Offshoring Response to High-Skilled Immigration: A Firm-Level Analysis *

For latest version of paper, click here

Devaki Ghose† Zhiling Wang ‡

World Bank Erasmus University Rotterdam

January 22, 2021

Abstract

Using a policy change in the Netherlands in 2012 that made it easier for firms to employ high-skilled non-EU workers and a matched employer-employee data, we show that firms in high-skill industries respond by both employing a higher share of non-EU immigrants and reducing the total amount of offshoring to non-EU countries. We find evidence that non-EU immigrant workers have a skill-set that complement the skills of native workers but can substitute for offshoring to non-EU countries. We then show that the offshoring status of a firm is important in understanding the labor market impact of immigration.

JEL Codes: F22, F16, J61, F66, F68.

Keywords: Immigration, Offshoring, Globalization.

*We thank seminar participants at Erasmus University Rotterdam and World Bank for constructive comments. We further thank Statistics Netherlands for providing data.

†Development Economics Research Group, The World Bank, dghose@worldbank.org.

‡Erasmus School of Economics, Erasmus University Rotterdam; Tinbergen Institute. z.wang@ese.eur.nl.

1 Introduction

Immigration of high-skilled workers and the relocation of jobs abroad by multinational firms (commonly known as offshoring), are two important engines of globalization. Both have been at the forefront of political debates across the globe. While proponents of high-skilled immigration argue that special policies attracting high-skilled immigrants are necessary to promote economic growth and create jobs, opponents argue that these policies actually displace native workers from certain jobs. However, what is often missed out in these debates is that creating jobs for natives and restricting jobs for immigrants is not a zero sum game. As several public statements by top executives show, firms can offshore jobs which they consider to be more suitable for foreign workers. [1] Understanding how changing the costs of hiring immigrants can affect offshoring, and hence domestic jobs, is imperative to any informed decision about immigration policies.

In this paper, combining detailed employer-employee matched data with firm level data in the Netherlands, we study how firms respond to changes in the cost of hiring high-skilled immigrants by changing their offshoring decisions. We exploit a change in Dutch immigration policy in 2012 that made it easier for firms to recruit high-skilled workers from non-EU countries.

We find that firms substitute offshoring with more high-skilled immigrant employment, but only for non-EU countries. Offshoring to EU countries does not change. The results hold for both the extensive and intensive margins of off-shoring: That is, some firms that were offshoring to non-EU countries stopped offshoring to these countries after the policy change and some firms reduced the amount of offshoring, while still continuing to offshore.

Our next set of findings relate to the mechanisms that can explain why firms substitute offshoring to non-EU countries with high-skilled non-EU immigrants. Offshoring is often motivated by the firm's desire to reduce labor costs, to move production closer to consumers, or to utilize

[1] Carbonite: "if [we] can't get them admitted to the United States, [we'll] staff up at Carbonite offices in Canada and Europe https://www.bostonglobe.com/business/2017/04/02/tech-industry-talent-shortage-claims-under-new-scrutiny/EsxYnPpoKBNv1iTjRl6lLL/story.html MaRS Discovery District, a technology hub in Toronto: "Toronto tech industry has been growing for a while. But the U.S. immigration crackdown accelerated that growth. Companies are locating here because they can get access to foreign talent faster" https://www.npr.org/2020/01/27/799402801/canada-wins-u-s-loses-in-global-fight-for-high-tech-workers

foreign workers with a different skill-set (Olney and Pozzoli, 2019). A similar set of considerations could induce firms to hire immigrant workers, if compared to natives, immigrants have a different skill-set. These similar sets of considerations mean that immigrant employment and offshoring could be substitutable in some respects.

We find that offshoring firms hire more non-EU immigrant workers compared to non-offshoring firms after the 2012 policy change, consistent with the mechanism that part of the work offshored by firms can be performed by immigrants. This finding is consistent with the mechanism that foreign workers are more suited for certain types of jobs compared to natives, irrespective of whether they perform these jobs in their home country (offshoring) or abroad (immigration). In that sense, immigrant workers in the destination country are competing with workers in their origin countries, but not necessarily with domestic workers.

If high-skilled immigrant workers compete with native workers for the same types of jobs, we would expect to see a fall in average wages of native workers following the 2012 policy change. A drop in average wages would make domestic production cheaper, thereby reducing the need for offshoring. We find no evidence that overall domestic wages fell. Instead, we show that after the 2012 policy change, native wages and employment expanded in high-skill relative to low-skill industries but only for offshoring firms. In a standard nested CES production function framework as in Ottaviano and Peri (2012), we introduce workers abroad with foreign expertise as an additional input that offshoring firms can access. The access to foreign expertise which complements native expertise helps explain our findings that native wages in the high-skill relative to low-skill industries only increase for offshoring firms.

This paper makes a number of contributions.

First, we contribute to a small but growing literature that examine whether increased availability of immigrant workers affects the need for firms to relocate jobs abroad (offshoring). Using Danish employer-employee matched data, Olney and Pozzoli (2019) shows that an influx of immigrants into a municipality reduces firm-level offshoring. Differently from Olney and Pozzoli (2019), we directly use firm-level immigrant employment and focus on a policy that changed the availability of only high-skilled immigrants. A closely related work, Glennon (2020) finds that restrictions on H-1B immigration in the US cause firm-level foreign affiliate employment to increase in some countries. While changes in the foreign affiliate employment as a proportion of multi-national employment can directly capture any relocation of firm activities within the boundaries of a multi-national corporation (MNC), it misses any arms length transactions, that is, foreign sourcing from unrelated suppliers (Hummels et al., 2018; Grossman et al., 2006), which we are able to capture.

Second, there are a few papers that use industry level employment data to examine the labor market impact of offshoring. Ottaviano et al. (2013) shows that immigration reduces offshoring in U.S. manufacturing industries. However, while Olney and Pozzoli (2019) finds that immigrants from the same country increase offshoring, Ottaviano et al. (2018) finds the opposite result. Our results contribute to this debate about whether immigration and offshoring are substitutes or complements. The policy we study was directed only at non-EU immigrants and not at EU immigrants who have a natural right to work in the Netherlands, thereby enabling us to study the impact of changes in high-skilled non-EU immigration on offshoring in EU and non-EU countries separately. We find evidence that firms substitute offshoring to non-EU countries with highly skilled non-EU workers. However, the availability of skilled non-EU workers does not change offshoring to EU countries.

Third, several papers in the immigration literature have shown that depending on whether immigrant and native workers are complements or substitutes, immigration may increase or decrease native employment and wages (Ottaviano and Peri, 2012; Peri and Sparber, 2009). The literature in this respect have been mixed. Borjas (2003) found that higher supply of immigrants can put downward pressure on wages. Other studies such as Friedberg (2001) have found negligible impact of immigration on wages. The margin of offshoring has typically not been accounted for in the literature above. We show that it is important to account for the firm's offshoring margin in understanding the labor market effects of immigration. The intuition for this result is that offshoring firms use foreign expertise which complements native expertise in production. Firms access foreign expertise either by recruiting immigrant workers or offshoring production abroad.

The paper is organized as follows. In section 2 we discuss the change in Dutch high-skilled immigration policy in 2012 and the employer employee matched data of the universe of Dutch firms that we use to study the effect of this policy on firm-level immigration and offshoring. In section 3 we discuss our empirical strategy, including identification. We provide evidence that firms hire more non-EU immigrant workers in response to a reduction in the cost of hiring non-EU immigrants and reduce the amount of offshoring to non-EU countries. Section 4 sheds light on the different mechanisms that are consistent with our finding in section 3 and discusses a modeling framework consistent with these findings. In this section we rule out the mechanism that immigration reduces offshoring by making domestic labor cheaper but instead find support for the mechanism that immigrant workers are good substitutes for some jobs that could be offshored. Section 5 discusses a slew of robustness checks, including using an alternative definition of offshoring, restricting the analysis to various sub-samples, and the threats to identification from concurrent policy changes.

2 Background, Data, and Summary Statistics

Our empirical analysis uses a change in Dutch high-skilled immigration policy and uses an employer-employee matched data from Statistics Netherlands. In this section, we provide background on the Dutch high-skilled immigration policy and then describe our data.

2.1 Expansion of knowledge migrant scheme to short-stay workers:

The institutional setting for migration to the Netherlands differs fundamentally between nationals of European Union member states (EU) and non-EU nationals. Every EU national has the right to settle in the Netherlands and seek employment in the Dutch labour market. Non-EU migrants need to apply for residence and work permits in the Netherlands. There are different schemes for different purposes of immigration. Most highly skilled migrants gain access to the Netherlands through the "Highly Skilled Migrants Scheme" (Kennismigrantenregeling), introduced in 2004, which guarantees quick processing and high acceptance rates for migrants whose wages are above a certain threshold (Berkhout et al., 2015).

However, high-skilled workers seeking short-term employment on an initial contract lasting less than two months are not eligible to work using this scheme. A new scheme was started in January 2012 for highly skilled workers who want to come to the Netherlands to work for less than two months. According to European Migration Network (2013), in order to gain admission on grounds of this pilot project, the following requirements were set:

- The employer has been admitted to the Highly Skilled Migrants Scheme.
- The salary must be at least proportionally equivalent to the salary as demanded for highly skilled migrants of 30 years and older.
- It must be apparent that the job relates to one that can be deemed to be that of a highly qualified worker.

It should be noted that all these provisions existed even before 2012. The only change this policy introduced was to include temporary workers in this scheme, that is, workers who came to work in the Netherlands for less than two months. Generally, work permit applications are subject to a labor market test, which entails that the employer submit information to the Dutch immigration authorities about the company, the job contract, and the recruitment process to show the position could not be filled by an EU/EEA or Swiss national.[2] The extension of the knowledge migrant scheme to temporary workers relaxed these restrictions as long as they meet the above salary and education requirements. This scheme made it easier for firms to employ high-skilled migrants from non-EU countries on a temporary basis post 2012 relative to low-skilled migrants. As shown in Figure 1, when we count registered non-EU migrants who moved in and out of the Netherlands in the same calendar year, workers under the "Highly Skilled Migrants Scheme" increased sharply relative to workers under normal labor migration visa after 2012. Since many firms find it costly to employ workers on a permanent basis, this scheme, in principle, could make it easier for some firms to access a pool of high-skilled workers which they could not previously afford. In this paper,

[2]Source: https://www.expatica.com/nl/moving/visas/netherlands-work-visas-108807/?utm_source=301&utm_medium=redirect&utm_campaign=2020-04-16

we use this scheme to study how firms respond to changes in the relative cost of hiring high-skilled non-EU immigrants.

2.2 Data Sources

Our dataset is an employer-employee matched dataset integrated from various sources provided by Statistics Netherlands. In total, it is an unbalanced panel of 120,000 firms and 9 million workers over the period 2009-2016.[3]

First, our firm data cover the universe of firms with at least 10 employees at the General Business Register over the period 1999-2016.[4] The data include detailed information on size, industry, location, number of establishments, productivity, and investment. Data between 2009 and 2016 are used for the main analysis on offshoring outcomes, and earlier data between 2004-2008 are used to analyze the pre-trend of firm-level immigrant hiring.

Second, employee data cover the population of all employees over the period 1999-2016. Every employee's entire working history can be tracked as detailed as per day. Besides the linked firm ID, there is information on the length of tenure at the firm, work experience, other individual characteristics such as age, gender, education and country of origin.

Third, trade data cover all firms in the Netherlands that have a VAT number and trade in goods with foreign countries over the period 2010-2016. The data include country of import, country of export, type of goods (8-digit Combined Nomenclature), value of import, and the value of export at the firm-level. Using this information, we construct both time-varying firm-by-destination-country and time-varying firm-level offshoring measures. This enables us to investigate whether offshoring to EU/ Non-EU countries is affected by the share of immigrants from this country at the firm level.

For an exhaustive list of data sources in Statistics Netherlands, see Appendix A.1.

[3]Results are based on calculations by Erasmus University Rotterdam using non-public microdata from Statistics Netherlands. Under certain conditions, these microdata are accessible for statistical and scientific research. For further information: microdata@cbs.nl."

[4]The selection of firm size is mainly to exclude self-employment.

2.3 Variables

2.3.1 Firm-level non-EU immigrant share

Our main independent variable of interest is the firm-level non-EU immigrant share in total firm employment. Non-EU immigration drives the majority of increase in total immigration in the Netherlands over the period 2009-2016, while EU immigration is low in level and its growth is almost linear. We first show the national trend of immigration in Figure 2 for non-EU countries and EU-28 countries.[5] The biggest boost in the increase in EU immigrants started to take place after 2004, when the largest expansion of EU took place. Ten countries (Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, and Slovenia) became EU member states, thus providing an important source of EU immigrants to the Netherlands. The trend of non-EU immigration, however, shows a distinctively different pattern. The percentage of non-EU immigrants remains at a steady level before 2012. In only 3 years' time after 2012, the percentage of non-EU immigration rises up by half a point, which exceeds the total percentage increase for the previous decade 2001-2011.

This coincides with the timing of the 2012 expansion in the knowledge migrant scheme which should only affect immigrants from non-EU countries. We thus further look into the fast-growing source countries of immigrants for Netherlands before and after 2012. Taking 2009, the period that our main analysis began, as the reference year, we calculate the growth rate in the share of immigrants for different countries and plot the top 10 countries in Figure 3. Besides the 3 new EU member states Poland, Romania and Bulgaria that joined the EU after 2004 , India ranked particularly high. This could be linked to the expansion in high-skilled immigrant policy, because the majority of Indian workers in the Netherlands are employed in the IT sector requiring high educational level.[6] We will provide rigorous evidence on how this scheme affected high-skilled non-EU immigration in section 3.2 on identification.

