IZA Institute of Labor Economics

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DISCUSSION PAPER SERIES

IZA DP No. 15791

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ISSN: 2365-9793

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ABSTRACT

Automation and Low-Skill Labor

Changes in the supply of low-skill labor may affect robot adoption by firms. We test this hypothesis by exploiting an exogenous increase in the local labor supply induced by a large influx of immigrants into Danish municipalities. Using the Danish employer-employee matched dataset over the period 1995-2019, we show in a shift-share regression that a larger share of migrants in a municipality leads to fewer imports of robots at the firm-level. We rationalize this finding in a simple model of robot adoption in which robots and low-skill workers are substitutes. As many advanced economies are facing labor shortages, this paper sheds light on the future of robotization.

JEL Classification: E22, J20, J61, R23

Keywords: labor supply, immigration, robots, shift-share

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1 Introduction

Many firms in advanced economies are currently facing difficulties in filling vacancies.[1] Tight immigration laws, the retirement of large baby boomer cohorts and Covid-induced exits from the labor market have lowered the supply of workers. Anecdotal evidence suggests that firms increasingly rely on automation technology when unable to hire in the labor market.[2] This happens against the background of rapid advances in robotization, which have enlarged the task set that machines can perform over the last years. While it is intuitive to predict that labor shortages cause firms to adopt automation technology[3], to the best of our knowledge there is no causal evidence to support this hypothesis, possibly because the supply of labor is endogenous to the production process.

This paper aims to fill the gap by exploiting a natural experiment, the quasi-random placement of immigrants across local labor markets in Denmark. We isolate plausibly exogenous variation in the share of migrant workers across municipalities by constructing a shift-share instrument. By linking this information with firm-level robot data, we show that immigration and automation are substitutes: a higher local share of migrant workers leads firms to adopt fewer robots. As migrants typically are less skilled than native workers and work in routine-intensive occupations, our result suggests that low-skill workers and robots are alternative channels through which firms overcome issues of labor shortages. We rationalize this finding in a simple model of endogenous robot adoption.

Denmark is a fitting setting for studying the relationship between labor supply and robot adoption for several reasons. First, 'push factors' in a number of foreign countries have led to a rapid and exogenous increase in the number of immigrants in Denmark since the 1980s. For many years, a large fraction of these immigrants got allocated to municipalities according to the refugee Spatial Dispersal Policy, which did not take into account immigrant characteristics or local economic conditions. Subsequent waves of immigrants often settled in the same municipalities as their countrymen. These features of Danish immigration provide a unique opportunity to identify exogenous shocks to low-skill labor supply, which has been exploited in various economic studies (Damm, 2009; Damm and Dustmann, 2014; Foged and Peri, 2015; Olney and Pozzoli, 2021). Second, according to the International Federation of Robotics (IFR), Denmark ranks among the top 10 robot-adopting countries in the world. As the large majority of these robots gets imported, we can approximate the actual installment of robots by using information on imports at the firm-level. To address potential shortcomings with this import based approach, we validate our measure in various ways, e.g. through a survey about actual robot use among Danish firms conducted by Statistics Denmark.

Our main hypothesis is that an influx of foreign workers increases the supply of low-skill labor and decreases labor costs. While it is possible that natives may leave in response to immigration or reallocate to different sectors or occupations (Peri and Sparber, 2009), this should have a small net effect on low-skill labor supply. By increasing supply, immigration lowers labor costs and

[1] See for example The Great Attrition: Facing the labor shortage conundrum, McKinsey, DECEMBER 6, 2021.
[2] Robots replace humans as labour shortages bite, Financial Times, SEPTEMBER 22 2021.
[3] This has also been suggested recently by Acemoglu et al. (2022).

thereby reduces the need for firms to automatize their jobs. In consequence, fewer robots get adopted in municipalities with a large share of migrant workers. Vice versa, robot adoption is more widespread in labor markets with a shortage of low-skill workers.

