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Migrants and Imports: Evidence from Dutch Firms^{*}

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Abstract

This paper examines the effect of hiring migrants on firms' imports using a rich employeremployee dataset from the Netherlands for 2010-2017. We use an instrumental variables strategy, and find that firms that employ migrants from a high-income country are more likely to import from that country. Our benchmark specification indicates that a one standard deviation increase in the share of migrant workers from a certain country raises their employer's probability of importing from those workers' origin country by 6.6 percentage points, explaining about a fifth of the standard deviation of importing from a given country. This result is robust to a battery of sensitivity checks, but does not hold for middle- and low-income countries. Digging deeper, we find that the effects are largely driven by migrants working in trade intermediaries that import final goods and inputs. Our results suggest that migrants help erode informational barriers and enable their employers to source goods from abroad.

JEL codes: F14, F16, F22 *Keywords:* migration, imports, market knowledge, employer-employee

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1 Introduction

The relationship between migrant workers and trade has been an important area of research for almost three decades. Papers have generally assumed that the direction of influence is from immigrants to trade, and empirical research showed evidence that hiring migrants can be beneficial in numerous ways, from cost advantages to market knowledge that enable firms to export to a specific country. On the other hand, there are only a few studies (Egger et al., 2019; Ariu, 2020) that examine the effect of migrant-specific market knowledge on firms' importing behavior, which is critical to understand in a world with burgeoning cross-border supply chains.

In this paper, we examine the relationship between hiring migrants and firms' imports using a rich employer-employee dataset from the Netherlands for 2010-2017. The Netherlands provides a suitable setting to conduct our analysis. Despite being a relatively small country, the Dutch economy has been an integral part of international trade and global value chains over the last three decades, increasing its imports by 22% in our sample period. The country has liberal economic policies providing a favorable commercial environment for all traders. Equally important for our study, the country has a large and wide mix of foreign nationalities with more than two million first- and second-generation immigrants, accounting for about a quarter of the total workforce in 2017.

Our hypothesis is that workers bring market knowledge to their employers to help find suppliers in their origin countries. This idea is grounded on earlier studies such as the one by Hiller (2013), who investigates whether firms benefit from hiring immigrants to increase their exports or whether immigrants in the firm's locality affect trade. Her results provide little evidence for the local presence of immigrants to enlarge boost sales, but they show large effects for firm-level hiring of migrants that help firms access personal and business networks.

To test our hypothesis, we follow the existing literature (Mitaritonna et al., 2017) Egger et al., 2019) and instrument the share of firms' workers that originate from a specific country by the exogenously arriving migrants from that country to the firm's municipality in the Netherlands. This instrumental variables strategy is supplemented by including a high-dimensional set of fixed effects, resulting in a conservatively restrictive specification. We include country-sector-year fixed effects that absorb all supply and demand shocks, municipality-country fixed effects that capture local characteristics, and firm-year fixed effects to close down time-varying firm channels such as productivity shocks.

We find that firms that employ first-generation migrants from a high-income country are more likely to import from that country. Our benchmark specification indicates that a one standard deviation increase in the share of migrant workers from a certain country raises their employers' probability of sourcing goods from their origin country by 6.6 percentage points, explaining about a fifth of the standard deviation of importing from a given country. We find that this effect is robust to a battery of sensitivity checks, including alternative clustering strategies, excluding outliers, and recentering our estimates by controlling for the simulated instrument (Borusyak and Hull, 2021). Interestingly, this result is not as strong for the intensive margin, and does not hold for middle- and low-income countries, with the caveat that our instrument is not sufficiently strong for these samples. When we relax our specification and drop municipality-country fixed effects, our instrument becomes stronger, and we find some evidence also for the intensive margin for high-income countries, and for the extensive margin for other countries.

Digging deeper, we find that the effect is largely driven by wholesalers and retailers that hire migrants from high-income countries. In terms of product groups, we find that the effects are particularly strong for these intermediaries' imports of final goods and inputs. These results are intuitive as migrant workers are especially likely to be useful for firms whose task is to match buyers and sellers in different countries. In the last part of the paper, for the first time in the literature, we take into account the share of second-generation immigrants employed by firms by instrumenting it with municipality-country birth rates 20-25 years ago. We find a positive but marginally insignificant coefficient for the share of second-generation migrants, while the share of first-generation migrants retains its positive and significant effect. Finally, we look at age groups of the first-generation, and find that the ones that arrived in the Netherlands at ages 35-50 were the most influential in helping their employers import from their respective origin countries.

This paper is mainly related to the empirical literature that examines the effect of migration on trade. This relationship is explained largely by firm-level productivity and cost advantages as a result of hiring immigrants (Hunt and Gauthier-Loiselle, 2010; Ottaviano and Peri, 2012; Peri, 2012; Mitaritonna et al., 2017) or facilitating trade through the superior market knowledge that the migrant workers have about their countries of origin (Gould, 1994; Head and Ries, 1998; Girma and Yu, 2002; Rauch and Trindade, 2002; Wagner et al., 2002; Andrews et al., 2017; Steingress, 2018) or a combination of both (Orefice et al., 2021). Similarly, it is also possible for immigrants to generate additional demand for the importation of ethnic products from their countries of origin, depending on their preferences (Gould, 1994; Head and Ries, 1998; Dunlevy and Hutchinson, 1999). Importantly, the significant part of these studies has been devoted to exports (Peri and Requena-Silvente, 2010; Hiller, 2013; Hatzigeorgiou and Lodefalk, 2016; Parrotta et al., 2016; Andrews et al., 2017; Mitaritonna et al., 2017; Marchal and Nedoncelle, 2019). The few studies that also take into account imports mostly attempt to compare the effectiveness of knowledge and preference channels by contrasting the effect on exports and imports (Gould, 1994; Head and Ries, 1998; Girma and Yu, 2002; Rauch and Trindade, 2002; Wagner et al., 2002; Aleksynska and Peri, 2014; Steingress, 2018).

The paper closest to ours in terms of its research question and identification strategy is by Egger et al. (2019). They investigate the link between migrants and supply chains by combining firmlevel import data with municipality-level migration data from Switzerland. Using an instrumental variables approach, they find that firms that are located in municipalities with migrant networks have more stable supply-chain relationships with origin countries of those migrants. They rationalize their finding by building a model where the knowledge emanating from the migrants removes the informational barriers to trade and thereby allows local firms to establish global value chain linkages. The work of Ariu (2020) is also similar to our paper in terms of its research question, although differs in methodology. He uses a difference-in-differences strategy and finds that firms in Swiss cantons that experienced an influx of migrants began importing higher-quality inputs from the origin countries of those migrants.

Despite having a similar inspiration, our paper has several key differences from the aforementioned studies. First, we use an employer-employee linked dataset that allows us to observe workers with different backgrounds employed by a firm and thus measure their effect directly, instead of relying on indirect linkages. Second, instead of focusing on manufacturers, we include firms from all sectors and that enables us to examine manufacturers and intermediaries separately. Third, we are able to incorporate and instrument for second-generation migrants, and examine age-specific heterogeneities thanks to the richness of our dataset.