[5] UK is still counted as a EU member as our main analysis period precedes Brexit.

[6] https://www.cbs.nl/en-gb/news/2019/30/indian-knowledge-migration-has-doubled

2.3.2 Firm-level offshoring measures

Our main dependent variables of interest are the firm-level offshoring measures. Following the well-established method of using import data to construct offshoring measures (Hummels et al., 2014), we construct a "narrow offshoring" measure based on whether firms import products that they also produce domestically at the HS4 level.[7] This firm level measure of offshoring is generally regarded as the "gold standard for accuracy" (Hummels et al., 2018).[8] We focus on two dimensions of offshoring: whether firms decide to offshore from a non-offshoring status and the total values of offshoring products conditional on the firm offshoring. More specifically, on the extensive margin, if firms import the same HS4 category products from any country as firm production, the variable is equal to 1 and 0 otherwise. On the intensive margin, the variable is the log of 1 plus the total value of goods offshored.

Figure 4 shows the extent of offshoring across Dutch industries. Offshoring is common in the secondary sector, plus wholesale and retail trade belonging to low-skill tertiary sector. This is consistent with the evidence in (Centraal Bureau voor de Statistiek, 2018), which shows that core activities in production of goods are the most commonly off-shored vacancies.

Figure 5 shows the basic time-series variation in firm-level offshoring at the national average level by destination. The extensive margin measure has an increasing trend, while the intensive margin remains relatively at the same level. Both time series are with certain fluctuations.

2.3.3 Control variables

We describe below the definitions of the firm workforce variables' used in this paper. *Male*: share of male workers among all workers. *Age*: average age of all workers. *Bachelor*: share of native works with a bachelor degree among all native workers.[9] *Tenure*: average workers' tenure. *Work*

[7]The Harmonized System (HS) is an internationally standardized system of names and numbers to classify traded products. This code has direct correspondence with the code of goods (Combined Nomenclature) in our data.

[8]According to Hummels et al. (2018), there are three limitations of using this measure that is worth noting here. One, it is available for a relatively small subset of countries. Two, the data are often times confidential and not accessible to all researchers. Three, while measures of merchandise imports are of high quality, services- imports coverage remains relatively weak.

[9]The information of educational level is only available for native workers, because the majority of them completed bachelor degrees at a Dutch university with records. However, for foreign workers, this information is not precise. The

Experience: average years of work experience.[10] In addition, the firm characteristics consist of the following variables. *Productivity*: the log of average daily income per employee. *Capital*: the log of total purchase value of the tangible fixed assets per worker. *Size1*: a dichotomous variable of small-sized firms equal to 1 if a firm has at least 10 and fewer than 50 workers. *Size2*: a dichotomous variable of medium-sized firms equal to 1 if a firm has at least 50 and fewer than 100 workers. *Size3*: a dichotomous variable of large-sized firms equal to 1 if a firm has at least 100 workers. *Multi-establishment*: a dichotomous variable equal to 1 if the firm has multiple establishments.

For regional fixed effects, we adopt the Nomenclature of Territorial Units for Statistics (NUTS) code for regions and choose the most disaggregate level NUTS3 to identify areas in the Netherlands. In total, there are 40 NUTS3 regions in the Netherlands. Every NUTS3 region contains a central municipality. Widely used in structural analyses of Dutch labour markets, NUTS3 is an appropriate spatial scale to define labour market areas (Corvers et al., 2009). Territorial disparities are substantial and the division has been used intensively to plan spatial policies by specific administrative bodies. Our research should control for regional fixed effects that capture the local labour market environment. The use of NUTS3 regions is more precise for our analysis than the use of municipalities at a geographically finer level, as cross-municipality commuting for work is prevalent due to well-connected transportation networks in the Netherlands.

For industry categories, we use the Dutch standard industrial classification in 2008 ("Standaard Bedrijfsindeling" or SBI in Dutch). The most detailed category is coded in a 5-digit number. As we are interested in exploiting the response of high-skill industries in response to the expansion of knowledge migrant scheme in 2012, we need to define the skill intensity of each sector. Figure 6 shows the share of bachelor degree holders among native population within each industry. The educational level varies substantially across industries. We use 50% as the threshold value to define high-skill industries. Therefore, we create a variable *HS Industry*: Equal to 1 if a firm belongs to education, consultant/ research/ business service, financial institutions or information/

earliest year of graduation records that can be obtained is 2000. Therefore, the reported educational level should be lower than the true value for the entire native population.

[10]The earliest employee data can only be traced back to 1999. Therefore the count of work experience is truncated at 1999 for every worker.

communication and 0 otherwise.

2.4 Descriptive Statistics

Table 1 presents descriptive statistics of offshoring, immigration, workforce and firm characteristics over the period 2009-2016. As the offshoring variables are only available between 2010 and 2016, the total number of observations is smaller than other control variables. 11.7% of firms engage in offshoring to non-EU countries based on the narrow definition. The share of non-EU immigrant workers at the firm level is about 6.5%, with a relatively high standard deviation. In terms of workforce characteristics, male workers make up 62.1% of all employees. On average, workers age 39 in a firm. Among native workers, the share of bachelor degree holders is 22.3% on average. An average worker has 7.9 years of work experience from 1999 onward, including 3.4 years of employment at the current firm. With regard to firm characteristics, the majority of firms (78%) are small-sized, and 37.8% of firms have more than 1 establishment.

In Table 2, we further show that offshoring firms and non-offshoring firms differ substantially in workforce and firm characteristics. On average, workers in offshoring firms are more likely to be foreign, male, older and more experienced. Offshoring firms also tend to provide higher salaries and are bigger in size. Due to these differences, we conduct our analysis separately by firm offshoring status later in section 4.

3 Empirical Strategy

In this section we discuss our empirical framework. Our main goal is to study how firm-level offshoring responds to changes in the cost of hiring immigrant workers.

3.1 Specification

Following Olney and Pozzoli (2019), we estimate the following equation:

$$Off_{ijmt} = \beta_o + \beta_1 Imm_{ijmt-1} + X'_{ijmt-1}\gamma_1 + W'_{ijmt-1}\gamma_2 + \gamma_i + \gamma_j + \gamma_m + \gamma_t + \epsilon_{ijmt} \quad (1)$$

where Off_{ijmt} is offshoring by firm i in industry j in region m at time t. Our analysis focuses on narrow offshoring at both the extensive and intensive margin. Imm_{ijmt-1} is the share of non-EU immigrant hiring out of total hiring by firm i in industry j in region m in year $t-1$. Immigration and other independent variables are lagged to account for the fact that it takes time for firms to adjust in response to changing economic conditions. X_{ijmt-1} includes a set of firm characteristics that can influence offshoring decisions. Specifically, we include variables *Productivity, Capital, Size*, and *Multi-establishment*. The vector W_{ijmt-1} includes detailed workforce characteristics including variables *Male, Age, Bachelor, Tenure* and *Work Experience*. We also include firm, industry, region, and time fixed effects. This equation is simply a relationship between equilibrium immigrant hiring and off-shoring at the firm level. Since both immigration and offshoring are determined in equilibrium by the firm, the same demand and supply shocks affect both and therefore β_1 in equation 1 is simply a correlation.

We report the results of estimating equation 1 in Tables 3 and 4 for the extensive and intensive margins of offshoring respectively. Column 1 of Table 3 shows that there is a positive relationship between immigrant employment and offshoring at the firm level. However, adding firm fixed effects and additional controls like firm and workforce characteristics, this effect goes away. In our most preferred specification, we find that the share of non-EU workers within a firm has no relationship with the probability of offshoring to non-EU countries (column 3) but is positively correlated with the probability of offshoring to EU countries (column 6). We find a similar relationship between the share of non-EU immigrant workers and the volume of offshoring to EU and non-EU countries in Table 4: The share of non-EU workers within a firm has no effect on the volume of offshoring to non-EU countries but positively affects the volume of offshoring to EU countries. The estimates are sensitive to the inclusion of fixed effects. For example, in a regression with only industry, region, and year fixed effects we find a significant positive association between non-EU immigrant share and offshoring at the firm level. After adding firm fixed effects the coefficient becomes insignificant and much smaller in magnitude (column 2). After adding time-varying firm and workforce characteristics the coefficient becomes even smaller and remains insignificant (column 3). Even the strictest specification, however, does not account for unobserved firm level shocks that are time-varying and correlated with both immigration and off-shoring. For example, firms that are growing over-time or expanding their multinational activities abroad, could tend to hire more immigrants as well as offshore more. Overtime, firms could also specialize or introduce certain products in their portfolios which require skills that are more available in foreign workers. These factors would induce a spurious positive correlation between immigrant employment and offshoring at the firm-level. We therefore turn to instrument the immigrant workers hired by firms using the 2012 policy change.

3.2 Identification

We exploit a 2012 policy change that made it easier for firms in the high-skill intensive sector to hire immigrant workers. In a two-stage least squares framework, we isolate the part of changes in immigrant hiring that was driven by changes in government immigration policy in the first stage and use this variation to see how firm level offshoring responds in the second stage. In other words, we analyze how firms adjusted their equilibrium offshoring decisions in response to changes in the cost of hiring immigrants induced by the 2012 policy change. This gives us an estimate of how policy induced changes in the costs of hiring immigrants affect firms' offshoring decisions in equilibrium through changing their optimal immigrant hiring.

To understand this effect of changes in the cost of hiring immigrants on firm offshoring decisions, we first need to study whether the 2012 policy had any effect on firm level immigrant hiring. Before showing how immigrant hiring changed in high-skill intensive industries compared to low-skill intensive industries post 2012 in a difference in difference framework, we plot the trend in EU and non-EU immigrants in the entire population. Figure 2 shows that while the share of EU immigrants has been growing at a constant rate over time, the share of non-EU immigrants has been stable until 2012 before spiking in 2013. To quantify the differential trend in non-EU immigrant hiring in high-skill intensive industries relative to low-skill intensive industries, we estimate the following:

$$Imm_{ijmt-1} = \beta_o + X'_{ijmt-1}\gamma_1 + W'_{ijmt-1}\gamma_2 + \gamma_i + \gamma_j + \gamma_m + \gamma_t + \alpha_{t-1} * \gamma_s + \epsilon_{ijmt-1} \quad (2)$$

Imm_{ijmt-1} is the share of non-EU immigrant hiring out of total hiring by firm i in industry j in region m in year $t-1$. γ_s is a dummy indicating whether the firm belongs to a high- skill or a low-skill industry. α_{t-1} measures the differential trend in immigrant hiring in high-skill intensive industries relative to low-skill intensive industries in year $t-1$. All firm and worker level characteristics as well as fixed effects are the same as in equation 1.

Since the 2012 policy directly increased the ease of hiring non-EU high-skilled immigrants, we expect α_t to be positive and significant from 2012 only for non-EU immigrants. We cluster the standard errors at the industry level since the 2012 scheme was targeted towards firms in high-skill industries. We show the event study graphs for the shares of non-EU, EU, and native employment in Figures 7, 8 and 9 respectively. Figure 7 shows that between 2004 to 2011, there was no increasing trend in non-EU employment share in high-skill relative to low-skill industries.[11] However, after the introduction of the high-skilled immigration scheme in January 2012, the share of non-EU immigrants in high-skill relative to low-skill industries started increasing every year. Pair-wise t-tests reported in Table 12 in the online appendix A.2 confirms that before 2011, the base year, there were no significant year by year differences in non-EU immigrant share in high-skill relative to low-skill industries.[12] However, starting from 2013, exactly an year after the high-skilled immigration policy was put in place, these year by year differences turn positive and significant. The share of EU immigrant employment in high-skill relative to low-skill industries does not show any pattern before and after the 2012 policy change (Figure 8). Native employment share reduces after the

[11] We chose 2004 as the start year to show the pre-trend because the first high-skilled migrants scheme was introduced in 2004.

[12] There is a slight increase in non-EU immigrant share from 2009 to 2010 but the pairwise t-test confirms that the difference in magnitudes is statistically insignificant. The year 2009 is a year of structural break in the data because of the recovery from the financial crisis. Both the non-EU and EU immigrant unemployment rate increased greatly during the recession. See for e.g Cerveny and Van Ours (2013). After the recovery, both the shares of EU and non-EU immigrant employment increased, especially in high-skill industries which were primarily affected by the recession.

2012 policy change, consistent with the fact that the employment shares should add up-to 1 (Figure 9). The tables corresponding to the event study graphs and the pairwise t-test results are available in Table 12 in the online appendix A.2.

Since offshoring and immigrant hiring in both high-skill and low-skill industries have been growing over time due to globalization, it is not enough to just look at how offshoring changed post 2012 in high-skill relative to low-skill industries to understand the impact of the changes in the costs of hiring immigrants on offshoring. To isolate the impact of changes in the cost of hiring immigrants on firm-level offshoring, we use two sources of variation: First, we use the fact that the 2012 policy primarily affected the high-skill intensive industry. Second, we use the historical tendency of immigrants to settle in areas that are already immigrant intensive.[13] Our empirical strategy is to use a two stage least squares framework using these two variations.