We test this hypothesis in firm-level regressions covering the time period 1995-2019. The regressions exploit variation in the migrant share both across time and municipalities. We instrument the share of migrant workers via a shift-share instrument which relies on the municipalities' share of migrants by country of origin in 1993, well before robot use became widespread. We find that a one percentage point increase in the share of non-Western migrants decreases the probability of robot adoption by 7%. We also estimate a significant negative coefficient on the intensive margin. These findings support the substitution hypothesis and survive through a battery of robustness checks, using different measures of immigration or robot adoption and different specifications of the estimation equation.[4] We study the drivers of this effect by considering immigration effects on wages. We find that a larger migrant share leads to lower low-skill wages, and that migrants even tend to have lower wages than native workers with comparable skill level. Higher wages are positively associated with the value of robot imports.

In the final part of the paper, we rationalize our empirical findings in a model where output is produced using high- and low-skill tasks. While native workers allocate to the task paying them the higher return, immigrants are confined to low-skill tasks. In the absence of robots, a higher share of migrant workers in the local labor market leads to a lower low-skill wage, in line with the empirical evidence. When robot technology becomes available through imports, firms in labor markets with a large number of migrants are less likely to obtain a cost advantage from automation, with the consequence that fewer robots get installed. This result relies crucially on the assumption that robots and low-skill workers are substitutes.

This paper relates to two strands of literature. First, the work on the relationship between immigrant shocks and technology adoption, where most papers use a very broad definition of production technology (Peri, 2012; Hornbeck and Naidu, 2014; Akgündüz and Torun, 2020; Olney and Pozzoli, 2021; Hegna and Ulltveit-Moe, 2021). To our knowledge, the only paper that explicitly focuses on automation technology is Lewis (2011). That study uses survey data on manufacturing firms from the early 1990s. We are able to track the adoption of automation technology over a longer time period and across all sectors in the economy. Furthermore, we are able to identify automation technology more precisely by focusing on robots. Danzer et al. (2020) study the effect of immigration on innovation in automation technology, which is different from adoption. Mandelman and Zlate (2022) consider automation and immigration along with offshoring as separate factors affecting employment and wages.

Second, we relate to the literature on robot adoption. Some papers in this area study firm-level data, but tend to focus on the effects of automation rather than the drivers, e.g. Koch et al. (2021), Bonfiglioli et al. (2020), Humlum (2021). There is even more evidence on the effect of automation at

[4]It is important to note that the substitution effect is likely to be attenuated in a labor market, like the Danish one, where collective agreements set a minimum wage for low-skilled workers and the informal sector is only a small portion of the economy. We therefore can interpret our results as lower bound estimates of the substitution effect. However, the Danish labor market is also quite flexible, different from those in many other European countries but more similar to those in the US and UK. It exhibits high turnover rates, low costs of hiring and layoffs and decentralization in wage setting (Dahl et al., 2013). This is a framework in which wage should best reflect marginal productivity.

the industry or commuting-zone level, see e.g. Autor and Dorn (2013); Graetz and Michaels (2018); Acemoglu and Restrepo (2020); Mann and Püttmann (2021). Abeliansky and Prettner (2020) and Acemoglu and Restrepo (2022) study a different type of negative labor supply shock, demographic aging, and find that aging leads to faster robot adoption. We consider our paper as complementary to their work.

The paper is organized as follows: Section 2 explains the data sources and details the construction of the main variables. Section 3 outlines the empirical strategy. Section 4 shows the regression set-up and estimation results, followed by the analytical model in Section 5. Section 6 offers some concluding remarks.

2 Data and Descriptive Statistics

2.1 Employer-employee matched data set

We create an employer-employee matched data set by combining several registers, which are administered by Statistics Denmark. The Firm Statistics Register (FIRM, henceforth) covers the universe of private-sector firms with more than 50 employees and a representative sample of smaller firms over the years 1995-2019. FIRM provides detailed information on the firms' characteristics, such as their total sales, size, industry and location within Denmark.[5] Based on a number of informal interviews with Danish robot distributors, we conclude that firms with fewer than 50 employees rarely purchase robots. We therefore only keep firms with more than 50 employees in the sample. However, in a refinement we also present the results obtained by using firms of all sizes.

Worker-level data is provided by the Integrated Database for Labor Market Research (IDA, henceforth) which covers the entire Danish working population over the period 1995-2019. Importantly, IDA contains information on each individual's country of birth, which allows us to measure the immigrant share of the workforce within a municipality. In addition, IDA provides a number of useful workforce characteristics such as education, age, gender, and work experience of employees.

