations	8,413,561	8,413,561	8,413,561
R-squared	0.571	0.671	0.659
Clusters	11132	11132	11132

Notes: The table presents the reduced form productivity estimations, where we add a forward of the FLM variable. All specifications are estimated with firm, industry·time and origin·time fixed effects. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** p<0.01, ** p<0.05, * p<0.1

A.3 Evidence from the Self-Selection of Emigrants

According to Borjas (1987) migrants are positively self-selected if income is more dispersed in the destination country.[27] We obtain data on the Gini index from the World Bank and divide origin-destination country pairs from our sample into those pairs where income in the destination is more dispersed than in the origin (positive selection cases) and those where it is not (negative selection cases). Figure A6 shows which pairs are classified as positive selection cases, and which are classified as negative selection ones. In line with previous literature, selection to the UK is mostly positive, whereas selection to Sweden or Germany is mostly negative.

We thus add one more dimension to the FLM variable. We aggregate all bilateral FLM dummies corresponding to country pairs with positive self-selection in the *Positive FLM variable* and FLM dummies that correspond to country pairs with negative self-selection in the *Negative FLM variable*.[28] Table A19 shows that negative effects of emigration on all three measures of labor productivity are stronger when emigrants are positively self-selected.[29] This result fits our hypothesis well because it confirms that firms experience a negative productivity shock when their qualified workers leave. It is also worth looking at other outcomes. Average personnel costs decrease in case of positive selection, likely because a firm loses its best and most expensive workers. On the contrary, if a firm loses negatively selected workers, then average personnel costs increase as only lower wage workers are leaving. Equally intuitive are the differential effects on the capital-labor ratio showing that negatively selected workers can be replaced by increasing capital, whereas positively selected (i.e. highly skilled) workers cannot.

Firms that lose positively selected workers do not change their total number of employees. They are thus rehiring, but those newly hired workers lack firm-specific knowledge, while there are less incentives to train them due to a higher turnover. Firms losing positively selected workers are hit particularly hard because it is more

[27] Another condition is that unobserved skill prices are sufficiently positively correlated, which is likely to be fulfilled in our context.

[28] Given that we do not have emigration data by skill group, we focus on the reduced form in this section.

[29] Our results are also robust to dropping some origin countries (Slovenia, Slovakia, Romania) who are likely to generate mostly positively or mostly negatively selected emigrants.

Figure A6: **Bilateral Matrix for Self-Selection**

Origin	AT	BE	CH	DE	DK	ES	FI	FR	GB
BG	-	-	-	-	-	-	-	-	+
CZ	+	+	+	+	-	+	+	+	+
EE	-	-	-	-	-	-	-	-	-
HR	-	-	+	-	-	-	-	-	+
HU	-	-	+	-	-	+	-	+	+
LT	-	-	-	-	-	-	-	-	-
LV	-	-	-	-	-	-	-	-	-
PL	-	-	-	-	-	-	-	-	-
RO	-	-	-	-	-	-	-	-	-
SI	+	+	+	+	+	+	+	+	+
SK	+	+	+	+	-	+	+	+	+

Origin	GR	IE	IS	IT	LU	NL	NO	PT	SE
BG	-	-	-	-	-	-	-	+	-
CZ	+	+	-	+	+	+	+	+	-
EE	-	-	-	-	-	-	-	+	-
HR	+	+	-	+	-	-	-	+	-
HU	+	+	-	+	+	-	-	+	-
LT	-	-	-	-	-	-	-	+	-
LV	-	-	-	-	-	-	-	+	-
PL	-	-	-	-	-	-	-	+	-
RO	-	-	-	-	-	-	-	-	-
SI	+	+	+	+	+	+	+	+	+
SK	+	+	-	+	+	+	+	+	-

Notes: We use data on country-level Gini indices (World Bank, year 2000) for NMS origins and EU15+4 destinations to proxy the self-selection of migration flows. In line with the Roy-Borjas model, migrants are positively (negatively) self-selected if inequality/the Gini index is higher (lower) in the destination compared to the origin. The rows give the origin and the columns the destination.

expensive to train highly skilled workers. These findings could be also in line with the spillover mechanism. If positively selected workers exert positive spillovers on others, then their emigration reduces positive spillovers, which results in lower TFP.