First Stage:

$$Imm_{ijmt-1} = \beta_o + X'_{ijmt-1}\gamma_1 + W'_{ijmt-1}\gamma_2 + \gamma_i + \gamma_j + \gamma_m + \gamma_{t-1} + \alpha_1 post * \gamma_s \\ + \alpha_2 post * Img_{mo} + \alpha_3 \gamma_s * Img_{mo} + \alpha_4 post * \gamma_s * Img_{m0} + \epsilon_{ijmt-1} \quad (3)$$

Second stage:

$$Off_{ijmt} = \beta'_o + \beta'_1 Imm_{ijmt-1} + X'_{ijmt-1}\gamma'_1 + W'_{ijmt-1}\gamma'_2 + \gamma'_i + \gamma'_j + \gamma'_m + \gamma'_t + \alpha'_1 post * \gamma'_s + \varepsilon_{ijmt}, \quad (4)$$

where post=1 if year > 2012. Img_{mo} is the proportion of non-EU immigrants in region m in year 1999. γ_s is a dummy indicating whether the firms belongs to a high-skill or a low-skill industry. This is a triple difference set up where: α_1 measures the differential trend in immigrant hiring in high-skill intensive industries relative to low-skill intensive industries post 2012. α_2 measures the differential trend in how higher existing immigrant population in region m affects immigrant hiring

[13]This theory was pioneered by Card (2001) and has been extensively used thereafter. See for example, Cascio and Lewis (2012), Boustan (2010) as couple of examples in this big literature.

post 2012. α_3 measures how higher existing immigrant population in region m affects immigrant hiring in firms in high-skill industries in region m relative to firms in low-skill industries. α_4 measures how the effect of higher existing immigrant population in region m on immigrant hiring in firms in high-skill industries in region m relative to firms in low-skill industries changed after 2012.

Since the expansion of the knowledge worker scheme in 2012 affected firms in high-skill intensive industry much more than firms in the low-skill intensive industry, we expect α_1 to be positive and significant if the policy was effective. If immigrants settle at a higher rate in areas with existing immigrant population as the vast literature on immigration has shown, we would expect firms in immigrant-intensive areas to have higher access to immigrant workers than firms in less immigrant-intensive areas. We would therefore expect firms in high-skill industries in areas that had higher existing immigrant population to hire more immigrants after 2012 compared to firms that are located in less immigrant intensive areas. We thus expect α_4 to be positive and significant.

The 2SLS estimate of $\beta_1^{'}$ thus measures the change in the firm's equilibrium offshoring in response to changes in the cost of hiring immigrants. The identification assumption behind the instrument is that if we see a rise in firm-level offshoring in high-skill industries relative to low-skill industries in areas that are intensive in non-EU immigrants after the 2012 policy change, it must be because firms adjust their offshoring activities in response to a reduction in the cost of hiring high-skilled immigrants. This is the most conservative specification as the interaction of the post 2012 dummy with the high-skill /low-skill industry dummy allows offshoring to change differently in high-skill intensive industries relative to low-skill intensive industries post 2012. In other words, the effect of lowering the cost of immigrant hiring on offshoring is only identified off the differential increase in immigrant hiring in high-skill industries relative to low-skill industries after the 2012 policy change in areas with varying degrees of historical immigration concentration.

Table 5 reports the results from the first stage. From column 1 of Table 5 we see that non-EU immigrant hiring increased in high-skill intensive industries relative to low-skill intensive industries and it increased more in firms located in areas that already have a higher share of non-EU immigrants. Column 2 shows that we do not see any corresponding changes in the share of EU hiring in high-skill relative to low-skill industries. The first stage F-stat at 14.32, passes the test for weak instrument.

3.3 Effect on firm-level off-shoring

In this section, we study how changes in the costs of hiring high-skilled immigrants affect firm level off-shoring.

3.4 Extensive Margin

In Table 6 we reports the results of estimating equation 4 on the extensive margin of offshoring to both non-EU and EU countries. Column 2 and column 4 are our most preferred specifications to understand the impact on extensive margin offshoring for Non-EU and EU countries respectively. These specifications controls for firm, region, and year fixed effects and include a battery of firm and workforce level controls. Reading off column 2, we find that a one percentage point increase in the non-EU immigrant share driven by changes in the costs of hiring non-EU immigrants is associated with a .011 decrease in the probability that a firm will offshore, which represents a 8.85 % decline relative to the mean. We find that there is no corresponding change in offshoring to EU countries. In columns 1 and 3 we show the results for non-EU and EU immigrants respectively, without taking into account firm and workforce characteristics. Both the signs and the magnitudes of the coefficients remain within the confidence intervals.

The results are close to Olney and Pozzoli (2019). They found that a one percentage point increase in immigration leads to a 6.4% decline in the probability that a firm will offshore. Our relatively larger magnitude can be explained by many factors. First, we are focusing exclusively on high-skill intensive industries, where the relationship between immigrant workers and offshoring could differ. Second, differently from Olney and Pozzoli (2019) which exploit regional changes in the immigrant population, we directly estimate how firms change their offshoring decisions to changes in immigrant hiring that are driven by exogenous changes in the cost of hiring non-EU immigrants at the firm level. Lastly, since the high-skilled immigration policy only affected non-EU immigrants, we study the impact on offshoring to both EU and non-EU countries. The significant and negative relationship between non-EU immigrant workers and the probability of offshoring is only observed for non-EU countries.

3.5 Intensive Margin

In Table 7 we report the results of estimating equation 4 on the intensive margin of offshoring to both non-EU and EU countries. Here, the dependent variable is the logarithm of offshoring across all firms in the sample.[14] Again, columns 2 and 4 are our most preferred specifications to understand the impact on intensive margin offshoring for Non-EU and EU countries respectively. We find that even after accounting for firm, region, and year fixed effects, and a battery of firm and workforce controls, firms respond to changes in the cost of hiring immigrants by substituting offshoring with immigrant workers: a one percentage point increase in the immigrant share is associated with a 9.18% decline in the volume of firm-level offshoring, which represents a 7.12% decline relative to the mean level of offshoring. Again, from column 4 we see that firms do not reduce the volume of off-shoring to EU countries. In columns 1 and 3 we show the results for non-EU and EU immigrants respectively, without taking into account firm and workforce characteristics. Both the signs and the magnitudes of the coefficients remain within the confidence intervals.

Overall, the results in Tables 6 and 7 provide compelling evidence that firms hire more non-EU immigrant workers in response to a reduction in the cost of hiring non-EU immigrants and reduce the amount of off-shoring to non-EU countries. In that sense, firms substitute offshoring with immigration. However, firms do not substitute offshoring to EU countries with non-EU workers. In that sense, non-EU workers are substitutes for off-shoring to non-EU countries but are not substitutes for off-shoring to EU countries.

[14] We add one to every observation here before taking logarithm so that we do not exclude firms that have no off-shoring in certain years.

4 Mechanisms

In this section, we explore the possible mechanisms that can explain why firms increase immigrant hiring and reduce offshoring to non-EU countries in response to a reduction in the cost of hiring non-EU immigrants. To do this, we will separately focus on the two groups of firms, firms that were already offshoring and firms that were not. We separately look at the wage and employment effects across offshoring and non-offshoring firms. From the data we see that in any given year, more than 70% of job switches happen within offshoring/non off-shoring firms. From the summary statistics in Table 2 we also know that these two types of firms employ workers who are very different in terms of their labor market experience and nativity. In our empirical analysis, we thus do not restrict these firms to operate in the same labor market.

We start with the observation that since at-least some Dutch firms offshore, there are five types of workers available in the economy depending on their regions of origin: Native workers, immigrant non-EU workers, non-EU workers abroad (corresponding to firms offshoring to non-EU countries), immigrant EU workers, and EU workers abroad (corresponding to firms offshoring to EU countries). Within the framework of Ottaviano and Peri (2012), it is useful to think of the option of offshoring as having access to a third type of worker: Workers abroad. The access to this third type of worker can have implications for the substitutability and complementarity of natives and immigrants within the nested CES production function framework of Ottaviano and Peri (2012), as outlined in the online appendix A.3. This, in turn, can change the implications of the labor market effects of immigration on native wages and employment, depending on the offshoring status of the firm.

First, foreign workers maybe more suited for certain types of jobs compared to natives, irrespective of whether they perform these jobs at their home country (offshoring) or abroad (immigration). In that sense, immigrant workers are competing with foreign workers abroad, but not necessarily with domestic workers. If immigrant workers are substituting for offshoring, then we anticipate that offshoring firms will employ a larger share of immigrant workers after the 2012 high-skilled immigration scheme. To formally test this, we first divide the set of firms into two categories: Firms that ever offshored between 2010 and 2016 and firms that never offshored between 2010 and 2016. We then test how the share of non-EU immigrant hiring changed post 2012 in high-skill intensive industries relative to low-skill intensive industries in these two sets of firms. Equation 5 below is the specification we use to test this. The firm and worker level controls and the set of fixed effects are the same as used in the previous specifications.

$$Imm_{ijmt} = \beta_o + X'_{ijmt-1}\gamma_1 + W'_{ijmt-1}\gamma_2 + \gamma_i + \gamma_j + \gamma_m + \gamma_t + \alpha post * \gamma_s + \epsilon_{ijmt} \tag{5}$$

We report the results in Table 8. In columns 1 and 2 we report the changes in the share of non-EU workers for offshoring and non-offshoring firms respectively, using the full set of fixed effects and firm and worker characteristics. Here a firm is defined to be an offshoring firm if it has ever offshored between 2010 and 2016. We find that, compared to high-skill industry non-offshoring firms, high-skill industry offshoring firms increased the share of non-EU immigrant workers more than three times after the 2012 policy change relative to their counterparts in the low-skill industry. This difference remains positive and statistically significant when we change the criterion of offshoring firms and define firms that offshored in 2010 as offshoring firms and firms that do not offshore in 2010 as non-offshoring firms (columns 3 and 4). Similar to Olney and Pozzoli (2019), we find evidence that firms substitute offshoring with immigrant workers.

Second, does higher availability of non-EU immigrants generate downward pressure on wages, especially the wages of native workers, who constitute about 90% of all employment? If wages fall, firms may just substitute offshoring with more domestic workers, irrespective of whether they are natives or immigrants. Table 9 shows that there is no evidence that overall wages fell in offshoring firms, the firms who hire the larger proportion of non-EU immigrants after the 2012 policy change. In fact, reading off columns 1 and 2 in Panel A of Table 9, we see that the wages of native and EU workers increased by 0.4% and 1.3% in high-skill relative to low-skill industries in offshoring firms. There are no changes in the wages of non-EU immigrant workers in high-skill relative to low-skill industries in offshoring firms (column 3). We thus rule out the mechanism via which higher labor supply reduces domestic labor costs and thus reduces offshoring. From columns 4 to 6 in Panel A we see that there is a fall in the wages of native workers by 0.2% and an increase in the wages of EU workers by 0.7% for non-offshoring firms. In Panel B, we repeat the regressions using the alternative criterion of offshoring. Our main finding that the wages of native workers increase in high-skill relative to low-skill industries in offshoring firms remains unchanged. The wages of EU workers in high-skill relative to low-skill industries in non-offshoring firms does not change significantly in this alternative specification. These differences in wage responses between offshoring and non-offshoring firms in the high-skill industries, along with the descriptive evidence of low worker mobility and differential worker characteristics between offshoring and non-offshoring firms, suggest that it is important to account for the possibility of offshoring when studying the impact of immigration on local labor markets.

In Table 10 we show how native, EU, and non-EU employment respond in offshoring and non-offshoring firms. From column 4 in Panel A of Table 10 we find evidence that offshoring firms in the high-skill intensive industry increased total employment by 4.1% relative to firms in the low-skill industry after the introduction of the 2012 high-skilled immigration policy scheme. Did this employment expansion only come from hiring more non-EU immigrants at the expense of offshoring abroad to non-EU countries? From column 1 we see that native employment increased by 3.6% in offshoring firms in the high-skill industry relative to offshoring firms in the low-skill industry after the 2012 scheme. However, there is no differential change in either native employment or total employment for non-offshoring firms in high-skill relative to low-skill industries. Our results for native employment and total employment do not change we when use the alternative criterion for offshoring, as in Panel B of Table 10.

The empirical evidence in this section suggests that it is important to account for firm's offshoring behaviour when looking at the impact of immigration on labor market. The evidence is consistent with an economic model where there are two types of firms in the economy: Offshoring and non-offshoring firms. These two types of firms employ different types of workers and workers cannot freely move between these firms in the short-run. Offshoring firms have access to an extra type of worker compared to non-offshoring firms: EU and non-EU workers abroad.

Non-offshoring firms produce using a nested CES production function where they only combine native and immigrant workers with different types of expertise. Offshoring firms, in addition, use another type of expertise, called foreign expertise, and only immigrant workers or workers abroad have this skill. With an influx of immigrants, offshoring firms substitute offshoring with more immigrant workers. Everything else equal, offshoring firms thus hire more non-EU immigrant workers compared to non-offshoring firms after the 2012 policy change, as documented in Table 10. Since foreign expertise complements the other types of expertise which native workers have, offshoring firms in high-skill relative to low-skill industries witness a higher percentage increase in native wages and employment compared to their non-offshoring counterparts (as documented in Tables 9 and 10).[15] A model reflecting the heterogeneous production function and imperfect labor mobility between offshoring and non-offshoring sectors that generate the above set of labor market effects are outlined in the online appendix A.3. This model, as outlined above and solved more formally in the online appendix A.3, is able to rationalize our empirical findings.

5 Robustness Checks

In this section, we do several types of robustness checks. The first type of robustness check is related to the type of offshoring measure that we use. The second type of robustness check is related to the sensitiveness of the results to different sub-samples. The last robustness check addresses some potential threats from concurrent immigration policy changes between 2009 and 2016, and conducts a placebo check.