Using the Firm-Integrated Database for Labor Market Research (FIDA), all workers in IDA are linked to their employers in FIRM using a unique identifier. The resulting data set is an unbalanced panel of approximately 3,000 firms located across 97 municipalities.[6] As documented by Foged and Peri (2015), Danish municipalities approximate commuting zones: only 10% of workers who change job across firms accept a job in a different municipality.

[5] The location of multi-establishment firms is determined by Statistics Denmark using the municipality of the headquarter establishment. We control for a multi-establishment dummy throughout the empirical analysis.

[6] Following Foged and Peri (2015), we use the larger municipality definition that aggregates several of the old municipalities, such as Frederiksberg and Copenhagen, to arrive at a total of 97 municipalities.

2.2 Robot imports

We follow the definitions of the International Organization for Standardization (ISO 8373), according to which a robot is an "automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes" This includes both industrial and service robots. As the large majority of robots in Denmark get imported, we use data on imports to approximate the extent to which firms adopt robots. Specifically, we rely on data from the Foreign Trade Statistics Register provided by Statistics Denmark, which can be linked to the other registers described in the previous section. Robots are defined by the Harmonized System (HS) product codes "847950 industrial robots" and "847989 other machines and mechanical appliances having individual functions". The reason for including the latter category is that the first category alone does not allow us to match statistics on robot shipments published by the IFR. When considering both categories jointly instead, the numbers on total imports roughly align.[7]

Using imports data as a proxy for adoptions creates several challenges. First, some robots get imported by distributors, who sell them to the end users. We address this issue by dropping firms in the wholesale industry that are specialized in machinery[8]. We lose about 25% of robot import events from this exclusion. Second, some importers are robot integrators, i.e. they program and outfit industrial robots in order to sell them to other firms. We identify robot integrators using a list of six-digit industry codes provided by Humlum (2021), and exclude them from the analysis. As an alternative, we exclude municipalities that are home to robot integrators or distributors in a robustness check in Section 4.2.

While these steps allow us to limit the number of false positives, our measure still suffers from the issue of false negatives. Our data may include firms that do not directly import robots but purchase them from domestic integrators or distributors. To assess the extent of these measurement errors, we validate our adoption measure by relying on a survey on firms' robot use, which was conducted in 2018 and subsequent years for a subset of Danish firms (see Appendix Section A.3 for further details). Comparing imports and survey data, we notice that instances of false positives are mainly prevalent among small firms. This is another reason why we exclude firms with fewer than 50 employees from our analysis. In Section 4.2 we also show a robustness check using only import data that are validated by the survey. To further attenuate measurement errors, we keep only firms that are active for at least 12 years during our sample period. This is particularly relevant when we focus on first-time robot adopters in a robustness check.[9] Appendix Table A1 provides an overview of the number of observations that we lose in every step and the final number of observations.

In our final data set, the number of robot imports per year grows from 112 in 1995 to 471 in 2019, which is an increase by 320%. The share of robot users also increases strongly over time, from 6% in 1995 to 20% in 2019.[10] The average value of purchased robots is about 870,000 Danish kroner and has slightly decreased over time. Roughly 50% of robots get imported by the manufacturing

[7]See Appendix Figure A.1. The same classification is used e.g. by Humlum (2021) and Acemoglu and Restrepo (2022). Our regression results are robust to using a narrower definition relying only on HS code 847950, see Section 4.2.