Having these distinct features, this paper makes three contributions to the literature. First, we find that migrants from high-income countries increase the probability of their employers to import from their origin countries. To the best of our knowledge, this is the first causal evidence in the literature that shows the positive effects of hiring migrants on imports using firm-level employment and trade data. Second, we find that this effect is largely driven by intermediaries that import final goods and inputs. Third, our results indicate that the migrants who arrived in the host country during their "experienced" working age (35-50) are the most influential on their employers' sourcing decisions. Taken together, these results reveal that migrants, especially experienced first-generation migrants, help erode informational barriers for their employers, particularly ones that engage in trade intermediation, to source goods from high-income countries. This is a novel result that reveals the importance of employee-specific market knowledge in matching buyers and sellers.

Our results are comparable with the conclusions of Egger et al. (2019) and Ariu (2020). Egger et al. (2019) suggest that firms engage in more stable sourcing relationships by reducing the total number of suppliers as a result of rising migration from their respective origin countries. In other words, immigrants help remove informational barriers to trade, and hence firms deal with a smaller number of suppliers while trading more with each of them. Whereas Egger et al. (2019) focus on the effect of migrants on reducing the number of suppliers, we show that migrants help their firms establish buyer-seller linkages with their origin countries. Our results on the differential effects of high-income country migrants also echoes the findings of Ariu (2020) who find that firms in Swiss cantons that received high-skilled migrants were more likely to import high-quality inputs.

This paper is organized as follows. In Section 2, we describe our instrumental variables strategy. Section 3 describes the data and presents summary statistics. Section 4 presents the results. Finally, Section 5 concludes and discusses further research.

2 Methodology

In order to examine the effect of migrant workers on firms' country-level imports, we estimate the following specification:

$$imp_{ijt}^{hs} = \beta_0 + \beta_1 \text{share of migrants}_{ijt-1} + \Theta_{jst} + \alpha_{hj} + \delta_{it} + \epsilon_{ijt}$$
 (1)

where imp_{ijt}^{hs} is the imports in Euros of firm *i* from country *j* in year *t*, and all firms have a municipality h and sector *s* dimension [] Depending on the specification, imp_{ijt}^{hs} is in logs, values, transformed via inverse hyperbolic sine (IHS) [] or is a dummy that indicates the presence of imports. Our main independent variable, share of migrants_{ijt-1}, is the share of total workers in firm *i* that are first-generation migrants from country *j* in year t - 1. We use a lagged independent variable since we expect the importing decision to follow the hiring decision with a lag. We include country-sector-year fixed effects (Θ_{jst}) that absorb all supply and demand shocks that are not firm-specific (including the "shift" in our shift-share instrument as explained below). We include municipality-country fixed effects (α_{hj}) that capture local characteristics of municipalities (including the "share" in our shift-share instrument as explained below). We also include firm-year fixed effects (δ_{it}) to control for factors such as productivity shocks that can influence both employment and imports. These fixed effects make sure that we are not capturing the effect that firms with more foreign workers might be importing more in general. Moreover, they control for all time-varying municipality shocks that might be influencing firms' imports and hiring decisions [3] Finally, ϵ_{ijt} is the error term, and we cluster standard errors at the municipality-country level, which is the level of the "shares" in our shift-share instrument.

Estimating equation (1) with OLS poses two types of endogeneity issues. First is the omission of certain firm-country-year variables (e.g. foreign ownership) that might be influencing imports and hiring decisions simultaneously.⁴ Second is the issue of reverse causality where the level of a firm's imports from a country might be influencing its decision to hire workers from that country. Using lags partially addresses this issue, but importing, especially its extensive margin, can be highly persistent over time. To tackle these concerns, we use an instrumental variables strategy akin to the one used by Egger et al. (2019).

We instrument share of migrants_{*ijt*} by a shift-share instrumental variable that is constructed in two steps. First, we define \widehat{M}_{hjt} :

$$\widehat{M}_{hjt} = \frac{M_{hj,2010}}{\sum_{h} M_{hj,2010}} M_{jt}$$
(2)

where the first part of the right-hand side (i.e. the "share") is the share of first- and second- generation migrants from country j in the Netherlands that reside in municipality h in 2010, and the second part (i.e. the "shift") is the number of first-generation migrants that arrive from country j in year t. We

 $^{^{1}}$ We fix locations and sectors of firms to the first time they appear during 2010-2017.

²The IHS transformation is used frequently to take zeros into account. Some recent examples include Conconi et al. (2018), Amiti et al. (2019), and Malgouyres et al. (2021).

³Note that we do not include firm-country fixed effects since including them prohibits us to have enough variation to have a strong instrument (we have a maximum of six observations per firm-country), leading to Kleibergen-Paap F-statistics below 7 (still, the coefficients remain positive). However, as explained below, excluding firm-country fixed effects is not a concern given that our identification relies on exogenous changes in migrant arrivals to municipalities and thus should not be directly related to firm-country imports.

⁴The firm-year fixed effects partially control for ownership, but the database does not disclose information on foreign ownership by country so we are not able to address this concern explicitly.

fix shares at 2010, one-year before the beginning of our sample period, so that they are not influenced by migrant arrivals during the regression sample period of 2011-2017. We then use \widehat{M}_{hjt} to create our imputed percentage change instrument the following way:

$$\widehat{m}_{hjt} = \frac{\widehat{M}_{hjt}}{\widehat{M}_{hjt} + (\sum_{j} M_{hj,2010} - M_{hj,2010})}$$
(3)

where the denominator is adjusted by $\sum_{j} M_{hj,2010} - M_{hj,2010}$ to avoid pure growth effects as suggested by Egger et al. (2019). The idea behind this IV strategy is that migrants that arrive from a certain country tend to locate in regions where their compatriots have already settled in (Casella and Rauch, 2002). Note that using this shift-share IV strategy requires stock-level data on migrants, and the Netherlands has this information only for a subset of 40 countries. As a result, our analysis is confined to these 40 countries. However, this limitation is rather innocuous since other countries have zero or minimal levels of migrants in the Netherlands, and thus most of the variation coming from those observations would have been washed away by country fixed effects.⁵ Note also that by including country-sector-year and municipality-country fixed effects, we are effectively controlling separately for the shift and the share components of our instrument.

We expect that β_1 is positive if migrant workers help their employers to start importing and/or increase imports from their origin countries. We assume that the effects are symmetric between increases and decreases in migrant shares, since a reduction in the share of migrants in a firm can also cause a firm to stop importing and/or decrease its imports from the origin country of those migrants. Following the literature, we also explore whether the effect differs between high-income versus other country migrants classified according to the World Bank, and as listed in Appendix Table A.1 In the Appendix, we also provide results using OLS and Poisson pseudo-maximum likelihood (PPML) methods to take zeros into account.⁶ However, our preferred specification is the 2SLS strategy which addresses the endogeneity of the hiring decision with respect to firms' imports.

3 Data

In this study, we use four micro datasets provided by the Dutch Central Bureau of Statistics (CBS). First, as mentioned before, our analysis is restricted to 40 countries due to data unavailability for other countries in constructing our instrument. To identify firms that import from at least one of these 40 countries, we use the *International Trade in Goods Report* database. This database also provides the value of firms' imports at the country-product-year level, where products are classified according to the 8-digit Combined Nomenclature (CN) system. [7] We obtain firms' 2-digit 2008 Standard Business

⁵Migrants from the 40 countries make up 78% of the total migrant workforce in 2017.

⁶PPML also deals with the potential bias in linearly estimated coefficients due to heteroskedasticity in the error term (Silva and Tenreyro, 2006).

⁷We use the product dimension when we examine the effect separately for final goods, inputs, and capital goods, by concording CN products to Broad Economic Categories (BEC) using the United Nation's correspondence tables.