5.1 Alternative measures of offshoring

In this paper, we have followed Hummels et al. (2014) in measuring offshoring as the imports of the same four-digit HS industries that importers produce domestically as a way to capture imported

[15]The result that native wages slightly fall (.16%-.2%) in non-offshoring firms is not inconsistent with the model. As Ottaviano and Peri (2012) shows, the net effect of immigration on native wages will depend on the skill and experience level of the distributions of new and existing immigrants and natives.

inputs. In contrast, Bernard et al. (2020) highlights that the imports of produced goods are another, often-overlooked type of off-shoring. They show that firms continue domestic production of the same goods that they offshore to low-wage countries. They show that the opportunity to offshore production of low-quality varieties free up domestic resources for the development of higher-quality varieties. With the aim of distinguishing produced-goods from the imports of inputs, they narrow the measure of offshoring to the same HS6 products that the firm produces at home. We repeat our results with this alternative measure of offshoring (columns 1 to 4 of Table 13 in the online appendix A.2). A one percentage point increase in the immigrant share is associated with a 7.29% decline in the total value of firm-level off-shoring, which represents a 6.34% decline relative to the mean, very close to the decline we found in our main specification. The extensive margin effect, even though negative, is no longer significant. The results for offshoring to EU destinations, both at the extensive and the intensive margins, remain unchanged. Following Bernard et al. (2020), we also use a third related measure of offshoring where we divide the imports of the same HS6 category as the firm produces at home by the total value of the firm's imports to decrease the possibility that we are simply capturing a trend of growing firms in high-skill industries that just import more (columns 5 and 6 of Table 13 in the online appendix). The results are statistically unchanged for offshoring to both EU and non-EU destinations.

5.2 Sub-sample regressions

This section presents four types of sensitivity checks on different sub-samples (Table 14 and Table 15 in the online appendix A.2).

First, the attrition rate of firms might bias our results if entering and exiting firms have particular characteristics related to offshoring measures. To alleviate the influences from the inflow and outflow of firms, we pick a sub-sample of firms who have been registered continuously in the data between 2010 and 2016. This criterion of selection cuts the sample by about one third. The estimates are very similar with the main results in terms of significance and magnitude. The coefficient for the EU countries remain insignificant still.

Second, our results might also be affected by firms clustered in several big cities. Potentially, these cities are more active in the economy and possess more international networks via immigrant workers and multinational firms. To reduce the impact of these cities, we exclude four biggest cities ("Big 4") in the Netherlands, i.e., Amsterdam, Rotterdam, Den Haag, and Utrecht. For non-EU destinations, both the offshoring decision and the total offshoring value have negative and significant estimates. The magnitudes of both estimates are much larger compared to the main result, implying that the substitution effect between immigration and offshoring is stronger among firms in less international cities. It is possible that firms in "Big 4" cities might still maintain their international activities and are less responsive to an increase in labor supply.

Third, our measure of offshoring relies on the fact that imports by firms are used as intermediate inputs but not final goods for sale. As retail re-selling with no value-added is common, we exclude wholesales and retail trade sectors from the sample following Hummels et al. (2014) and Hummels et al. (2018). This exclusion minimizes the chances that imported goods are used for sale. Results are very consistent with our main results.

Lastly, our results might be affected by the presence of large trading partners and any bilateral policies that can affect immigration between the large trading partners and the Netherlands. Besides US, one of the biggest non-EU trading partner, India and China are two major emerging non-EU trading partners of the Netherlands and also major sources of immigrants as shown earlier in Figure 3. We repeat our results by dropping India, China and US respectively. This means that the dropped country is neither included as a possible offshoring destination nor as a source of immigrant workers. Coefficient estimates remain almost identical to our main estimates in percentage terms and the significance remains. Our result is not driven in particular by any of these important countries.

5.3 Concurrent policies

Concurrent policies that are most likely to confound our regression are some changes in immigration policy between 2009-2016. We check related concurrent policies and test for the channels that might affect our results (Table 16 in the online appendix A.2).

The first policy we take into account is the Dutch expatriate tax regime (known as the 30% ruling). Foreign workers with special skills or expertise which is scare on the Dutch labor market are entitled to tax subsidies. Some amendments were issued in 2012, among which EU immigrant workers living close to Dutch border are directly affected. The amendment stated that foreign workers living in the border area of 150 kilometers from the Dutch borders no longer qualify for the 30% ruling. This distance range mainly applies to Belgium, Germany and Luxembourg. If high-skilled immigrant workers from the three countries respond strongly and stopped working at Dutch companies, firms' hiring strategy of foreign workers might be different under a shortage of high-skilled EU workers. Here we explicitly test for the change in firm-level immigrant share from Belgium, Germany and Luxembourg. The results show that there are no significant differences in employment shares from these three countries before and after the 2012 policy change.

The second policy we look at is the migration restriction lift for Romanians and Bulgarians working in EU countries in 2014. Although Romanians and Bulgarians have had the right to settle freely in the EU since the countries' accession in 2007, they still needed a permit in order to work in EU member states. This condition was added to prevent mass migration out of these countries into other EU countries and remained in force until 2014. Since the average percentage of high-skilled workers from Romania and Bulgaria is higher than the national average for the foreign population in the Netherlands, it is important to check if this policy led to changes in firm-level hiring of Romanians and Bulgarians differently across high and low-skill industries. If we see an increasing pattern after 2014, this might directly affect firm-level hiring of non-EU immigrant workers as well. However, the result does not show significant changes, alleviating the concern about the impact of this migration restriction lift on firm-level hiring outcomes.

Lastly, as a placebo check, we study the employment outcome for a special group of immigrants who are supposed to be unaffected by the 2012 policy amendments in short-stay regulations. We use the firm-level share of migrants who came to the Netherlands for "other" reasons, that is, reasons unrelated to jobs, family reunification or education.[16] We do not find any differential increase in the employees of high-skill industries who come to the Netherlands for reasons not related to jobs, family, or education, relative to low-skill industries.

6 Conclusion

This paper examines how firms respond to an increased access to high-skilled immigrant workers made available through a national change in visa policy by changing their offshoring decisions. Using a detailed matched employer-employee data covering the universe of Dutch firms from 2010-2016, we find that firms respond to this increased availability of high-skilled immigrants from non-EU countries by reducing offshoring to non-EU countries. We find evidence for the mechanism that non-EU immigrant workers have skills that make them substitutes for offshoring tasks performed in other non-EU countries, but not in EU countries. This effect operates both on the extensive and intensive margins: Some firms that were offshoring to non-EU countries stop offshoring after the 2012 change in high-skilled immigration policy and firms that continue offshoring reduce their volume of offshoring.

This is an important finding in the background of global controversies surrounding immigration and offshoring, where both are politically incendiary topics but are not commonly studied together. In fact different countries have taken different directions concerning high-skilled immigration policies in recent years, where the issue of offshoring is rarely mentioned. While in recent years the US government has tried to restrict the H1B visas issued to skilled immigrants to protect American jobs and workers, Glennon (2020) showed that it actually increased the offshoring of jobs abroad.[17] Some countries like the Netherlands, on the other hand, have tried to introduce policies to increase the supply of high-skilled workers in recent years. We show that this policy has in-fact done the

[16] Note that due to the 2012 scheme people coming to the Netherlands for family reunification motives will increase in the high-skill industries relative to low-skill industries. That is why we cannot use family reunification motive as a placebo check.

[17] "Since his 2016 campaign, Trump has railed against the H-1B program — which he said suppresses American wages and employment rates and is rife with employer abuse. (Vox, May 24, 2020) https://www.vox.com/2020/5/24/21266920/trump-h1b-opt-visa-immigration-student

opposite of what many populist leaders fear: Instead of reducing native wages, it increased native wages in firms that offshore more and hire more immigrants.

Our findings have important implications for the immigration literature that studies the impact of immigration on native labor market outcomes. We find that native wages and employment only increase in the high-skill intensive industries relative to the low-skill intensive industries for offshoring firms. Native employment decreases slightly in non offshoring firms. This paper suggests that the additional access to foreign workers abroad could change the impact of immigration on native employment according to the offshoring status of the firm.

The high-skill immigration policy has also "brought back" some jobs from non-EU countries in the sense that firms substitute offshoring with more in-home production. Substituting offshoring with more high-skilled immigrant employment can be beneficial for the country in several ways: High-skilled immigrants tend to earn and spend more (Ortega and Peri, 2014), increase innovation and product diversity (Mazzolari and Neumark, 2012; Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010). Our findings show that when designing policies regarding high-skilled immigration, policy makers cannot separate the issue of offshoring since changes in the costs of hiring immigrants will affect firm level offshoring decisions.

References

Berkhout, E., A. Heyma, M. Volkerink, S. van der Werff, et al. (2015). Attracting and retaining highly skilled migrants in the netherlands. *SEO-report 88*.

Bernard, A. B., T. C. Fort, V. Smeets, and F. Warzynski (2020). Heterogeneous globalization: Offshoring and reorganization. Technical report, National Bureau of Economic Research.

Borjas, G. J. (2003). The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market. *The Quarterly Journal of Economics 118*(4), 1335–1374.

Boustan, L. P. (2010). Was postwar suburbanization “white flight”? evidence from the black migration. *The Quarterly Journal of Economics 125*(1), 417–443.

Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics 19*(1), 22–64.

Cascio, E. U. and E. G. Lewis (2012). Cracks in the melting pot: immigration, school choice, and segregation. *American Economic Journal: Economic Policy 4*(3), 91–117.

Centraal Bureau voor de Statistiek (2018). Internationaliseringsmonitor 2018-II Werkgelegenheid. Technical report.

Cerveny, J. and J. C. Van Ours (2013). Unemployment of non-western immigrants in the great recession. *De Economist 161*(4), 463–480.

Corvers, F., M. Hensen, and D. Bongaerts (2009). Delimitation and coherence of functional and administrative regions. *Region Studies 43*(1), 19–31.

European Migration Network (2013). Attracting highly qualified and qualified third-country nationals: Emn focussed study 2013. *European Commission*.

Friedberg, R. M. (2001). The impact of mass migration on the israeli labor market. *The Quarterly Journal of Economics 116*(4), 1373–1408.

Glennon, B. (2020). How Do Restrictions on High-Skilled Immigration Affect Offshoring? Evidence from the H-1B Program. *SSRN Electronic Journal*, 1–47.

Grossman, G. M., E. Rossi-Hansberg, et al. (2006). The rise of offshoring: it's not wine for cloth anymore. *The New Economic Geography: Effects and Policy Implications 2006*.

Hummels, D., R. Jogersen, J. Munch, and C. Xiang (2014). The wage effects of offshoring: evidence from danish matched worker-firm data. *American Economic Review 104*(6), 1597–1629.

Hummels, D., J. R. Munch, and C. Xiang (2018). Offshoring and labor markets. *Journal of Economic Literature 56*(3), 981–1028.

Hunt, J. and M. Gauthier-Loiselle (2010). How much does immigration boost innovation? *American Economic Journal: Macroeconomics 2*(2), 31–56.

Kerr, W. R. and W. F. Lincoln (2010). The supply side of innovation: H-1b visa reforms and us ethnic invention. *Journal of Labor Economics 28*(3), 473–508.

Mazzolari, F. and D. Neumark (2012). Immigration and product diversity. *Journal of Population Economics 25*(3), 1107–1137.

Olney, W. W. and D. Pozzoli (2019). the Impact of Immigration on Firm-Level Offshoring. *Review of Economics and Statistics 24*(3), 272–284.

Ortega, F. and G. Peri (2014). Openness and income: The roles of trade and migration. *Journal of International Economics 92*(2), 231–251.

Ottaviano, G. I. and G. Peri (2012). Rethinking the effect of immigration on wages. *Journal of the European Economic Association 10*(1), 152–197.

Ottaviano, G. I., G. Peri, and G. C. Wright (2013). Immigration, offshoring, and American jobs. *American Economic Review 49*(5), 117–151.

Ottaviano, G. I., G. Peri, and G. C. Wright (2018). Immigration, trade and productivity in services: Evidence from U.K. firms. *Journal of International Economics 112*, 88–108.

Peri, G. and C. Sparber (2009). Task specialization, immigration, and wages. *American Economic Journal: Applied Economics 1*(3), 135–69.

Tables

Table 1: Descriptive Statistics 2009-2016

	count	mean	sd
Dependent variables			
Extensive margin of offhsoring to non-EU	442,776	0.117	0.321
Intensive margin of offshoring measured in 1 million euros to non-EU	136,793	17.345	296.976
Extensive margin of offhsoring to EU	442,776	0.083	0.276
Intensive margin of offshoring measured in 1 million euros to EU	136,793	22.673	368.472
Workforce variables			
Share of non-EU immigrant workers (firm level)	512,701	0.065	0.123
Male	512,701	0.621	0.286
Age	512,701	39.061	6.956
Obtained a bachelor degree (only applicable for natives)	506,138	0.223	0.252
Tenure	512,701	3.418	2.283
Work experience	512,701	7.895	2.127
Firm variables			
Log of average daily income per employee	512,701	4.421	0.497
Log of capital stock per employee	512,701	5.422	3.730
The number of employees is smaller than 50	512,701	0.780	0.414
The number of employees is between 50 and 100	512,701	0.105	0.307
The number of employees is larger than 100	512,701	0.114	0.318
Multi-establishment	512,701	0.378	0.485
Observations	512,701		
Number of firms	120,849		

Table 2: Descriptive Statistics by Offshoring Status

	Offshoring		Non-offshoring			
	mean	sd	mean	sd	t-test	
Non-EU immigrant share (firm level)	0.085	0.103	0.055	0.103	-0.0298***	(-53.80)
EU immigrant share (firm level)	0.042	0.066	0.028	0.078	-0.0141***	(-34.27)
Male	0.743	0.176	0.606	0.291	-0.136***	(-92.18)
Age	41.935	4.515	39.723	6.446	-2.213***	(-66.76)
Obtained a bachelor degree (only applicable for natives)	0.258	0.197	0.239	0.261	-0.0189***	(-13.95)
Tenure	4.772	2.129	4.061	2.083	-0.711***	(-63.08)
Work experience	8.972	1.320	8.176	1.861	-0.797***	(-83.14)
Log of average daily income per employee	4.744	0.313	4.437	0.446	-0.307***	(-133.79)
Log of capital stock per employee	7.348	2.810	5.373	3.801	-1.975***	(-100.52)
The number of employees is smaller than 50	0.535	0.499	0.733	0.443	0.198***	-80.92
The number of employees is between 50 and 100	0.196	0.397	0.125	0.33	-0.0715***	(-38.66)
The number of employees is larger than 100	0.269	0.443	0.143	0.35	-0.126***	(-63.57)
Multi-establishment	0.379	0.485	0.409	0.492	0.0293***	-11.08
Observations	41,800		195,056		236,856	
Number of firms	5,225		24,382		29,607	

Notes: The sample is restricted to firms that always exist between 2009-2016 and have offshoring information in 2010.