Table A19: **Positive and Negative Selection, Reduced Form**

VARIABLES	(1) TFP LP	(2) Y/L	(3) Y/(WL)	(4) Costs per employee	(5) Assets/L	(6) N employees
$Positive\ FLM_{oit}$	-1.337***	-1.991***	-0.823***	-0.925***	-0.712***	0.150***
	(0.244)	(0.263)	(0.186)	(0.067)	(0.064)	(0.041)
$Negative\ FLM_{oit}$	-0.581**	-0.437	-0.641***	0.316***	0.149*	0.075**
	(0.254)	(0.272)	(0.188)	(0.055)	(0.077)	(0.032)
Age_{ft}	0.286***	0.804***	-0.131***	0.879***	0.464***	0.233***
	(0.016)	(0.017)	(0.012)	(0.013)	(0.012)	(0.006)
Age^2_{ft}	-0.120***	-0.367***	0.007	-0.341***	-0.178***	0.037***
	(0.010)	(0.011)	(0.007)	(0.006)	(0.005)	(0.004)
$GDPpercap,\ PPP_{ot-1}$	-0.356	0.728***	-0.666***	1.667***	1.294***	-0.159***
	(0.222)	(0.236)	(0.160)	(0.055)	(0.070)	(0.032)
$FDI\ inflow_{ot-1}$	0.016***	0.022***	0.009***	0.009***	0.005***	0.000
	(0.003)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)
$Value\ added_{it-1}$	0.041***	0.037**	0.025**	-0.002	0.010	-0.003
	(0.015)	(0.018)	(0.011)	(0.008)	(0.010)	(0.005)
$Investment_{oit-1}$	0.032**	0.052***	0.034***	0.011**	0.049***	-0.007**
	(0.016)	(0.017)	(0.012)	(0.005)	(0.006)	(0.003)
$Import\ share_{oit-1}$	0.076	0.154**	0.094**	0.047	0.156***	-0.046**
	(0.054)	(0.062)	(0.041)	(0.032)	(0.037)	(0.018)
Observations	8,413,568	8,413,568	8,413,568	8,413,568	8,413,568	8,413,568
R-squared	0.556	0.655	0.641	0.813	0.830	0.880
Clusters	11139	11139	11139	11139	11139	11139
FE	idc year	idc year	idc year	idc year	idc year	idc year

Notes: The table presents reduced form firm-level estimation results of higher within-EU labor mobility on various firm outcomes. The columns show the results for the following outcomes: firm TFP, labor productivity, wage-adjusted labor productivity, costs per employee, capital labor ratio and the number of employees. All specifications are estimated with firm fixed effects and time dummies. Standard errors (in parentheses) are clustered at the origin-industry-year level.
*** p<0.01, ** p<0.05, * p<0.1

A.4 Data Appendix

A.4.1 Overview of Migration Data

Data collected from the National Statistical Offices

Austria

Main Association of Austrian Social Security Institutions: posteingang.allgemein@hvb.sozvers.at
Source: Austrian social security data, universe of workers who are subject to social security contributions

Migrants identified by nationality
Available for 2000-2016

Belgium

1)

Belgian statistical office: demos@economie.fgov.be
Source: Statbel (Direction générale Statistique - Statistics Belgium), Labour Force Survey
Migrants identified by country of birth
Available for 2000-2017

2)

Belgian crossroad bank for social security : https://www.ksz-bcss.fgov.be/en
Source: administrative data from the Belgian national registry data, universe of workers subject to social security contributions
Migrants identified by country of birth
Available for 2008-2017

Finland

Statistics Finland, Population and Social Statistics: www.stat.fi
Source: Universe of workers in Finland based on a compilation from Statistics using different administrative and statistical data
Migrants identified by country of birth
Available for 2000-2016

France

Réseau Quetelet, ADISP https://quetelet.casd.eu
Source: Population census https://www.insee.fr/fr/information/1303686
Migrants identified by country of birth
Available for 1999, 2006, 2011, 2016 (possible to obtain only for every five years)

Norway

Statistics Norway okonomi@ssb.no
Source: NAV's Employee Register (Aa Register) and A-ordninge, data from coordinated digital collection of employment, income and tax deductions for the Tax Administration, NAV and Statistics Norway
Migrants identified by country of birth
Available for 2000-2018