Classification (SBI) sector and location (i.e. 446 municipalities) from the *General Business Register* database. The 85 sectors include both tradable (e.g. SBI 29 *Manufacture of motor vehicles*) and non-tradable industries (e.g. SBI 52 *Warehousing and support activities for transportation*). This results in 93,529 unique importers, which make up around three-quarters of Dutch imports, and around half of total employment in the Netherlands in 2010-2017.

We then use the Jobs and Wages Report database to identify the employees of the firms in our sample, using unique firm IDs. This results in a linked employer-employee dataset. Utilizing unique worker IDs, we supplement this data with information on employee characteristics such as country of origin (first- and second-generation separately) and age using the *Report on Personal Characteristics* database. Immigrants in the Netherlands are categorized by their generations according to the CBS formulation as illustrated in Table []. If the parents were born in a country other than the Netherlands, the place of birth determines whether their children can be grouped into the first- or second-generation migrants. If the parents were born in the Netherlands, then their children are assumed to be non-migrants regardless of their place of birth. Our study primarily focuses on first-generation migrants, but also incorporates second-generation migrants in a subsection. As a result, this formal and more accurate definition of immigrants distinguishes our study from others in which only foreign-born individuals are assumed to be immigrants.

Table 1: Definition of Immigrants by CBS Formulation

Both parents born in the NL?	No	Born in the NL yourself?	No Yes	Migrant	First Generation Second Generation
	Yes			Dutch	

Source: The Dutch Central Bureau of Statistics (CBS).

We sum up the number of workers from each origin country, and aggregate the data to the firmcountry-level as required by our empirical specification (1). Finally, for each firm that imports in a given year, we fill in zeros for countries that it does not import from, and thus rectangularize the dataset at the firm-country level for each year. Our regression sample covers 2012-2017 for our dependent variable, and 2011-2016 for our independent variable due to our lagged structure. Table 2) presents summary statistics for the benchmark sample, which has about 7 million observations, of which around 8% are positive flows. Most notably, the statistics show that the average probability of importing from one of the 40 countries is 7.7%. When we split the sample into high-income and middle- and low-income countries, we find that the average probabilities of importing from these groups of countries are 13.3% and 4.7% respectively. The average share of country-specific first-generation migrants employed by importers (including observations with zero imports and shares) is fairly stable across the two groups of countries, with an average of 0.22% for the 40 countries. This share is lower for second-generation migrants at 0.14%. The standard deviations of these shares are much higher (around two percentage points each), which is useful for our identification.

	All count	tries (40)	High-inc	ome (14)	Other	s(26)
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
imports in $Euros_{ijt}$	€156K	${\scriptstyle {\textcircled{\bullet}}7,258K}$	€323K	€9,129K	€67K	€6,013K
$IHS(imports)_{ijt}$	0.865	3.138	1.576	4.190	0.482	2.297
$\ln(\text{imports})_{ijt}$	10.567	3.339	11.158	3.201	9.658	3.341
import $\operatorname{dummy}_{ijt}$	0.077	0.266	0.133	0.340	0.047	0.211
share of migrants _{$ijt-1$} (first-generation)	0.215%	0.025	0.241%	0.022	0.200%	0.026
share of migrants _{$ijt-1$} (second-generation)	0.135%	0.018	0.180%	0.020	0.111%	0.017
Observations Positive observations	7,075 543	5,400 ,472	2,470 329	5,390 ,374	4,599 214	9,010 ,098

Table 2: Summary statistics

Notes: The regression sample includes firms that import from at least one of the 40 countries in 2012-2017. The variables are at the firm-country-year (ijt) level.

3.1 Migrants in the Netherlands

In this subsection, we provide some statistics regarding migrants in the Netherlands. Table 3 shows key features of the diverse workforce in the Netherlands, where the number of jobs increased by 300,000 during 2010-2017, reaching 8.8 million workers. First, notice that first- and second-generation migrants are the driving force of the growing domestic labor stock, as their numbers in total increased by 16% whereas the size of the Dutch native workforce stayed essentially the same. This meant that the share of workforce that are first- and second-generation migrants increased by around 3 percentage points, reaching 25% in 2017.

Looking at the rows below, we see that the rise in migrant workforce is driven by two groups: firstgeneration migrants from high-income countries, and second-generation migrants from other countries, which increased by 41% and 34% in numbers in 2010-2017 respectively. For example, the number of first-generation workers from Poland more than doubled in 2010-2017. First-generation migrants from the UK, Belgium, and Italy also increased during this period. We also see that some countries' firstgeneration migrants such as the ones from Suriname, Turkiye, and Morocco, had lost some of their prominence in Dutch labor markets due to reduced inflows of migrants from these countries. On the other hand, these three countries' second-generation migrants have become the driving force of the increase in total migrant workforce, making up more than 3% of total workforce in 2017. Note that separating workers with foreign ties into first- and second-generations reveals that the size of the second-generation workforce is almost the same as the size of the first-generation workforce.

3.2 Imports and migrant shares

In this subsection, we show some descriptive evidence regarding the relationship between imports and migrants in the Netherlands. Figure 1 panel (a) shows the evolution of Netherlands' imports during

Domestic labor	Number of workers 2010 2017		Log change	Share in workforce 2010 2017	
Total workforce	8,525,290	8,804,535	3.2%	•	•
First- and second-generation [*]	1,872,380	2,200,217	16.1%	22.0%	25.0%
First-generation	893,728	$1,\!037,\!413$	14.9%	10.5%	11.8%
First-generation (40 countries)	$685,\!640$	807,271	16.3%	8.0%	9.2%
First-generation (14 high-income)	221,940	333,460	40.7%	2.6%	3.8%
- Poland	48,118	$117,\!524$	89.3%	0.6%	1.3%
- Netherlands Antilles	50,777	46,440	-8.9%	0.6%	0.5%
- UK	$25,\!639$	$27,\!148$	5.7%	0.3%	0.3%
- Belgium	$18,\!228$	$19,\!135$	4.9%	0.2%	0.2%
- Italy	10,326	$18,\!636$	59.0%	0.1%	0.2%
First-generation (26 others)	463,700	473,811	2.2%	5.4%	5.4%
- Suriname	$116,\!522$	$97,\!053$	-18.3%	1.4%	1.1%
- Turkiye	91,368	$77,\!562$	-16.4%	1.1%	0.9%
- Morocco	$74,\!525$	64,910	-13.8%	0.9%	0.7%
- China	17,745	23,614	28.6%	0.2%	0.3%
- Indonesia	29,707	$23,\!207$	-24.7%	0.3%	0.3%
Second-generation	703,104	825,689	16.1%	8.2%	9.4%
Second-generation (40 countries)	478,735	$589,\!288$	20.8%	5.6%	6.7%
Second-generation (14 high-income)	204,720	202,606	-1.0%	2.4%	2.3%
- Germany	$85,\!398$	64,729	-27.7%	1.0%	0.7%
- Netherlands Antilles	$23,\!221$	$31,\!981$	32.0%	0.3%	0.4%
- Belgium	30,209	$29,\!952$	-0.9%	0.4%	0.3%
- UK	$16,\!419$	$18,\!802$	13.6%	0.2%	0.2%
- Italy	$11,\!431$	$12,\!111$	5.8%	0.1%	0.1%
Second-generation (26 others)	$274,\!015$	$386,\!682$	34.4%	3.2%	4.4%
- Turkiye	$70,\!578$	99,300	34.1%	0.8%	1.1%
- Suriname	74,246	$95,\!783$	25.5%	0.9%	1.1%
- Morocco	$58,\!296$	87,326	40.4%	0.7%	1.0%
- Indonesia	38,444	42,106	9.1%	0.5%	0.5%
- China	$4,\!661$	7,591	48.8%	0.1%	0.1%

Table 3: Migrant workforce in the Netherlands

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Notes: * indicates that this group includes migrants with unknown generation as well (around 15%). Countries that are presented for each category are the top-5 countries ranked according to the number of workers in 2017. Appendix Table A.1 lists the 40 countries according to income groups. *Source:* Authors' calculations based on data from the Dutch Central Bureau of Statistics (CBS).