Table 3: OLS results: Immigration and the Extensive Margin of Offshoring

VARIABLES	(1) Ex: Non-EU	(2) Ex: Non-EU	(3) Ex: Non-EU	(4) Ex: EU	(5) Ex: EU	(6) Ex: EU
Share of non-EU workers within firm	0.157***	0.0138	0.00906	0.118***	0.0231**	0.0210*
	(0.0475)	(0.0109)	(0.0114)	(0.0350)	(0.0108)	(0.0120)
Secondary#Post	0.00397	0.00628	0.00710	-0.00878*	-0.0111**	-0.00977**
	(0.00713)	(0.00671)	(0.00665)	(0.00499)	(0.00466)	(0.00470)
Tertiary#Post	-0.00365	-0.000328	0.000343	-0.000264	2.59e-05	0.000909
	(0.00563)	(0.00507)	(0.00515)	(0.00360)	(0.00283)	(0.00287)
Observations	379,804	365,050	362,172	379,804	365,050	362,172
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes	yes	yes
Firm Fixed Effects	no	yes	yes	no	yes	yes
Firm and Workforce Characteristics	no	no	yes	no	no	yes
Mean Y	0.120	0.120	0.120	0.0800	0.0800	0.0800

Notes: The dependent variable is a binary variable indicating whether the firm offshores to Non-EU/ EU. Robust standard errors clustered at 2-digit SBI industry code. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: OLS Results: Immigration and the Intensive Margin of Offshoring

	(1) In: Non-EU	(2) In: Non-EU	(3) In: Non-EU	(4) In: EU	(5) In: EU	(6) In: EU
Share of non-EU workers within firm	2.315***	0.0970	0.0429	1.744***	0.313**	0.294*
	(0.815)	(0.119)	(0.125)	(0.530)	(0.136)	(0.149)
Secondary#Post	0.0389	0.0636	0.0719	-0.120*	-0.142**	-0.127**
	(0.0798)	(0.0759)	(0.0739)	(0.0681)	(0.0593)	(0.0606)
Tertiary#Post	-0.0499	-0.0203	-0.0135	-0.0148	0.00223	0.0118
	(0.0582)	(0.0540)	(0.0542)	(0.0508)	(0.0364)	(0.0374)
Observations	379,804	365,050	362,172	379,804	365,050	362,172
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes	yes	yes
Firm Fixed Effects	no	yes	yes	no	yes	yes
Firm and Workforce Characteristics	no	no	yes	no	no	yes
Mean Y	1.290	1.290	1.290	1.100	1.100	1.100

Notes: The dependent variable is the natural log of 1 plus firm-level offshoring values to non-EU/ EU. Robust standard errors clustered at 2-digit SBI industry code. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: First Stage: Changes in Immigrant Employment Post 2012

VARIABLES	(1) Share: Non-EU	(2) Share: EU
NonEUImg0#HS Industry	-0.0116	
	(0.00590)	
NonEUImg0#Post	-0.0494***	
	(0.00345)	
HS Industry#Post	0.00132**	-0.00244
	(0.000151)	(0.00132)
NonEUImg0#HS Industry#Post	0.0212***	
	(0.00168)	
EUImg0#HS Industry		-0.0777
		(0.0434)
EUImg0#Post		0.0158
		(0.0214)
EUImg0#HS Industry#Post		-0.0228
		(0.0192)
Observations	474,586	474,586
R-squared	0.939	0.903
Industry/ Region/ Year Fixed Effects	yes	yes
Firm Fixed Effects	yes	yes
Firm and Workforce Characteristics	yes	yes

Notes: In column 1, the dependent variable is the share of non-EU immigrant workers within firm. NonEUImg0 is the proportion of non-EU immigrants at the regional level in year 1999. In column 2, the dependent variable is the share of EU immigrant workers within firm. EUImg0 is the proportion of EU immigrants at the regional level in year 1999. Robust standard errors clustered at broad industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: IV Results: Immigration and the Extensive Margin of Offshoring

VARIABLES	(1) Ex: Non-EU	(2) Ex: Non-EU	(3) Ex: EU	(4) Ex: EU
Share of non-EU workers within firm	-1.139**	-1.063**	-0.440	-0.450
	(0.462)	(0.429)	(0.496)	(0.459)
Secondary#Post	0.00859	0.00946	-0.0102**	-0.00873*
	(0.00713)	(0.00696)	(0.00509)	(0.00519)
Tertiary#Post	0.00171	0.00211	0.000846	0.00168
	(0.00620)	(0.00608)	(0.00280)	(0.00288)
Observations	365,050	362,172	365,050	362,172
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes
Firm and Workforce Characteristics	no	yes	no	yes
Second Stage: F-stat p value	0.00405	0.000807	0.0345	0.0179
First stage: KP F-stat	10.70	14.32	10.70	14.32
Mean Y	0.120	0.120	0.0800	0.0800

Notes: The dependent variable is a binary variable indicating whether the firm offshores to Non-EU/ EU. Robust standard errors clustered at 2-digit SBI industry code. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: IV Results: Immigration and the Intensive Margin of Offshoring

VARIABLES	(1) In: Non-EU	(2) In: Non-EU	(3) In: EU	(4) In: EU
Share of non-EU workers within firm	-10.41**	-9.177**	-4.157	-4.340
	(4.991)	(4.603)	(6.746)	(6.189)
Secondary#Post	0.0846	0.0921	-0.133**	-0.117*
	(0.0785)	(0.0756)	(0.0644)	(0.0662)
Tertiary#Post	-0.00168	0.00164	0.0101	0.0195
	(0.0647)	(0.0625)	(0.0357)	(0.0370)
Observations	365,050	362,172	365,050	362,172
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes
Firm and Workforce Characteristics	no	yes	no	yes
Second Stage: F-stat p value	0.00652	0.000158	0.0429	0.0127
First stage: KP F-stat	10.70	14.32	10.70	14.32
Mean Y	1.290	1.290	1.100	1.100

Notes: The dependent variable is 1 plus the natural log of firm-level offshoring values to non-EU/ EU. Robust standard errors clustered at 2-digit SBI industry code. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Changes in Non-EU Immigrant Hiring Post 2012

	Share of Non-EU Immigrant Workers			
VARIABLES	(1)	(2)	(3)	(4)
Post#HS Industry	0.00706**	0.00220*	0.00682**	0.00257**
	(0.00116)	(0.000625)	(0.000943)	(0.000449)
Firm Offshoring Status	Yes	No	Yes	No
Offshore Status Criterion	A	A	B	B
Observations	60,255	175,716	41,736	194,235
R-squared	0.944	0.940	0.946	0.940
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes
Firm and Workforce Characteristics	yes	yes	yes	yes

Notes: The dependent variable is the share of non-EU immigrant workers within firm. The sample is restricted to firms that always exist between 2009-2016. Criterion A is whether firms ever offshored between 2010 and 2016. Criterion B is whether firms offshored in 2010. Robust standard errors clustered at broad industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Effect of Non-EU Immigration on Wages

	Dep. Var. Log of Wage					
	A-Criterion: Whether firms ever offshored between 2010 and 2016					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Natives	Non-EU	EU	Natives	Non-EU	EU
Post#HS Industry	0.00387***	0.00651	0.0133**	-0.00207*	0.000916	0.00663*
	(0.000290)	(0.00551)	(0.00277)	(0.000550)	(0.000566)	(0.00167)
Firm Offshoring Status	Yes	Yes	Yes	No	No	No
Offshoring Status Criterion	A	A	A	A	A	A
Observations	60,255	46,062	38,748	175,716	98,507	72,286
R-squared	0.991	0.860	0.853	0.994	0.853	0.865
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes	yes	yes
Firm and Workforce Characteristics	yes	yes	yes	yes	yes	yes
	B-Criterion: Whether firms offshored in 2010					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Natives	Non-EU	EU	Natives	Non-EU	EU
Post#HS Industry	0.00454***	-0.00368	-0.00490	-0.00165*	0.00219	0.00946
	(0.000247)	(0.00549)	(0.00296)	(0.000474)	(0.00103)	(0.00447)
Firm Offshoring Status	Yes	Yes	Yes	No	No	No
Offshoring Status Criterion	B	B	B	B	B	B
Observations	41,736	32,927	28,133	194,235	111,642	82,901
R-squared	0.991	0.859	0.849	0.994	0.857	0.867
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes	yes	yes
Firm and Workforce Characteristics	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is the log of average wage for native, non-EU and EU workers respectively. The sample is restricted to firms that always exist between 2009-2016. Robust standard errors clustered at broad industry level. *** p<0.01, ** p<0.05, * p<0.1.

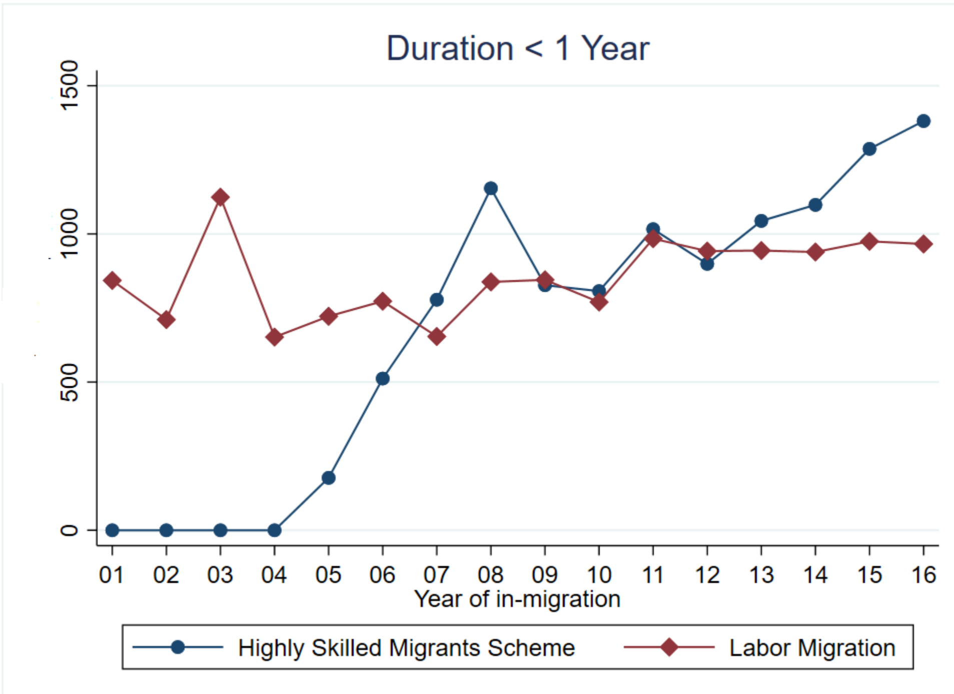
Table 10: Effect of Non-EU Immigration on Employment

	Dep. Var. Log of Employment							
	A-Criterion: Whether firms ever offshored between 2010 and 2016							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Natives	Non-EU	EU	Total	Natives	Non-EU	EU	Total
Post#HS Industry	0.0361*	0.108**	-0.0223	0.0405*	0.00285	0.00888	-0.0400**	0.00125
	(0.0110)	(0.0147)	(0.0152)	(0.0110)	(0.0162)	(0.00508)	(0.00814)	(0.0152)
Firm Offshoring Status	Yes	Yes	Yes	Yes	No	No	No	No
Offshoring Status Criterion	A	A	A	A	A	A	A	A
Observations	60,255	46,062	38,748	60,255	175,716	98,507	72,286	175,716
R-squared	0.976	0.958	0.935	0.977	0.967	0.939	0.911	0.968
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Firm and Workforce Characteristics	yes	yes	yes	yes	yes	yes	yes	yes
	B-Criterion: Whether firms offshored in 2010							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Natives	Non-EU	EU	Total	Natives	Non-EU	EU	Total
Post#HS Industry	0.0364*	0.0854**	-0.0244	0.0432*	0.00248	0.0205*	-0.0382*	0.00126
	(0.0122)	(0.0126)	(0.00995)	(0.0125)	(0.0142)	(0.00601)	(0.0107)	(0.0131)
Firm Offshoring Status	Yes	Yes	Yes	Yes	No	No	No	No
Offshoring Status Criterion	B	B	B	B	B	B	B	B
Observations	41,736	32,927	28,133	41,736	194,235	111,642	82,901	194,235
R-squared	0.976	0.958	0.935	0.977	0.968	0.941	0.915	0.969
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Firm and Workforce Characteristics	yes	yes	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is the log of firm-level employment size for native, non-EU and EU workers respectively. The sample is restricted to firms that always exist between 2009-2016. Robust standard errors clustered at broad industry level. *** p<0.01, ** p<0.05, * p<0.1.