Sweden

Statistics Sweden, Microdata Unit: www.scb.se
Source: administrative registers
Migrants identified by country of birth
Available for 2000-2016

Spain

National Statistics Institute, INE, https://www.ine.es/en/index.htm
Source: Labor Force Survey
Migrants identified by nationality
Available for 2006, 2008, 2010, 2012, 2014, 2016

Switzerland

Federal Statistical Office, https://www.bfs.admin.ch/bfs/en/home.html
Source: Swiss Labour Force Survey (SAKE)
Migrants identified by country of birth
Available for 2000-2018

United Kingdom

Office for national statistics https://www.ons.gov.uk
Source: Annual Population Survey data
Migrants identified by country of birth
Available from 2000 to 2018; the dataset from our request is published here
Link to data

Proxy data for missing migration data

We used Eurostat data on migration stocks at year, destination and origin (country of birth) level (migr_pop3ctb). For missing data, we used another migration dataset at year, destination, and country of citizenship level (migr_pop1ctz). The correlation between stocks of migrants by birth and by nationality is 0.927.

We completed missing Eurostat data from the OECD International Migration Database (Dataset MIG, Stocks of immigrants by country of birth in OECD countries).

For every country-pair, if some internal observations were missing, we linearly interpolated them using the STATA command ipolate

To "distribute" migrant stocks from each origin country by industry (two-digit level, NACE Rev. 2) in the destination country, we requested Eurostat migration data: by year, destination, region of origin (aggregated to EU3 and EU10), and industry at two-digit level. From these data we obtained the distribution of EU3 and EU10 migrants across industries in old EU member states for each year. The assumption here is that migrants from the same region of origin (EU3 or EU10) work in same industries.

Correlation of the proxy data with non-missing migration data collected from the national statistical offices is 0.72

A.4.2 TFP Calculation Description

Theoretically, TFP is calculated by dividing value added by the weighted average of labor and capital. When estimating it practically, however, one runs into endogeneity challenges due to the simultaneity of inputs and outputs. The literature on productivity estimations has comprehensively discussed this issue (Olley and Pakes 1996). If productivity shocks are observed by managers, they strategically choose their input, which creates a bias in the estimation due to simultaneity. Olley and Pakes (1996) were the first to introduce a semi-parametric estimation strategy that overcomes the endogeneity by using inputs of capital to proxy for the observed part of the productivity shock. Levinsohn and Petrin (2003) further develop the method and make it more feasible to estimate it empirically by using variable inputs such as materials as a proxy for the observed part of the productivity shock. As we observe materials in our dataset, we can apply the Levinson & Petrin methodology. We use the *prodest* command in STATA to easily implement it (Mollisi and Rovigatti 2017). This methodology has been extensively used in the literature (Blalock and Gertler 2004; Topalova and Khandelwal 2011) and further developed by Wooldridge (2009) and we check the robustness of our estimations using this methodology. The results are identical.

A.4.3 ORBIS Dataset Description

ORBIS is a commercial firm-level database conducted by Bureau van Dijck (BvDEP). It is a collection of business statements, ownership, ratings and news of mostly firms from the private sector. The firm's capital is measured in terms of book values, the number of employees provides information on labor inputs and consolidated or unconsolidated accounts shed light on the financial situation of the firm.