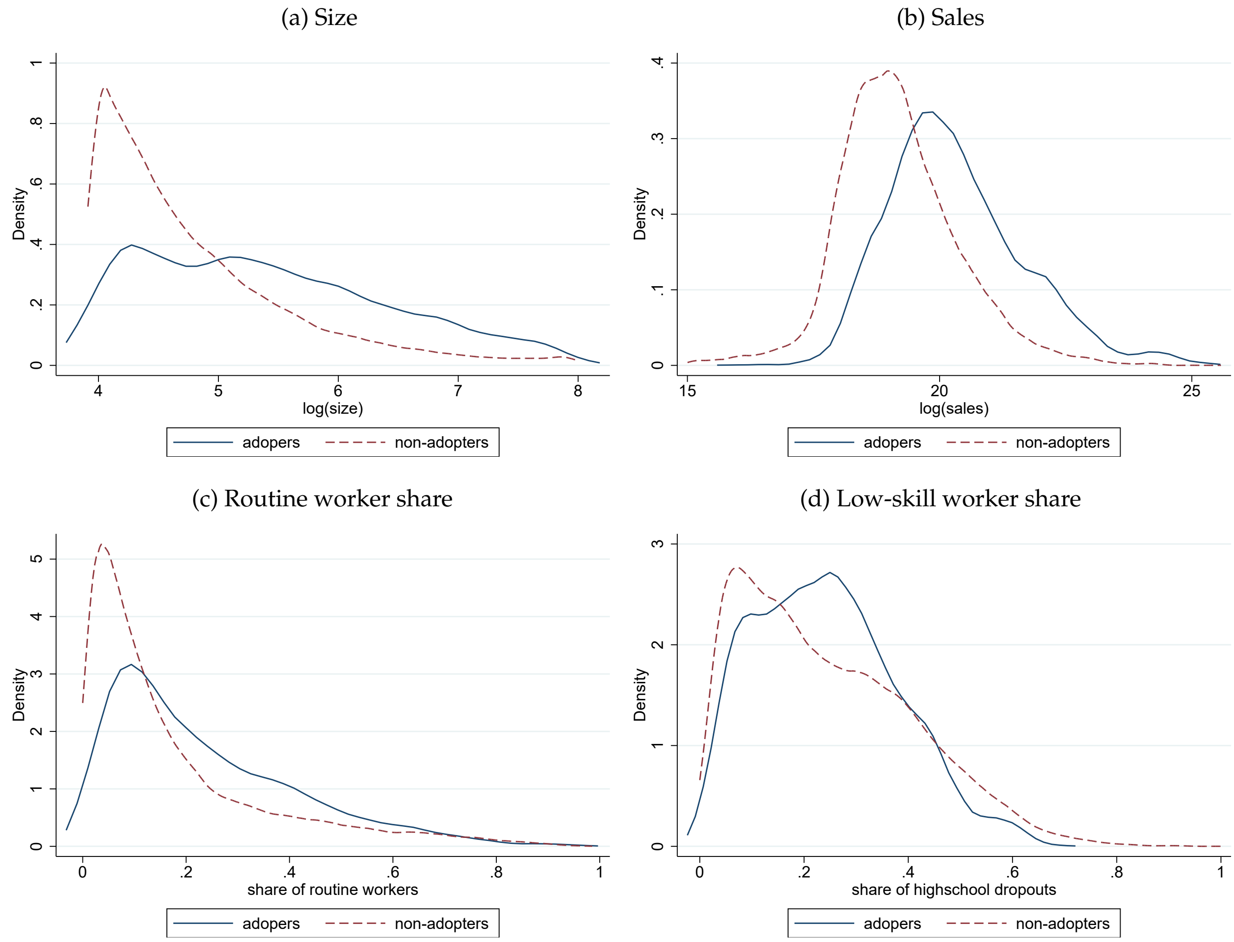
[8]Industries codes: 466100, 466200, 466300, 466400, 466900.

[9]The IFR assumes that robots fully depreciate after 12 years.

[10]Be mindful that the number for 1995 is a lower bound as we do not observe robot imports before 1995.

sector. This is also the sector in which the share of robot-using firms is the largest, at 33%. Only around 5% of firms use robots in the service sector according to our definition. In contrast to other studies, such as Humlum (2021), we do not find that robot investment is lumpy. Roughly two thirds of robot adopters import robots during several years.[11]

Figure 1: Density plots for robot adopters vs. non-adopters



Note: Size is the (log of the) number of full-time equivalent workers, sales is the (log of the) kroner value of sales (in constant 2015 units). Routine workers are defined following Autor and Dorn (2013) and Mihaylov and Tijdens (2019). Low-skill workers are workers without high-school degree. For the sake of clarity of exposition, we show only $\ln(size) \in [4, 8], \ln(sales) > 15$.

Figure 1 shows that in the year before robot adoption, adopters are larger and have higher sales than non-adopters. They also differ in the composition of their workforce: adopters tend to employ more workers at routine-intensive tasks and have a larger share of low-skill workers.