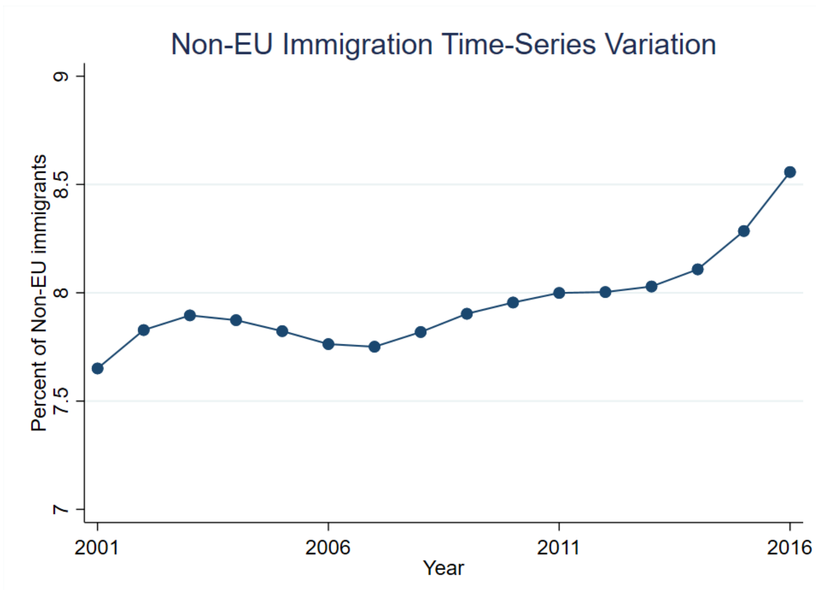
Figures

Figure 1: Short-Stay Non-EU Immigrants



Notes: The Y-axis shows the total number of registered out-migration for migrants who immigrated in the same year.