2010-2017 from the 40 countries on the left-axis, and the share of first-generation migrant workers in total workforce on the right-axis. The trend is increasing for both variables despite a period of relatively flat imports during 2012-2016. When we separate the sample into high-income versus other countries in panels (b) and (c) respectively, we see that the positive relationship between imports and share of migrants is largely due to high-income countries, but also partially due to other countries in the latter part of our sample period. Panel (b) indicates that the Netherlands increased its imports from high-income countries by 22% in 2010-2017, while the share of migrants from these countries in total workforce increased from 2.6% to 3.8%. Panel (c) illustrates that the share of migrants from other countries fluctuated, but by 2017 it was almost at the same value as in 2010 at 5.5%, while imports from these countries increased by 22% as well.

Figure 1: Imports and share of migrants in the Netherlands, 2010-2017



Source: Authors' depictions using data from the Dutch Central Bureau of Statistics (CBS).

In Figure 2 following our identification strategy presented in Section 2 we map changes in log imports and first-generation migrant shares over 2010-2017 by municipality. The maps show changes in imports and migrant shares by municipality respectively for all 40 countries in panels (a) and (b), for 14 high-income countries in panels (c) and (d), and for 26 middle- and low-income countries in panels (e) and (f). The scales are given below each map, with colors ranging from blue to green to yellow and to red as figures rise. Municipalities that are in white either have no data or too few migrants for the CBS to disclose the information publicly.

Looking at panel (a), we see that firms in most municipalities increased their imports in the sample period, but some in the northwest such as Medemblik and Texel (in red) have increased their imports by a staggering 400% in 2010-2017. Panel (b) shows that most municipalities have become more "foreign" in terms of their workforce, but some such as Nuenen, Gerwen en Nederwetten (in red) experienced an increase in migrant share of around 10 percentage points, whereas others such as Westland experienced a reduction in migrant shares of almost 9 percentage points (in blue). However, the correlation between the change in imports and migrant shares is -0.13 and not statistically significant.

In panels (c) and (d), we focus on high-income countries, and observe similar patterns for imports since around three-quarters of imports are from high-income countries, but the change in migrant

Figure 2: Change in imports and migrant shares by municipality, 2010-2017

- (a) All countries (40), change in log imports
- (c) High-income (14), change in log imports



(e) Others (26), change in log imports



(b) All countries (40), change in migrant shares



(d) High-income (14), change in migrant shares



(f) Others (26), change in migrant shares



Notes: The maps show changes in log imports and first-generation migrant shares in workforce by municipality respectively for all countries (40) in panels (a) and (b), for high-income countries (14) in panels (c) and (d), and for middle- and low-income countries (26) in panels (e) and (f). The scales are given below each map, with colors ranging from blue to green to yellow and to red as figures rise. Municipalities that are in white either have no data or too few migrants for the CBS to disclose it publicly. *Source:* Authors' depictions using data from the Dutch Central Bureau of Statistics (CBS).

shares show very different patterns than to the one for all countries, with municipalities such as Nijkerk and Westland (in red) experiencing an increase of high-income migrant shares of more than 15 percentage points. In fact, the correlation for the two changes for this high-income country sample is 0.16, significant at the 1% level. In panels (e) and (f), we turn to middle- and low-income countries, and see that both increases in imports and migrant shares have been substantial for this group of countries, with municipalities such as Medemblik (in red) increasing its imports from these countries by more than 400%, and increasing its share of migrants from these countries by 11.5 percentage points. The correlation between the two changes for the middle- and low-income countries is 0.17, significant at the 1% level.

Overall, the maps reveal that splitting the sample is important for our analysis since the significant positive correlation exists only when we examine high-income and other countries separately. In the next section, we show whether these relationships hold in a more rigorous empirical exercise.

4 Results

4.1 Main effects

Table 4 presents the results of estimating equation (1) using our IV strategy. The top panel shows results for all 40 countries, and the middle and bottom panels show results for the 14 high-income and 26 middle- and low-income countries respectively. The dependent variable in column 1 is the IHS-transformed imports. In columns 2 and 3, we focus on the intensive and extensive margins by changing the dependent variable to log imports (which excludes zeros) and the indicator for importing respectively. The three coefficients in the top panel indicate that there is a positive impact of hiring migrants on imports, but this effect is not statistically significant at the conventional levels. Importantly, as shown in the last row of the top panel, the instrument is positive and significant at the 1%level in all three specifications, but the Kleibergen-Paap (KP) F-statistics are above the critical value of 16 based on a 10% maximal IV size only for columns 1 and 3. This means that our identification is coming mostly by including the observations with zero imports. This is not surprising given that to achieve proper identification with a 2SLS specification with high-dimensional fixed effects, we need a large enough sample such as the ones used in columns 1 and 3. In fact, when we relax the specification by dropping municipality-country fixed effects (but still controlling for municipality-country "shares" explicitly), the KP statistics rise to levels that are comfortably higher than the critical value and we find positive and significant coefficients for almost all columns. These results are presented in Appendix Table A.2

The results in the middle panel shows that there is a positive and significant impact of hiring migrants from high-income countries on imports from these countries, but only for the extensive margin since the instrument is not strong enough for the intensive margin sample in column 2 as indicated by the low KP statistic. The coefficient on column 3 illustrates that a one standard deviation (2.2 percentage points) increase in the share of migrant workers from j increases the probability of

importing from that country by 6.6 percentage points. This explains about a fifth of the standard deviation of the probability of importing from a given country (34 percentage points).

In the bottom panel, we focus on the 26 middle- and low-income countries and find positive but statistically insignificant coefficients, with relatively low KP statistics. The contrast between the middle and the bottom panels reveals that the effect of hiring on imports is mostly relevant for high-income countries, hinting that migrants from those countries provide potentially more substantive market knowledge regarding suppliers in their own countries, compared to migrants from other countries. We find that this effect is largely due to the extensive margin, and thus we focus on the extensive margin results for the rest of the paper.