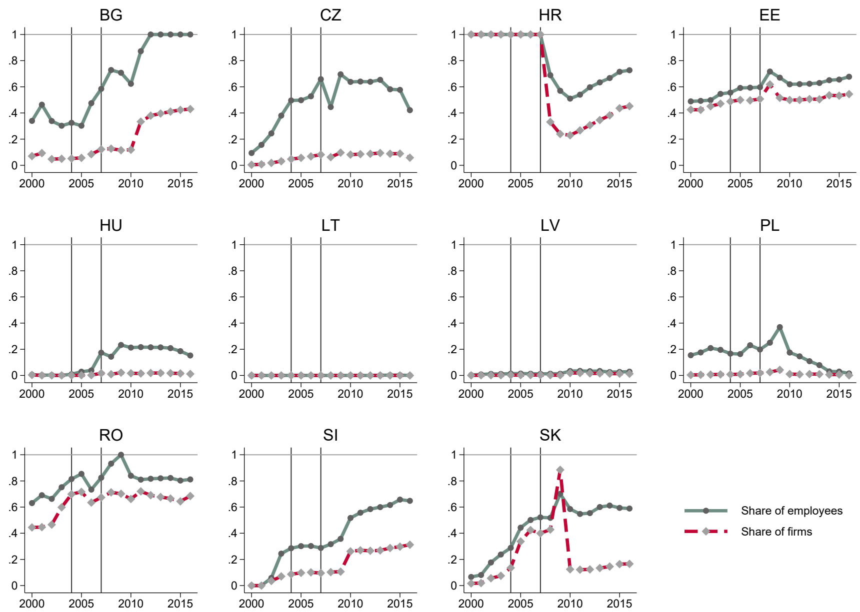
ORBIS contains data from more than 40 different sources, usually official institutions, with the aim of collecting company data to meet legal requirements. In addition, they are presented in a standard form to simplify the search and comparison of different companies.

Information about firms goes back 10 years. Information more than 10 years ago is not necessarily consistent, but can be purchased additionally.

ORBIS contains information for more than 375 million companies. Although the ORBIS database claims to cover all countries, coverage varies mainly from country to country, but also by sector, time and variables. As coverage can be very low for many countries, only a minority of countries can actually be used for comparative analysis.

The ORBIS dataset is not representative for the entire population of firms. Bajgar et al. (2020) find that the average ORBIS firm is larger, older and more productive. However, restricting the sample to only the best-covered countries and imputing missing value added improves the representativeness. To check representativeness of our dataset, we aggregate the number of employees and the number of firms per origin country and year and compare these indicators with the aggregates from the Eurostata Structural Business Statistics (Figure A7). Coverage varies by country: while it is rather good for Bulgaria, Estonia and Romania, we have only

Figure A7: **Comparison of Orbis and Eurostat Aggregate Figures**



Notes: This figure compares aggregate number of firms and number of employees per NMS and year between our ORBIS sample and Eurostat Structural Business Statistics. A dashed line shows the share of firms from Eurostat that we cover with ORBIS data and a continuous line shows the share of covered employees. Eurostat data for Croatia (HR) is available starting from 2008

few firms in Latvia, Lithuania, and Poland. It can be also seen that on average firms are larger: with a smaller share of firms we cover larger shares of employees. Coverage also varies over time. Therefore, we use ORBIS sample to study within-firm effects of emigration.

The data have been successfully used in academic economic research, mainly by papers studying multinational enterprises (Egger et al. 2009; Beer and Loeprick 2015). Moreover, Gal (2013) also uses ORBIS data to measure total factor productivity at the firm level. More information on the methodology and access formalities can be found online.[30]

[30] https://www.bvdinfo.com/en-us/our-products/data/international/orbissecondaryMenuAnchor0/

A.4.4 Correspondence Tables

One challenge with the independent variables at the two-digit industry level (migration data, training, structural business statistics, etc.) arises from the change in NACE classification (Revision 2 changed Revision 1 in 2008). Some of our data are thus available only in Revision 1 and some only in Revision 2. At a two-digit level, we run into a problem of the many-to-many relation (several NACE Revision 1 codes can potentially map into several NACE Revision 2 codes).[31] We overcame this problem by creating a country-specific conversion matrix using Orbis data for 2009, where we can observe both Revision 1 and Revision 2 NACE codes for the same firm. For each NACE Revision 1 two-digit code, we obtain a corresponding weight (share) for each NACE Revision 2 code. The weights range between 0 and 1, sum to 1, and equal to the share of firms reporting a given Revision 2 code in the total number of firms with a given Revision 1 code.

To capture industry-specific time-varying shocks in the regression analysis, we employ interaction terms between industry and year dummies. We take industries at a one-digit Nace Rev. 2 level, but further subdivide the manufacturing sector in the following categories: food and beverages (Nace Rev. 2 codes 10-12), textile (13-15), wood (16-18), coke and metals (19, 24-25), chemicals and pharmaceuticals (20-21), rubber and plastic (22-23), computers, electronics and machinery (26-28), transport items (29-30), other (31-33).

[31]Correspondence tables are well-defined at a four-digit level, but we do not always have data available at that level.

A.5 Anecdotes from the Media