Figure 2: Percentage of Immigrants over Time



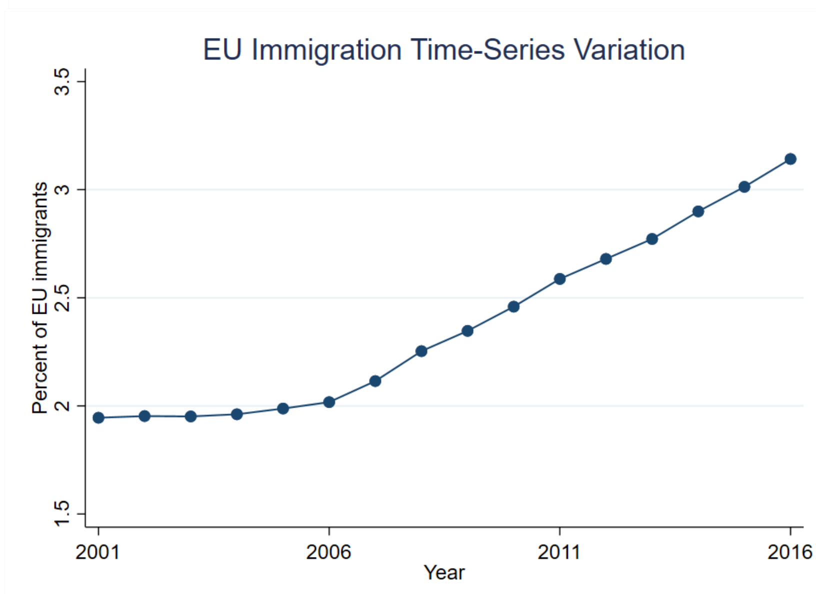


Figure 3: Fast-Growing Countries of Origin

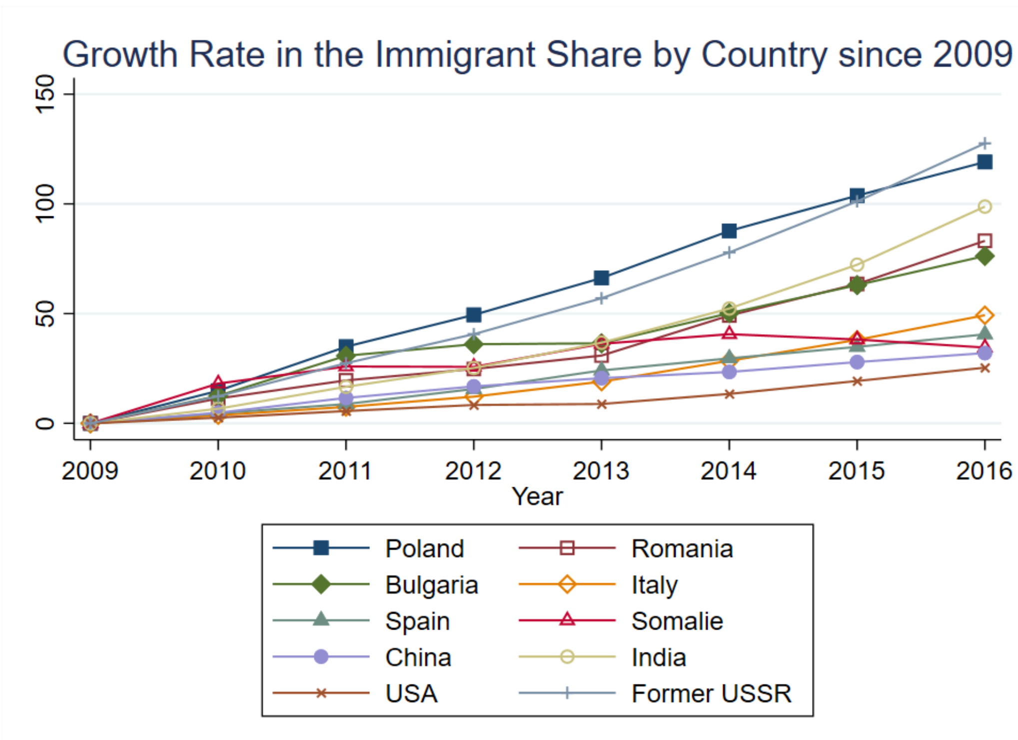


Figure 4: Offshoring by Industry

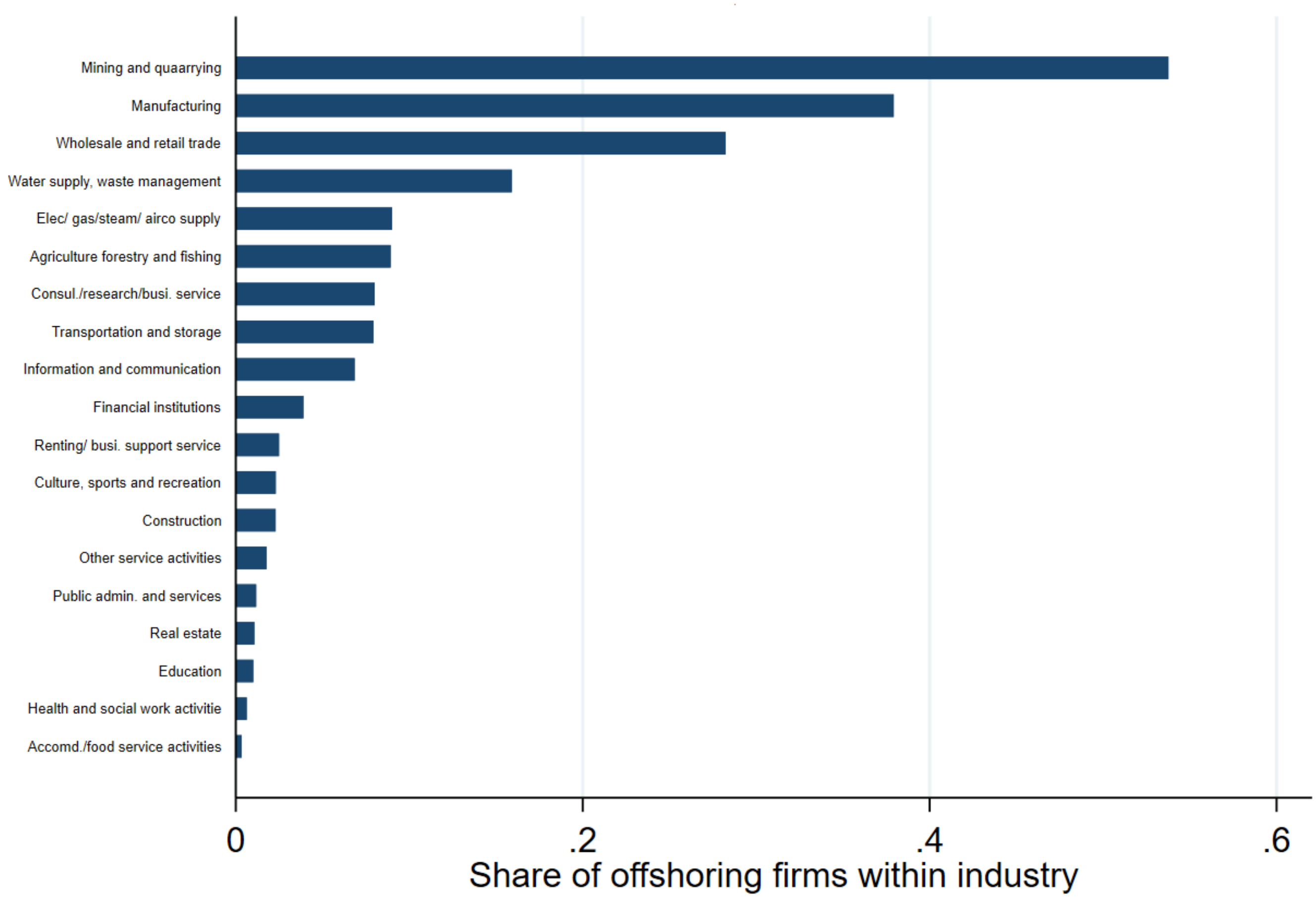


Figure 5: Offshoring Time-Series Variation

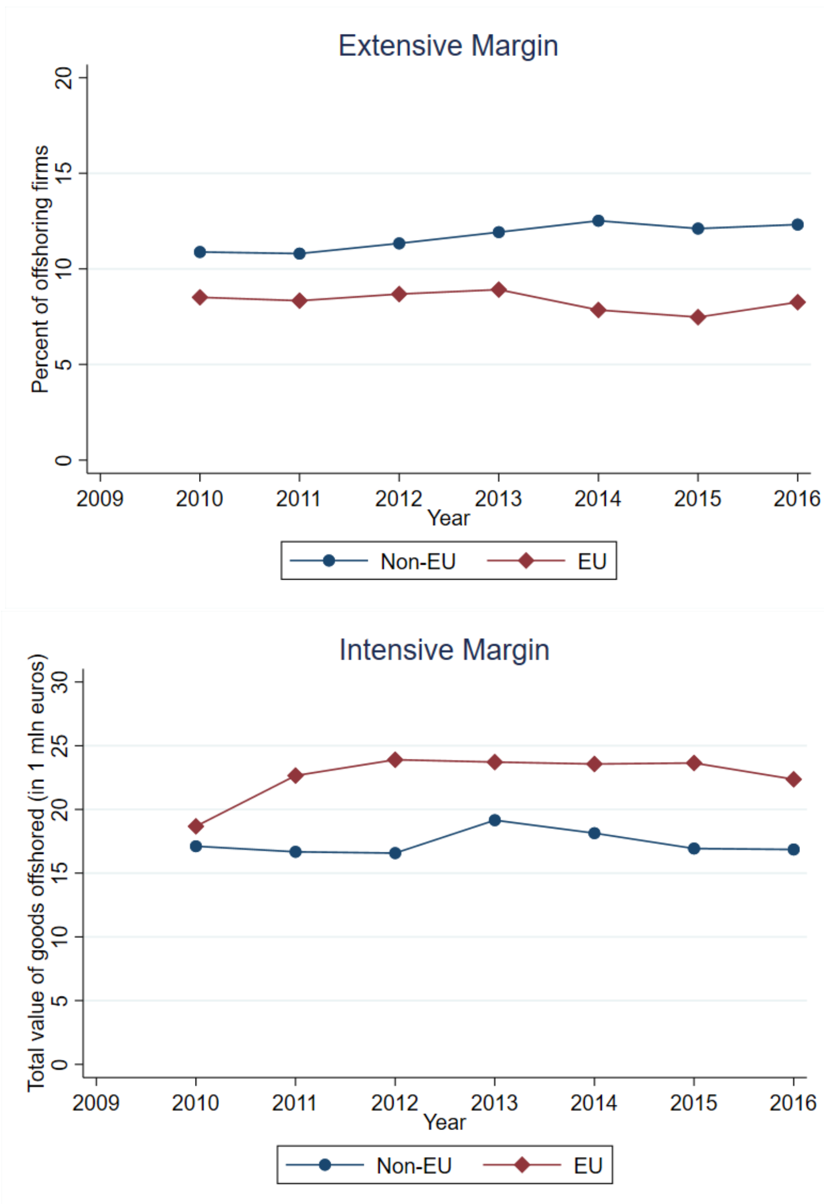


Figure 6: Skill by Industry

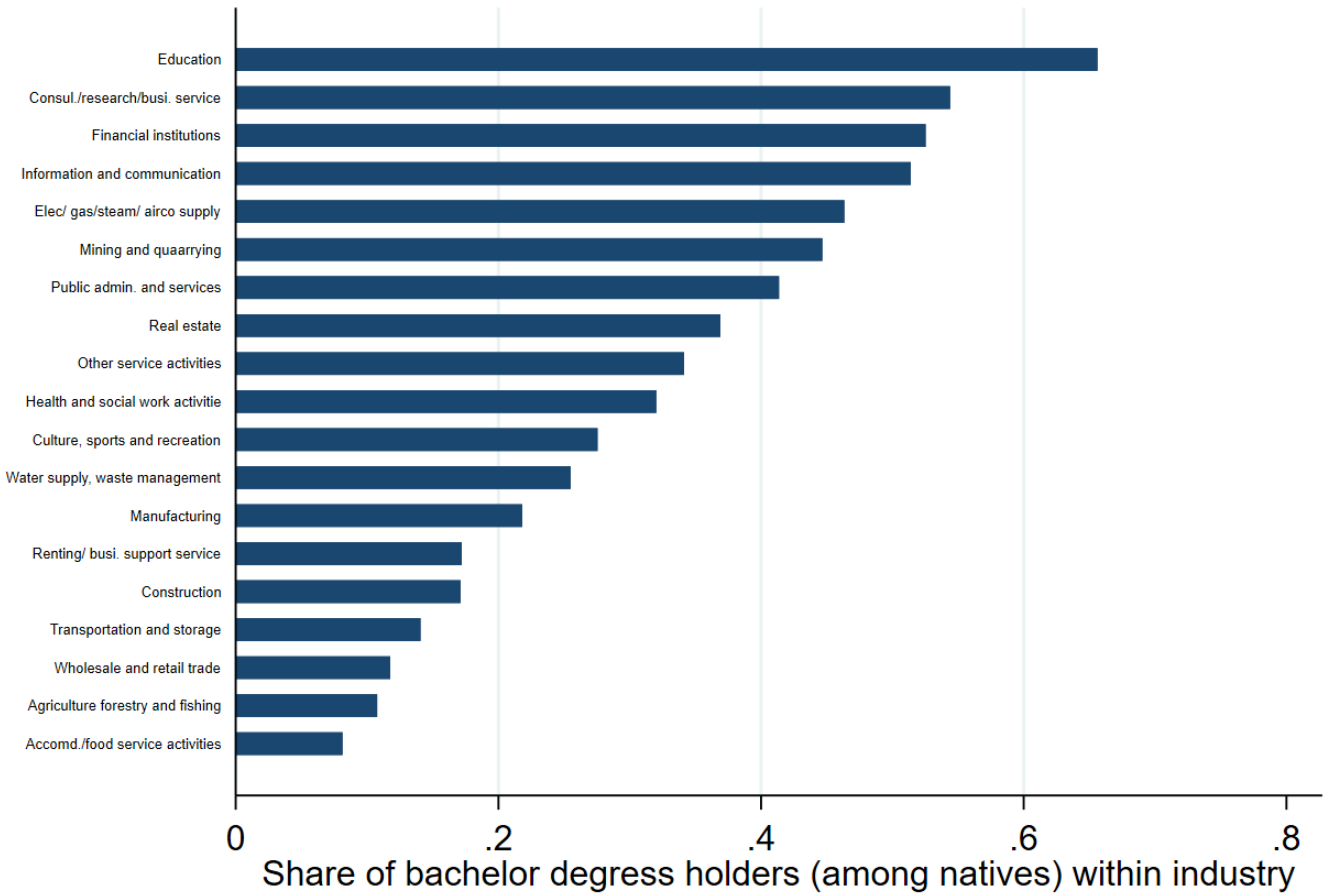


Figure 7: Event Study of Firm Share of Non-EU Employment

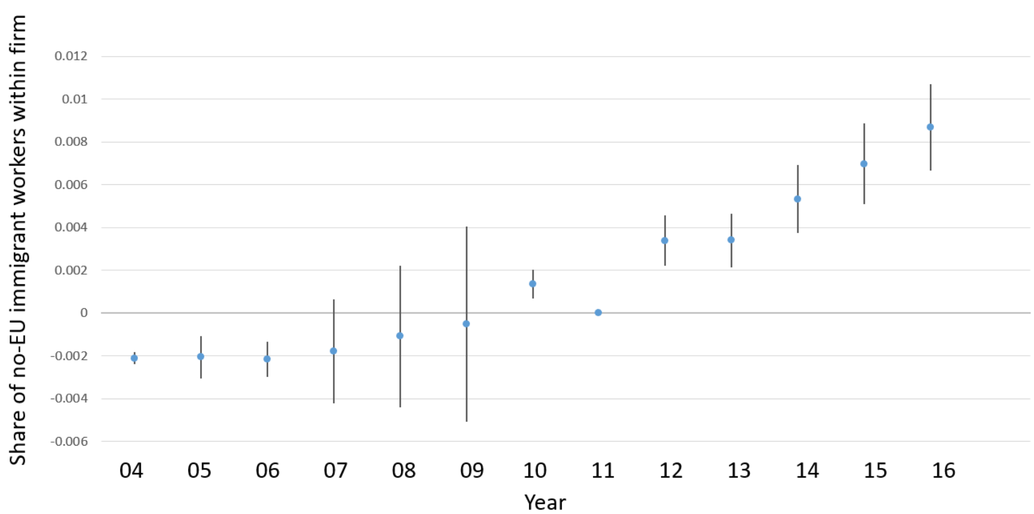


Figure 8: Event Study of Firm Share of EU Employment

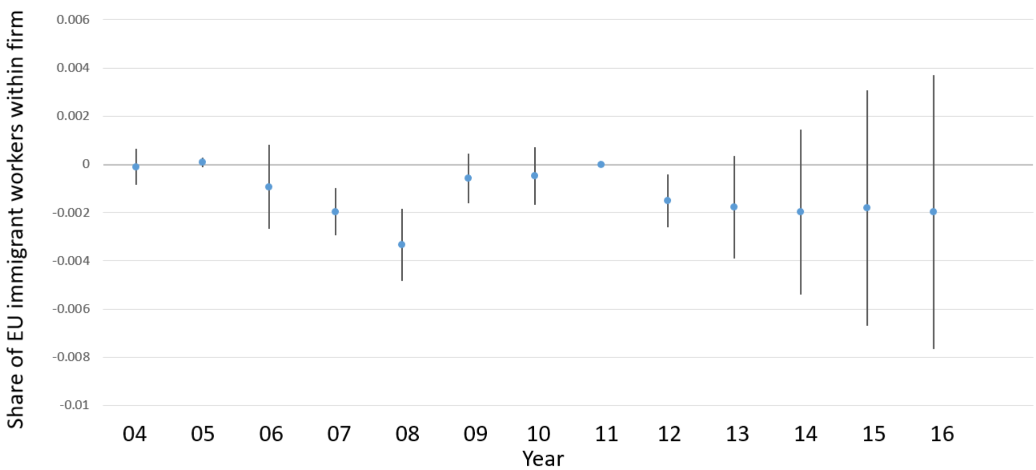
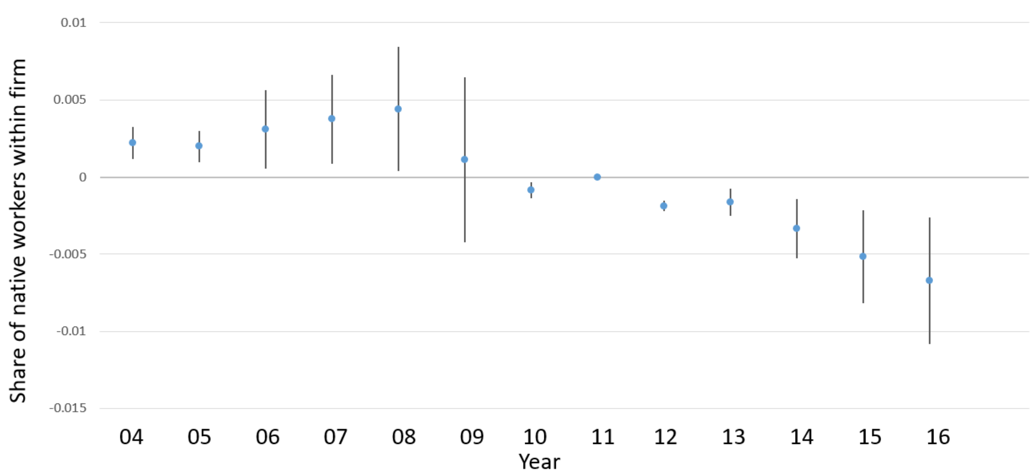


Figure 9: Event Study of Firm Share of Native Employment



A Online Appendix

A.1 Detailed Data Sources

Table 11: Full List of Data Sources in Statistics Netherlands

Main data	Dutch names	English translation
Firm	ABR	General business register
	BAANPRSJAARBEDRAGTAB	Annual wages of employees
	INVESTERINGEN	Total investments in tangible and intangible fixed assets
Employee	BAANKENMERKENBUS	Characteristics of employees' jobs
	GBAPERSOONTAB	Individual characteristics of all persons registered in the municipal records
	HOOGSTEOPLTAB	Highest attained and highest followed educational level in the Netherlands
	GBAADRESOBJECTBUS	Address characteristics of persons ever registered in the municipal records
	VSLGWBTAB	Municipal, district and neighborhood codes of a residential object
	GBAMIGRATIEGEBEURTENISBUS	Migration characteristics of persons ever registered in the municipal records
	VRLMIGMOTBUS	Migration motives of immigrants with a foreign nationality
Trade	IHG	International trade in goods
	PRODCOM	Industrial products by product group

A.2 Supplementary Tables

Table 12: Trends in Immigration and the 2012 Policy Change

	(1)	(2)	(3)	**Pairwise t-tests of coefficients in column 1**	
VARIABLES	Share: Non-EU	Share: EU	Share: Native	F statistics	p-value
2004#HS Industry	-0.00211***	-0.000105	0.00222**	N/A	N/A
	(6.47e-05)	(0.000176)	(0.000241)		
2005#HS Industry	-0.00206**	7.69e-05	0.00199**	0.08	0.8023
	(0.000228)	(4.47e-05)	(0.000235)		
2006#HS Industry	-0.00216***	-0.000939	0.00310**	0.28	0.6492
	(0.000190)	(0.000404)	(0.000593)		
2007#HS Industry	-0.00179*	-0.00196**	0.00375**	0.9	0.442
	(0.000565)	(0.000230)	(0.000671)		
2008#HS Industry	-0.00108	-0.00332**	0.00440**	10.92	0.0807
	(0.000768)	(0.000348)	(0.000935)		
2009#HS Industry	-0.000525	-0.000582	0.00111	1.61	0.3318
	(0.00106)	(0.000236)	(0.00125)		
2010#HS Industry	0.00135**	-0.000492	-0.000860**	3.6	0.1975
	(0.000160)	(0.000278)	(0.000123)		
2012#HS Industry	0.00338***	-0.00151**	-0.00187***	151.84	0.0065
	(0.000274)	(0.000257)	(7.89e-05)		
2013#HS Industry	0.00340***	-0.00178*	-0.00162**	0.68	0.4965
	(0.000293)	(0.000497)	(0.000206)		
2014#HS Industry	0.00533***	-0.00197	-0.00337**	722.38	0.0014
	(0.000365)	(0.000797)	(0.000448)		
2015#HS Industry	0.00697***	-0.00182	-0.00515**	356.94	0.0028
	(0.000439)	(0.00114)	(0.000701)		
2016#HS Industry	0.00870***	-0.00197	-0.00674**	1916.45	0.0005
	(0.000475)	(0.00132)	(0.000952)		
Observations	1,036,799	1,036,799	1,036,799		
R-squared	0.626	0.576	0.640		
Industry/ Region/ Year Fixed Effects	yes	yes	yes		
Firm Fixed Effects	yes	yes	yes		
Firm and Workforce Characteristics	yes	yes	yes		
Mean Y	0.0600	0.0300	0.910		

Notes: The dependent variable is the share of non-EU, EU, and native workers within firm respectively. Robust standard errors clustered at broad industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 13: Robustness Check: Alternative Measure of Offshoring

	Measures constructed by HS 6-digit goods				Share of produced-goods import over total import	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Ex: Non-EU	Ex: EU	In: Non-EU	In: EU	neu	eu
Share of non-EU workers within firm	-0.650	-0.459	-7.287*	-4.382	-0.691*	0.0572
	(0.442)	(0.491)	(4.126)	(6.748)	(0.387)	(0.180)
Secondary#Post	0.00946*	-0.00787	0.103	-0.0990	0.00712	-0.00269
	(0.00553)	(0.00473)	(0.0625)	(0.0610)	(0.00497)	(0.00274)
Tertiary#Post	0.00206	0.00218	0.0115	0.0185	-0.000310	-0.000739
	(0.00403)	(0.00213)	(0.0441)	(0.0338)	(0.00367)	(0.00226)
Observations	362,172	362,172	362,172	362,172	351,109	351,109
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes	yes	yes
Firm and Workforce Characteristics	yes	yes	yes	yes	yes	yes
Second Stage: F-stat p value	0.000105	0.00345	8.99e-05	0.00356	0.0466	0.135
First stage: KP F-stat	14.32	14.32	14.32	14.32	11.92	11.92
Mean Y	0.110	0.0800	1.150	1.020	0.0400	0.0500

Notes: In columns 1 to 4, the dependent variable is a binary variable indicating whether the firm offshores to Non-EU/ EU, which is constructed by HS 6-digit goods. In columns 5 and 6, the dependent variable is a ratio of imports of the same HS6 goods as firm production by the total value of the firm's total imports for non-EU and EU countries respectively. Robust standard errors clustered at 2-digit SBI industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 14: Robustness Check: Sub-sample Analysis I