Appendix Table A.3 replicates our results using the OLS specification. We find that all coefficients for both margins and set of countries are positive and significant. Comparing the OLS coefficient in Table A.3 panel (b) column 3 (high-income countries, extensive margin) to the analogous one in Table 4 reveals that the OLS coefficients are biased downwards, suggesting that either there is an omitted variable that affects hiring migrants and imports in opposite ways, or more plausibly that firms that already import from a country are less likely to hire additional migrants from that country. Appendix Table A.4 uses the PPML specification and finds qualitatively similar results. Note that both OLS and PPML results show positive effects for the intensive margin, which is not apparent when we use the 2SLS strategy. However, this does not mean that there are no effects at the intensive margin, but that our IV strategy with restrictive fixed effects is only able to identify the effects at the extensive margin, 8

4.2 Robustness checks

In Table 5, we provide several robustness checks to the high-income countries' extensive margin results presented in Table 4 panel (b) column 3. First, in column 1, we cluster our standard errors at a more aggregate city-country level to take into account spatial correlation of shocks within cities across municipalities, and the results stay robust 9 Second, if the share of first-generation migrants is correlated with the share of second-generation migrants from the same country in the same firm, one might be concerned that our effect might be picking up the effect of second-generation migrants. We find that this correlation is low but positive at 0.02. Notice also that our instrument exploits migrant arrivals to the Netherlands and thus it is constructed to predict hiring of first-generation migrants. Still, in column 2 we control for the second-generation migrant share, and find that results are unchanged.¹⁰

In columns 3 and 4, we deal with outliers. In column 3, we exclude firms whose total annual imports are below the 5^{th} or above the 95^{th} percentile, and in column 4, we exclude firms whose total number of workers are below the 5^{th} or above the 95^{th} percentile. Neither of these sample modifications

⁸Again, the 2SLS results without municipality-country fixed effects in Appendix Table A.2 panel (b) show effects for the intensive margin as well.

 $^{^9\}mathrm{We}$ aggregate the 446 municipalities to 87 cities.

 $^{^{10}}$ We take the endogeneity of the second-generation share into account in subsection 4.4

Table 4:	Main	results -	2SLS	
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	(1)	(a) All countries (40)	(3)		
Dependent variable:	(I) IHS(imports) _{<i>ijt</i>}	$\ln(\text{imports})_{ijt}$	(3)import dummy _{<i>ijt</i>}		
share of migrants _{$ijt-1$}	16.862	27.835	1.443		
(first-generation)	(10.960)	(22.331)	(0.983)		
KP	20.3	8.77	20.3		
Observations	7,075,400	472,183	7,075,400		
\widehat{m}_{hjt-1}	0.049***	0.299***	0.049***		
	(0.011)	(0.101)	(0.011)		
	(b)	High-income countries	(14)		
	(1)	(2)	(3)		
Dependent variable:	$\operatorname{IHS(imports)}_{ijt}$	$\ln(\text{imports})_{ijt}$	import $\operatorname{dummy}_{ijt}$		
share of $\operatorname{migrants}_{ijt-1}$	38.776**	57.832	3.016^{**}		
(first-generation)	(15.550)	(45.635)	(1.211)		
KP	29.4	3.64	29.4		
Observations	$2,\!476,\!390$	264,956	$2,\!476,\!390$		
\widehat{m}_{hjt-1}	0.204^{***}	0.169^{*}	0.204^{***}		
	(0.038)	(0.089)	(0.038)		
	(c) Other countries (26)				
	(1)	(2)	(3)		
Dependent variable:	$IHS(imports)_{ijt}$	$\ln(\text{imports})_{ijt}$	import $\operatorname{dummy}_{ijt}$		
share of migrants _{$iit-1$}	6.754	5.267	0.410		
(first-generation)	(9.159)	(31.465)	(0.997)		
KP	13.4	6.05	13.4		
Observations	$4,\!599,\!010$	$143,\!024$	$4,\!599,\!010$		
\widehat{m}_{hjt-1}	0.028^{***}	1.294^{**}	0.028^{***}		
	(0.008)	(0.526)	(0.008)		
Country-sector-year FE	Yes	Yes	Yes		
Municipality-country FE	Yes	Yes	Yes		
Firm-year FE	Yes	Yes	Yes		

Notes: The table shows 2SLS results for all 40 countries in panel (a), 14 high-income countries in panel (b), and 26 other countries in panel (c). IHS(imports)_{*ijt*} is the IHS transformed value of imports, $\ln(\text{imports})_{ijt}$ is the natural log of imports, and import \dim_{ijt-1} indicates whether firm *i* imports from country *j* in year *t*. share of $\operatorname{migrants}_{ijt-1}$ is the share of migrants in firm *i*'s workforce from country *j* in year *t* – 1. KP stands for the Kleibergen-Paap *F*-statistic. The row for the instrumental variable \widehat{m}_{hjt-1} shows the first-stage coefficient. Robust standard errors clustered by municipality-country are in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

change our results meaningfully. In column 5, we exclude the nine municipalities that make up the two largest cities Amsterdam and Rotterdam that have migrant employment shares that are around 20% (above the 95th percentile), and continue to find a positive and significant effect.

Finally, we address the issue that firms might be heterogeneously exposed to migrant arrival shocks due to the "share" part of the instrument. We assume that in our setting both the shifts and the

	City- country cluster (1)	Second- generation migrants (2)	Excl. small and large importers (3)	Excl. small and large employers (4)	Excl. AMS and ROT (5)	Recentered IV (6)
share of migrants _{$ijt-1$} (first-generation)	3.016^{**} (1.184)	3.040^{**} (1.227)	$\begin{array}{c} 4.040^{***} \\ (1.342) \end{array}$	$3.914^{***} \\ (1.431)$	2.735^{**} (1.207)	2.883^{*} (1.625)
share of migrants _{$ijt-1$} (second-generation)		-0.043 (0.029)				
simulated \widehat{m}_{hjt-1}						$0.202 \\ (1.645)$
Country-sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality-country FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-year FE	Yes	Yes	Yes	Yes	Yes	Yes
KP	37.3	28.7	22.5	23.2	27.2	13.8
Observations	$2,\!476,\!390$	$2,\!476,\!390$	$2,\!261,\!154$	2,142,140	$2,\!172,\!730$	$2,\!476,\!390$

Table 5: Robustness checks

Notes: The table shows 2SLS results for 14 high-income countries. The dependent variable is import dummy_{ijt}, which indicates whether firm *i* imports from country *j* in year *t*. share of migrants_{ijt-1} is the share of migrants in firm *i*'s workforce from country *j* in year *t* – 1. Column 1 clusters standard errors at the city-country level. Column 2 controls for the share of second-generation migrants. Column 3 excludes firms that are below the 5th or above the 95th percentiles of import value. Column 4 excludes firms that are below the 5th or above the 95th percentiles of workforce. Column 5 excludes Amsterdam and Rotterdam. Column 6 controls for the simulated IV to recenter the estimates. KP stands for the Kleibergen-Paap *F*-statistic. Robust standard errors clustered by municipality-country are in parentheses (in column 1, standard errors are clustered at the city-country level). Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

shares (since they are based on pre-sample period 2010) are exogenous to the firm.¹¹ However, as a further check, we follow Borusyak and Hull (2021) and include a simulated IV to purge our estimates from the potential bias due to this heterogeneous exposure.¹² This implies that as long as the migrant arrivals are exogenous to the firm, even if the shares are endogenous to firm-country imports, our shift-share identification strategy remains valid.

We construct our simulated IV by randomly allocating M_{jt} across the 40 countries for 2010-2017. We do this randomization 1,000 times, and following steps (2) and (3) described in Section 2, create 1,000 placebo IVs. Finally, we take the average of these IVs to create our simulated IV. In column 6, we include this simulated IV in our 2SLS regressions to control for firms' inherent exposure to migration shocks due to their location, and thus "recenter" our estimates. Note that with the set of fixed effects and the simulated IV, the specification becomes highly restrictive. Still, it is reassuring that our coefficient of interest is statistically significant with a similar magnitude.