	A-Firms that always exist between 2010-2016			
	(1)	(2)	(3)	(4)
VARIABLES	Ex: Non-EU	Ex: EU	In: Non-EU	In: EU
Share of non-EU workers within firm	-1.070**	-0.458	-9.124*	-3.395
	(0.460)	(0.473)	(5.459)	(6.368)
Secondary#Post	0.0103	-0.00789	0.100	-0.0989
	(0.00843)	(0.00510)	(0.0946)	(0.0642)
Tertiary#Post	0.00137	0.00267	-0.00953	0.0320
	(0.00738)	(0.00292)	(0.0797)	(0.0381)
Observations	240,212	240,212	240,212	240,212
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes
Firm and Workforce Characteristics	yes	yes	yes	yes
Second Stage: F-stat p value	0.00495	0.0161	0.000198	0.00338
First stage: KP F-stat	10.35	10.35	10.35	10.35
	B-Exlude "Big 4" cities in the Netherlands			
	(1)	(2)	(3)	(4)
	Ex: Non-EU	Ex: EU	In: Non-EU	In: EU
Share of non-EU workers within firm	-1.589**	-0.218	-14.93**	-0.859
	(0.763)	(0.507)	(7.316)	(7.354)
Secondary#Post	0.0121**	-0.00842*	0.125*	-0.107*
	(0.00607)	(0.00455)	(0.0668)	(0.0603)
Tertiary#Post	0.00545	0.00134	0.0390	0.0182
	(0.00447)	(0.00312)	(0.0446)	(0.0402)
Observations	310,339	310,339	310,339	310,339
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes
Firm and Workforce Characteristics	yes	yes	yes	yes
Second Stage: F-stat p value	0.00412	0.00408	0.000142	0.00364
First stage: KP F-stat	25.43	25.43	25.43	25.43
	C-Exclude wholesales and retail			
	(1)	(2)	(3)	(4)
	Ex: Non-EU	Ex: EU	In: Non-EU	In: EU
Share of non-EU workers within firm	-0.968**	-0.128	-7.813*	0.401
	(0.456)	(0.293)	(4.473)	(3.622)
Secondary#Post	0.00934	-0.0103**	0.0894	-0.139**
	(0.00690)	(0.00500)	(0.0747)	(0.0624)
Tertiary#Post	0.00118	0.00194	-0.0120	0.0137
	(0.00609)	(0.00257)	(0.0612)	(0.0320)
Observations	279,437	279,437	279,437	279,437
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes
Firm and Workforce Characteristics	yes	yes	yes	yes
Second Stage: F-stat p value	0.0136	0.100	0.0130	0.0699
First stage: KP F-stat	13.27	13.27	13.27	13.27

Notes: In columns 1 and 2, the dependent variable is a binary variable indicating whether the firm offshores to Non-EU/ EU. In columns 3 and 4, the dependent variable is the natural log of 1 plus firm-level offshoring values to Non-EU/ EU. Robust standard errors clustered at 2-digit SBI industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 15: Robustness Check: Sub-sample Analysis II

	A-Remove India as an offshoring destination			
	(1)	(2)	(3)	(4)
VARIABLES	Ex: Non-EU	Ex: EU	In: Non-EU	In: EU
Share of non-EU workers (excl. India) within firm	-1.034**	-0.433	-9.049**	-4.248
	(0.416)	(0.444)	(4.492)	(5.976)
Secondary#Post	0.00934	-0.00879*	0.0914	-0.117*
	(0.00687)	(0.00515)	(0.0750)	(0.0657)
Tertiary#Post	0.00197	0.00162	0.000647	0.0189
	(0.00595)	(0.00286)	(0.0615)	(0.0369)
Observations	362,172	362,172	362,172	362,172
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes
Firm and Workforce Characteristics	yes	yes	yes	yes
Second Stage: F-stat p value	0.000734	0.0184	0.000145	0.0131
First stage: KP F-stat	13.87	13.87	13.87	13.87
Mean Y	0.120	0.0800	1.290	1.100
	B-Remove China as an offshoring destination			
	(1)	(2)	(3)	(4)
VARIABLES	Ex: Non-EU	Ex: EU	In: Non-EU	In: EU
Share of non-EU workers (excl. China) within firm	-1.063**	-0.446	-9.133*	-4.245
	(0.429)	(0.462)	(4.622)	(6.218)
Secondary#Post	0.00928	-0.00882*	0.0905	-0.118*
	(0.00693)	(0.00517)	(0.0754)	(0.0659)
Tertiary#Post	0.00210	0.00167	0.00152	0.0193
	(0.00603)	(0.00286)	(0.0621)	(0.0369)
Observations	362,172	362,172	362,172	362,172
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes
Firm and Workforce Characteristics	yes	yes	yes	yes
Second Stage: F-stat p value	0.000895	0.0167	0.000183	0.0119
First stage: KP F-stat	14.89	14.89	14.89	14.89
Mean Y	0.120	0.0800	1.290	1.100
	C -Remove USA as an offshoring destination			
	(1)	(2)	(3)	(4)
VARIABLES	Ex: Non-EU	Ex: EU	In: Non-EU	In: EU
Share of non-EU workers (excl. USA) within firm	-1.101**	-0.457	-9.367*	-4.296
	(0.458)	(0.480)	(4.849)	(6.464)
Secondary#Post	0.00931	-0.00881*	0.0906	-0.118*
	(0.00697)	(0.00519)	(0.0756)	(0.0660)
Tertiary#Post	0.00207	0.00165	0.00111	0.0190
	(0.00611)	(0.00289)	(0.0626)	(0.0371)
Observations	362,172	362,172	362,172	362,172
Industry/ Region/ Year Fixed Effects	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes
Firm and Workforce Characteristics	yes	yes	yes	yes
Second Stage: F-stat p value	0.000618	0.0164	0.000106	0.0120
First stage: KP F-stat	13.30	13.30	13.30	13.30
Mean Y	0.120	0.0800	1.290	1.100

Notes: In columns 1 and 2, the dependent variable is a binary variable indicating whether the firm offshores to Non-EU/ EU, with the alternative set excluding India in Panel A, China in Panel B and USA in Panel C. In columns 3 and 4, the dependent variable is the natural log of 1 plus firm-level offshoring values to Non-EU/ EU, with the alternative set excluding India in Panel A, China in Panel B and USA in Panel C. Robust standard errors clustered at 2-digit SBI industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table 16: Robustness Check: Concurrent Policies

VARIABLES	(1) Workers from Belgium, Germany and Luxembourg	(2) Workers from Romania and Bulgaria	(3) Non-EU workers with migration motivation being ”other”
2010#HS industry	0.000133**	0.000102	-0.000230
	(2.35e-05)	(4.48e-05)	(0.000384)
2011#HS industry	-7.85e-05	0.000187	-0.000340
	(8.52e-05)	(7.60e-05)	(0.000686)
2012#HS industry	0.000144	0.000191	-0.000669
	(0.000123)	(8.73e-05)	(0.000363)
2013#HS industry	0.000179	0.000254	-0.000627
	(0.000139)	(0.000109)	(0.000483)
2014#HS industry	0.000176	-2.79e-05	-0.000697
	(0.000177)	(7.98e-05)	(0.000799)
2015#HS industry	0.000366	-0.000164	-0.000755
	(0.000146)	(0.000171)	(0.000539)
2016#HS industry	0.000364	-0.000424	-0.000228
	(0.000143)	(0.000233)	(0.000645)
Observations	474,586	474,586	260,033
R-squared	0.791	0.689	0.710
Industry/ Region/ Year Fixed Effects	yes	yes	yes
Firm Fixed Effects	yes	yes	yes
Firm and Workforce Characteristics	yes	yes	yes
Mean Y	0.00610	0.00160	0.0130

Notes: The dependent variable is the share of a certain type of workers within firm. Robust standard errors clustered at broad industry level. *** p<0.01, ** p<0.05, * p<0.1.

A.3 Theoretical Framework

We start with the observation that since at-least some Dutch firms offshore, there are five types of workers available in the economy depending on their region of origin: Native workers, immigrant non-EU workers, non-EU workers abroad (corresponding to firms offshoring to non-EU countries), immigrant EU workers, and EU workers abroad (corresponding to firms offshoring to EU countries).

There are two types of firms in the economy: Offshoring and non-offshoring firms. Each of these firms can exist in the high- or low-skill sector of the economy. For simplicity, we assume that only high-skilled workers (college educated) work in the high-skill sector and only low-skilled workers (no college education) work in the low-skill sector.[18]

Consider an aggregate Cobb Douglas production function:

$$Y = AL^{\alpha}K^{1-\alpha} \tag{6}$$

Y is aggregate output, A is exogenous total factor productivity, K is physical capital, L is a CES aggregate of different types of labor, $\alpha \in (0, 1)$ is the income share of labor. We borrow the CES nested structure from Ottaviano and Peri (2012). Suppose there are $N + 1$ characteristics numbered n=0,...N. Characteristic 0 is common to all workers. Workers are first partitioned into groups $i_1 = 1, ...M_1$ that differ according to characteristic 1. Then each of these groups is itself partitioned into groups $i_2 = 1,,,, M_2$ that differ according to characteristic 2 and so on up-to characteristic N. The index $n = 0...N$ identifies the characteristic used to partition workers into the corresponding groups. $i(n)$ is a group/ type of workers defined by common characteristics up to n, and define $L_{i(n)}$ as the corresponding labor supply. The CES aggregator at the generic level n is then defined as:

[18] In the data, 58% of all native workers in high-skill industries have a college, while the corresponding number is 22% in the low-skill sector. This assumption is no way central to generate the key findings from the model. All we need is that the share of high-skill workers in high-skill industries is significantly higher than the corresponding share in low-skill industries.

$$L_{i(n)} = \left[\sum_{i(n+1) \in i(n)} \theta_{i(n+1)} (L_{i(n+1)})^{\frac{\sigma_{\sigma_{n+1}-1}}{\sigma_{n+1}}} \right]^{\frac{\sigma_{n+1}}{\sigma_{n+1}-1}} \tag{7}$$

$n = 0....N$

The relative productivity level of type $i(n)$ is standardized so that $\sum_{i(n) \in i(n-1) \theta_{i(n)} = 1}$. The fact that sequential partitioning of workers lead to fewer and fewer heterogeneous groups $i(n)$ as n increases is captured by assuming that $\sigma_{n+1} > \sigma_n$.

For this model, we assume that for non-offshoring firms the first level of characteristic (characteristic 1) that defines worker differences is expertise: High and low expertise workers. High expertise workers are those who have worked for more than 8 years and low experience workers are those who have worked for less than 8 years. Non-offshoring firms do not have access to workers abroad. However, offshoring firms, in addition, use another type of expertise, called foreign expertise, and only immigrant workers or workers abroad have that skill. To fix ideas, let $i_1 = L, H$ such that there are low, and high experience workers. Offshoring firms in addition use foreign expertise, denoted by $i_1 = EU$, $i_1 = non - EU$.

Each of these high and low experienced workers are further defined by their level of education. Following Ottaviano and Peri (2012) we assume that low-skilled workers can be divided into workers with no degree and high school degree. High-skilled (college educated) workers can be divided into workers with some college degree (including diplomas) and completed college degrees.

Following Ottaviano and Peri (2012) we define the lowest level of characteristic (characteristic N) as the origin of the worker: native, EU immigrants, non-EU immigrants when $i_1 = L, H$. If $i_1 = EU/Non - EU$, the workers can be divided into EU/ Non-EU immigrant workers and EU/Non-EU workers abroad (offshoring). Recall that only offshoring firms can access the EU/Non-EU workers abroad but both types of firms can access immigrant workers. This is the new dimension we introduce in the Ottaviano and Peri (2012) model. For simplicity, these are the only characteristics we define. However, one can include any numbers of characteristics in the model and our central results will not change so long as the n=1 and n=N characteristics are unchanged.

Using the general structure and notation, we can calculate the profit-maximizing wage of worker of type $i(N)$ as the value of the worker's marginal productivity for $N > 2$:

$$ln(w_{i(N)}) = ln(\alpha A k^{1-\alpha}) + \frac{1}{\sigma} ln(L) + \sum_{n=1}^{N} ln(\theta_{i(n)}) - \sum_{n=1}^{N-1} \Big(\frac{1}{\sigma_n} - \frac{1}{\sigma_{n+1}}\Big) ln(L_{i(n)}) - \frac{1}{\sigma_N} ln(L_{i(N)}) \quad (8)$$

The percentage impact of a change in labor supplied by workers of type $i(N)$ on the wage of a worker of type $j(N)$ with the same characteristics upto m is given by:

$$\frac{\Delta w^m_{j(N)/w^m_{j(N)}}}{\Delta L_{i(N)/L_{i(N)}}} = \frac{s^m_{i(N)}}{\sigma_1} > 0, m = 0 \quad (9)$$

$$\frac{\Delta w^m_{j(N)/w^m_{j(N)}}}{\Delta L_{i(N)/L_{i(N)}}} = \frac{s^0_{i(N)} - s^1_{i(N)}}{\sigma_1} > 0, m = 1 \quad (10)$$

$$\frac{\Delta w^m_{j(N)/w^m_{j(N)}}}{\Delta L_{i(N)/L_{i(N)}}} = -\sum_{n=0}^{m-1} \frac{s^{n+1}_{i(N)} - s^n_{i(N)}}{\sigma_{n+1}} < 0, m = 2...N \quad (11)$$

Note that since labor cannot move between offshoring and non-offshoring firms, these equations hold separately for offshoring and non-offshoring firms and the percentage wage changes depend on the shares of type $i(N)$ workers in offshoring and non-offshoring firms separately.

An increase in the labor supply of a certain type $i(N)$ causes an increase in the wage of another type $j(N)$ only if the two types differ in terms of characteristic 1, ie, expertise. If the two types share at-least characteristic 1, then a rise in the labor supply of $i(N)$ always depresses the wage of $j(N)$.

Since foreign expertise is characteristic 1, that is, no native workers have foreign expertise, by equation (10) an increase in immigrant workers with foreign expertise increases wages of all native workers in offshoring firms in the high-skill industry relative to firms in the low-skill industry. This additional positive effect on native wages does not exist in non-offshoring firms. For further details on derivations, see appendix A of Ottaviano and Peri (2012).