¹¹One potential issue might be that firms move to municipalities with certain migrants to hire them to import from their origin countries. To avoid this, we fix the location of firms to the first time they appear in our dataset in 2010-2017. ¹²In addition to Borusyak and Hull (2021), see Adão et al. (2019), Goldsmith-Pinkham et al. (2020), and Borusyak et al. (2021) for recent improvements in shift-share research designs.

4.3 By sectors and product groups

The results above show that hiring migrants from a high-income country helps firms import from those workers' origin countries. Does this result hold for all sectors and product groups? In Table 6 columns 1-3, we focus on three groups of macro sectors: manufacturing, wholesaling and retailing (i.e. intermediaries), and other sectors (these include mostly services sectors), respectively. Results show that the effect is positive for manufacturers and intermediaries, but statistically significant only for the latter. Note that the KP statistics are sufficiently high only for this sector, thanks largely due to the large number of observations.¹³ Interestingly, the low KP statistic in column 3 indicates that our instrument fails to identify hiring decisions made by firms in other sectors.

	Manu. (1)	Intermed. (2)	Other sectors (3)	$ \begin{array}{c} \text{Final} \\ \text{goods} \\ (4) \end{array} $	Inputs (5)	$\begin{array}{c} \text{Capital} \\ \text{goods} \\ (6) \end{array}$
share of migrants _{$ijt-1$} (first-generation)	3.164 (2.799)	2.923^{**} (1.177)	-1.984 (13.717)	$2.666^{***} \\ (0.910)$	2.281^{**} (1.099)	$0.262 \\ (0.705)$
Country-sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality-country FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-year FE	Yes	Yes	Yes	Yes	Yes	Yes
KP	7.83	31.5	0.13	29.4	29.4	29.4
Observations	462,098	1,211,560	$802,\!536$	$2,\!476,\!390$	$2,\!476,\!390$	$2,\!476,\!390$

Table 6: By sectors and product groups

Notes: The table shows 2SLS results for 14 high-income countries. The dependent variable is import dummy_{ijt}, which indicates whether firm *i* imports from country *j* in year *t*. share of migrants_{ijt-1} is the share of migrants in firm *i*'s workforce from country *j* in year t-1. Columns 1, 2, and 3 restrict the sample to manufacturers, wholesalers/retailers (intermediaries), and firms from other sectors respectively. Columns 4, 5, and 6 focus on the imports of final goods, intermediates, and capital goods respectively. KP stands for the Kleibergen-Paap *F*-statistic. Robust standard errors clustered by municipality-country are in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

In Table 6 columns 4-6, we show the results by product groups: final goods, inputs, and capital goods, respectively. We do this by concording CN products to these categories using the BEC classification of the United Nations. We find that the result holds for final goods and inputs with similar magnitudes, but not for capital goods. This result is not surprising given that capital goods are imported less frequently (4.6% of the time versus 5.5% and 11.0% for final goods and inputs respectively).

To understand the mechanism that generates the heterogeneous results, we dig deeper by looking at sectors within each product group. Table 7 shows results for final goods, inputs, and capital goods in top, middle, and bottom panels respectively. The first column focuses on manufacturers, the second column on intermediaries, and the third column on other sectors. Panels (a) and (b) columns 2 show that the effect we find for intermediaries holds for both final goods and inputs. The coefficient on panel (b) column 1 indicates that there is a positive effect on importing inputs for manufacturers, albeit this estimate is marginally insignificant possibly due to the relatively low KP. We do not find

 $^{^{13}}$ Among the 93,529 firms, 37,505 are in wholesaling and retailing, 12,948 are in manufacturing, and 46,452 are in other sectors.

an effect for importing capital goods in any of the three sector groups. These results suggest that trade intermediaries are the primary beneficiaries of hiring migrant workers that enable them to source final goods and inputs and distribute them in the Netherlands. This is intuitive as these firms' main objective is to match buyers and sellers, and migrants are arguably workers with the most amount of market knowledge to establish these connections.

		(a) Final goods	
	(1)	(2)	(3)
	Manu.	Intermed.	Other sectors
share of migrants _{<i>i</i>$it-1$}	1.162	2.471***	9.851
(first-generation)	(1.734)	(0.910)	(27.284)
KP	7.83	31.5	0.13
Observations	462,098	$1,\!211,\!560$	802,536
		(b) Inputs	
	(1)	(2)	(3)
	Manu.	Intermed.	Other sectors
share of migrants _{<i>iit</i>-1}	2.926	2.442**	-8.691
(first-generation)	(2.732)	(0.972)	(28.122)
KP	7.83	31.5	0.13
Observations	462,098	$1,\!211,\!560$	802,536
		(c) Capital goods	
	(1)	(2)	(3)
	Manu.	Intermed.	Other sectors
share of migrants _{<i>iit</i>-1}	0.665	0.346	-4.921
(first-generation)	(1.508)	(0.571)	(18.191)
KP	7.83	31.5	0.13
Observations	462,098	$1,\!211,\!560$	802,536
Country-sector-year FE	Yes	Yes	Yes
Municipality-country FE	Yes	Yes	Yes
Firm-year FE	Yes	Yes	Yes

Table 7: By sectors within product groups

1

Notes: The table shows 2SLS results for final goods in panel (a), inputs in panel (b), and capital goods in panel (c). The dependent variable is import dummy_{*ijt*}, which indicates whether firm *i* imports from country *j* in year *t*. share of migrants_{*ijt-1*} is the share of migrants in firm *i*'s workforce from country *j* in year t - 1. Columns 1, 2, and 3 restrict the sample to manufacturers, wholesalers/retailers (intermediaries), and firms from other sectors respectively. KP stands for the Kleibergen-Paap *F*-statistic. Robust standard errors clustered by municipality-country are in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

4.4 Generations and age groups

In this section, we take into account the second-generation migrants that are employed by the firms in our dataset. Since the share of second-generation migrants from country j employed by firm i in year t is also endogenous with respect to firms' import decisions, we instrument it with the share of second-generation migrants from country j that were born in municipality h 20-25 years ago and now entering the workforce. We do not observe this information, but we can proxy it using the share of 20-25 year old population in municipality h that are second-generation migrants from country j. This share is likely to influence firms' hiring decisions, and arguably satisfies the exclusion restriction since it should not have a direct impact on firms' imports. This exercise is novel as the existing literature has not taken later generations into account when examining the effect of migrants on trade.

Table S column 1 shows that the coefficients for both generations are positive but not statistically significant. This is potentially due to the collinearity of our second instrument, which proxies for municipality-country birth rates, with municipality-country fixed effects, ¹⁴ resulting in a low KP statistic. ¹⁵ Thus, in column 2, we relax the specification by excluding municipality-country fixed effects, and instead explicitly control for the "share" of our shift-share instrument. This doubles the KP statistic, and the coefficient for the first-generation migrants becomes statistically significant, while the one for the the second-generation remains marginally insignificant (with a *p*-value of 0.103) but still positive. In fact, when we test for the equality of the two coefficients, we find that they are not statistically different from each other. This novel result suggests that second-generation migrants also have some positive effect on their employers' importing decisions, albeit this result is not as strong as the one for the first-generation migrants. This could be due to the larger stock of knowledge of first-generation migrants the effects are possibly limited to linguistic and cultural similarities.

In our final exercise, we separate first-generation migrants into four age groups to see which ones are driving the effect we find. We expect that immigrants' age when they arrive in their host country to work could be decisive for firms' imports. In our estimations, we consider four age groups: younger than 19 years old, between 19 and 34 years old, between 35 and 50 years old, and older than 50 years old. We construct separate instruments for the four variables by replacing M_{jt} with with the number of migrant arrivals corresponding to that age group in equation (2) and construct the IV as in equation (3). We estimate the regressions separately for each age group since otherwise the instruments become highly collinear, disallowing identification.¹⁶

Table $\underline{8}$ columns 3 to 6 instrument for one age group at a time, and control for others. Note that the correlation of the four measures (ranging from 0.02 to 0.10, always significant at the 1% level) makes it difficult to have a sufficiently high KP statistic. Only in column 5, where we instrument for the age group 35-50, we get adequate level of identification, and find a positive and significant effect of hiring migrants from this age group on the probability of importing. We also get a positive and significant coefficient in column 3, where we instrument for the youngest age group, but this is likely driven by their arrival with their parents to the country.¹⁷

Overall, with the caveat that we estimated our regressions separately for the four age groups, our

¹⁴This is the case since birth rates are persistent over time: the correlation between the share and its lag is 0.97.

 $^{^{15}}$ The correlation between the two instruments is also high (0.39) and significant at the 1% level.

 $^{^{16}}$ The pairwise correlation between the four instruments ranges from 0.89 to 0.99, always significant at the 1% level.

 $^{^{17}}$ The share of first-generation migrants from high-income countries employed by firms in this age group is less than 2%.

	both generations	Without hj FE	Ages < 19	Ages 19-34	$\begin{array}{c} \text{Ages} \\ 35\text{-}50 \end{array}$	Ages >50
	(1)	(2)	(3)	(4)	(5)	(6)
share of migrants _{$ijt-1$}	1.516	1.511^{*}				
(first-generation)	(1.610)	(0.846)				
share of migrants _{$ijt-1$}	2.721	1.316				
(second-generation)	(1.773)	(0.806)				
$\frac{M_{hj,2010}}{\sum_{k} M_{hj,2010}}$		0.317^{**}				
		(0.160)				
share of $\operatorname{migrants}_{iit-1}$			69.507^{*}	-0.540	-0.222	-0.167
(first-generation, ages <19)			(41.498)	(0.492)	(0.227)	(0.288)
share of migrants _{$ijt-1$}			0.079	5.287	-0.256	-0.175
(first-generation, ages 19-34)			(0.066)	(3.483)	(0.258)	(0.274)
share of migrants _{$ijt-1$}			0.147^{***}	-0.263	4.755^{*}	-0.390
(first-generation, ages 35-50 $)$			(0.040)	(0.308)	(2.684)	(0.462)
share of migrants _{$ijt-1$}			0.183^{***}	0.046	-0.042	21.620
(first-generation, $ages > 50$)			(0.042)	(0.110)	(0.147)	(16.584)
Country-sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality-country FE	Yes	No	Yes	Yes	Yes	Yes
Firm-year FE	Yes	Yes	Yes	Yes	Yes	Yes
KP	6.63	13.7	9.86	6.49	11.9	2.53
Observations	$2,\!476,\!390$	$2,\!476,\!418$	$2,\!476,\!390$	$2,\!476,\!390$	$2,\!476,\!390$	$2,\!476,\!390$

Table 8: By generations and age groups

Notes: The table shows 2SLS results for 14 high-income countries. The dependent variable is import dummy_{*ijt*}, which indicates whether firm *i* imports from country *j* in year *t*. share of migrants_{*ijt*-1} is the share of migrants in firm *i*'s workforce from country *j* in year t - 1. In columns 1 and 2, both independent variables are instrumented. In columns 3 to 6, only the age share variable that is specified in the title of the column is instrumented, controlling for the other three age shares. KP stands for the Kleibergen-Paap *F*-statistic. Robust standard errors clustered by municipality-country are in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

more robust finding for the 35-50 age group is intuitive as these are the workers that have accumulated enough market knowledge to be able to help their employers import (and also the ones that, along with the 19-34 age group, make up around 80% of the first-generation high-income migrant workforce).

5 Conclusion

In this paper, we examined the effect of hiring migrant workers on firms' sourcing behavior from those workers' origin countries. To do so, we first created a rich employer-employee dataset linked with firmcountry level imports for the Netherlands in 2010-2017. Descriptive statistics revealed that during our sample period, the Netherlands increased its imports substantially and its workforce became much more "foreign," both at the aggregate and at the municipality level.

To examine the causal effect of hiring migrants on imports, we used an instrumental variables strategy, where we instrumented firm-level shares of migrants with the exogenously arriving migrants to the firms' municipalities. We included several high-dimensional fixed effects in our specification and developed a conservative identification strategy. Our benchmark specification indicated that a one standard deviation increase in the share of migrant workers from a certain country raised their employers' probability of sourcing goods from their origin country by 6.6 percentage points – around a fifth of the standard deviation of importing. We found that this effect exists only for high-income countries, but is robust to a battery of sensitivity checks.

Digging deeper, we found that the effects are driven by intermediaries that hire migrants and import final goods and inputs from high-income countries, and that the effects for manufacturers are not as strong. Moreover, for the first time in the literature, we took into account the share of secondgeneration immigrants employed by firms by instrumenting it with municipality-country birth rates 20-25 years ago, and found a positive but marginally insignificant effect for these migrants. Finally, we explored age-specific heterogeneities, and found that the ones that arrived in the Netherlands at ages 35-50 were the most influential in their employers' import decisions.

Our results contribute to the literature on the effects of migrants' market knowledge on firms' trading decisions, especially in terms of finding suppliers, and complement the results of Egger et al. (2019) and Ariu (2020). Future research should utilize occupation information to understand the mechanism behind the market knowledge effect we find. Our study also raises potential additional research questions. For example, future research can examine whether migrant workers help their firms sustain buyer-seller relationships when faced with abrupt negative shocks.

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A Appendix Tables

High-income (14)	Others (26)			
Aruba	Afghanistan			
Belgium	Bosnia-Herzegovina			
France	Brazil			
Germany	Bulgaria			
Greece	Cape Verde			
Hungary	China			
Italy	Colombia			
Netherlands Antilles	Egypt			
Poland	Eritrea			
Portugal	Ethiopia			
Romania	Ghana			
Spain	India			
UK	Indonesia			
USA	Iran			
	Iraq			
	Morocco			
	Pakistan			
	Philippines			
	Russia			
	Somalia			
	South Africa			
	Suriname			
	Syria			
	Thailand			
	Turkiye			
	Vietnam			
Notes: Countries are	grouped according to the			
World Bank classificatio	n (https://datahelpdesk.			

Table A.1: List of 40 countries

906519-world-bank-country-and-lending-groups).

	(a) All countries (40)				
	(1)	(2)	(3)		
Dependent variable:	$\operatorname{IHS}(\operatorname{imports})_{ijt}$	$\ln(\text{imports})_{ijt}$	import $\operatorname{dummy}_{ijt}$		
share of migrants _{<i>i</i>, i_{t-1}}	31.781***	32.147***	2.357***		
	(6.045)	(6.888)	(0.446)		
$\frac{M_{hj,2010}}{\sum}$	0.030	-1.517	0.009		
$\sum_{h} W_{hj,2010}$	(0.190)	(0.965)	(0.017)		
KP	32.5	54.7	32.5		
Observations	7,075,480	473,732	7,075,480		
\widehat{m}_{hit-1}	0.276^{***}	0.453^{***}	0.276^{***}		
	(0.048)	(0.061)	(0.048)		
	(b)	High-income countries	s (14)		
	(1)	(2)	(3)		
Dependent variable:	$\operatorname{IHS}(\operatorname{imports})_{ijt}$	$\ln(\text{imports})_{ijt}$	import $\operatorname{dummy}_{ijt}$		
share of migrants _{<i>i</i>, i_{t-1}}	41.946***	43.436***	2.702***		
	(8.051)	(8.589)	(0.566)		
$\frac{M_{hj,2010}}{\sum M_{1,2010}}$	2.580*	1.529	0.288*		
$\sum_{h} h^{mn} h^{j} 2010$	(1.522)	(1.036)	(0.160)		
KP	61.6	43.6	61.6		
Observations	$2,\!476,\!418$	$265,\!373$	$2,\!476,\!418$		
\widehat{m}_{hit-1}	0.367^{***}	0.399^{***}	0.367***		
	(0.047)	(0.060)	(0.047)		
		(c) Other countries (2	6)		
	(1)	(2)	(3)		
Dependent variable:	$\mathrm{IHS}(\mathrm{imports})_{ijt}$	$\ln(\text{imports})_{ijt}$	import $\operatorname{dummy}_{ijt}$		
share of migrants _{$ijt-1$}	15.072***	-4.235	1.634^{***}		
5	(4.410)	(12.405)	(0.441)		
$\frac{M_{hj,2010}}{\sum M_{1,20210}}$	-0.163*	0.084	-0.018**		
$\sum_{h} m_{nj,2010}$	(0.089)	(1.320)	(0.008)		
KP	15.5	7.30	15.5		
Observations	4.599.062	144.338	4,599.062		
\widehat{m}_{hit-1}	0.156***	1.754***	0.156***		
10JU I	(0.040)	(0.649)	(0.040)		
Country-sector-year FE	Yes	Yes	Yes		
Firm-year FE	Yes	Yes	Yes		

Table A.2: 2SLS results without municipality-country FE

Notes: The table shows 2SLS results for all 40 countries in panel (a), 14 high-income countries in panel (b), and 26 other countries in panel (c). IHS(imports)_{*ijt*} is the IHS transformed value of imports, $\ln(\text{imports})_{ijt}$ is the natural log of imports, and import \dim_{ijt} indicates whether firm *i* imports from country *j* in year *t*. share of $\operatorname{migrants}_{ijt-1}$ is the share of $\operatorname{migrants}$ in firm *i*'s workforce from country *j* in year *t* – 1. KP stands for the Kleibergen-Paap *F*-statistic. The row for the instrumental variable \widehat{m}_{hjt-1} shows the first-stage coefficient. Robust standard errors clustered by municipality-country are in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

	(a) All countries (40)				
	(1)	(2)	(3)		
Dependent variable:	$\mathrm{IHS}(\mathrm{imports})_{ijt}$	$\ln(\text{imports})_{ijt}$	import $\operatorname{dummy}_{ijt}$		
share of migrants $_{iit-1}$	5.459***	4.413***	0.456***		
(first-generation)	(0.366)	(0.250)	(0.034)		
$\operatorname{Adj} R^2$	0.32	0.46	0.32		
Observations	7,075,400	472,183	7,075,400		
	(b) High-income countries (14)				
	(1)	(2)	(3)		
Dependent variable:	$\operatorname{IHS}(\operatorname{imports})_{ijt}$	$\ln(\text{imports})_{ijt}$	import $\operatorname{dummy}_{ijt}$		
share of migrants _{<i>i</i>, i_{t-1}}	2.585***	5.611***	0.187***		
(first-generation)	(0.295)	(0.560)	(0.021)		
$\operatorname{Adj} - R^2$	0.44	0.43	0.44		
Observations	2,476,390	$264,\!956$	2,476,390		
	(c) Other countries (26)				
	(1)	(2)	(3)		
Dependent variable:	$\operatorname{IHS}(\operatorname{imports})_{ijt}$	$\ln(\text{imports})_{ijt}$	import $\operatorname{dummy}_{ijt}$		
share of migrants _{<i>i</i>, i_{t-1}}	6.265^{***}	3.378^{***}	0.535***		
(first-generation)	(0.413)	(0.300)	(0.038)		
$\operatorname{Adj} - R^2$	0.29	0.50	0.29		
Observations	4,599,010	143,024	4,599,010		
Country-sector-year FE	Yes	Yes	Yes		
Municipality-country FE	Yes	Yes	Yes		
Firm-year FE	Yes	Yes	Yes		

Table A.3: OLS results

Notes: The table shows OLS results for all 40 countries in panel (a), 14 high-income countries in panel (b), and 26 other countries in panel (c). IHS(imports)_{*ijt*} is the IHS transformed value of imports, $\ln(\text{imports})_{ijt}$ is the natural log of imports, and import dummy_{*ijt*} indicates whether firm *i* imports from country *j* in year *t*. share of migrants_{*ijt-1*} is the share of migrants in firm *i*'s workforce from country *j* in year *t - 1*. Adj- R^2 stands for the adjusted R-squared. Robust standard errors clustered by municipality-country are in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

	(a) All countries (40)		
	(1)	(2)	(3)
Dependent variable:	$imports_{ijt}$	$\begin{array}{c} \operatorname{imports}_{ijt} \\ (\operatorname{excluding zeros}) \end{array}$	import $\operatorname{dummy}_{ijt}$
share of migrants _{<i>i</i>,<i>i</i>,$t=1$}	8.159***	6.512***	3.459^{***}
(first-generation)	(0.686)	(0.804)	(0.115)
Pseudo- R^2	0.84	0.85	0.34
Observations	4,879,938	472,183	4,879,938
	(b) High-income countries (14)		
	(1)	(2)	(3)
Dependent variable:	$imports_{ijt}$	$\begin{array}{c} \operatorname{imports}_{ijt} \\ (\operatorname{excluding zeros}) \end{array}$	import dummy_{ijt}
share of migrants _{<i>i</i>, t_{-1}}	9.084***	8.049***	1.779***
(first-generation)	(0.915)	(1.002)	(0.120)
Pseudo- R^2	0.85	0.85	0.31
Observations	$1,\!359,\!973$	$264,\!956$	$1,\!359,\!973$
	(c) Other countries (26)		
	(1)	(2)	(3)
Dependent variable:	$imports_{ijt}$	$\begin{array}{c} \operatorname{imports}_{ijt} \\ (\operatorname{excluding zeros}) \end{array}$	import dummy_{ijt}
share of migrants _{<i>i</i>,<i>i</i>,$t=1$}	10.537***	5.110***	4.085***
(first-generation)	(1.504)	(1.700)	(0.148)
Pseudo- R^2	0.91	0.94	0.34
Observations	2,048,060	143,024	2,048,060
Country-sector-year FE	Yes	Yes	Yes
Municipality-country FE	Yes	Yes	Yes
Firm-year FE	Yes	Yes	Yes

Table A.4: PPML results

Notes: The table shows PPML results for all 40 countries in panel (a), 14 high-income countries in panel (b), and 26 other countries in panel (c). imports_{*ijt*} is value of imports, and import dummy_{*ijt*} indicates whether firm *i* imports from country *j* in year *t*. share of migrants_{*ijt*-1} is the share of migrants in firm *i*'s workforce from country *j* in year t - 1. Robust standard errors clustered by municipality-country are in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.