2.3 Immigration

Our main immigration measure is the share of non-Western migrant workers in the total number of workers in a municipality.[12] As discussed in Olney and Pozzoli (2021), three historical features

[11]This was also confirmed in our interviews with robot distributors. Firms often start by automatizing a minor part of their work processes and if successful, subsequently implement automation on a broader scale.

[12]Non-Western immigration includes foreign workers from all countries outside the EU15 (the EU member states prior to Eastern enlargement), North America, Oceania and Japan. In a robustness check, we focus exclusively on refugees

Table 1: Descriptive Statistics of Natives and Immigrants

	Whole sample					
Variables	**Employed natives**		**Non western employed immigrants**		**Western immigrants**	
	Mean	*S.d.*	*Mean*	*S.d.*	*Mean*	*S.d.*
Age	40.36	11.49	35.12	11.91	43.41	12.18
Low-skill share	0.22	0.43	0.36	0.48	0.12	0.33
Hourly wages (real)	219.38	134	185.79	97.90	243.33	185.3
Work experience (years)	18.04	11.82	7.02	7.24	12.54	10.40
Managers and middle manager share	0.16	0.35	0.05	0.22	0.18	0.37
Blue collar share	0.84	0.91	0.95	0.62	0.82	0.87
Routine manual score	0.05	0.18	0.09	0.24	0.04	0.16
Routine cognitive score	0.11	0.23	0.15	0.21	0.10	0.21
N	42,200,839		2,006,956		765,557	
	Municipalities with below average automation rates					
Variables	**Employed natives**		**Non western employed immigrants**		**Western immigrants**	
	Mean	*S.d.*	*Mean*	*S.d.*	*Mean*	*S.d.*
Age	37.91	12.89	33.35	11.23	42.79	11.50
Low-skill share	0.33	0.47	0.41	0.49	0.16	0.37
Hourly wages (real)	218.88	101.89	192.29	76.16	239.42	130.17
Work experience (years)	17.68	9.57	6.59	7.39	12.88	10.19
Manager and middle manager share	0.29	0.44	0.12	0.33	0.36	0.47
Blue collar share	0.71	0.45	0.88	0.61	0.64	0.76
Routine manual score	0.08	0.23	0.15	0.30	0.07	0.21
Routine cognitive score	0.12	0.26	0.16	0.23	0.12	0.24
N	3,453,476		176,327		51,712	

Notes: All descriptive statistics are calculated as averages over the period 1995-2019 for the whole workforce. The manual and cognitive routine scores are calculated as in Mihaylov and Tijdens (2019) following Autor and Dorn (2013). A higher value means a higher share of routine manual (cognitive) job tasks. The low-skill share is the share of workers without completed secondary education.

of Danish immigration make migrant workers an appealing segment of the workforce to study.

First, their share increased from about 1.5% in 1995 to almost 8% in 2019 (compared to a stable share of Western migrants), providing a unique opportunity to examine the economic implications of immigration. This increase was largely driven by exogenous factors, such as political unrest in Yugoslavia and some African countries in the 1990s and by European Union enlargement in the 2000s. Refugees and new-EU immigrants account for the majority of the growth in immigration (see Figure A.2).

Second, since robots tend to replace workers who perform routine, low-skilled tasks, firm-level automation decisions may be particularly responsive to non-Western immigration. Demographic characteristics reported in Table 1 show that non-Western immigrant workers are on average younger (and with less work experience), have less education and are paid a lower wage, and are more likely to in work blue-collar jobs compared to natives and Western immigrants. Non-Western migrants are also more likely to be employed in occupations that are intensive in both manual and cognitive routine tasks. Furthermore, non-Western migrant workers in municipalities with below average automation rates tend to have even fewer skills compared to natives and Western migrants and to be employed in even more routine intensive occupations as reported in the second panel of Table 1.

Third, the Spatial Dispersal Policy, in place between 1986 and 1998, assigned refugees quasi-randomly to municipalities within Denmark, thus providing an appealing natural experiment

and Eastern European immigrants.

(Damm, 2009; Damm and Dustmann, 2014). The aim of the policy was to allocate refugees more evenly across the country and to create, when possible, enclaves of immigrants of the same nationality. Importantly, the allocation was not influenced by the skill level of the immigrant, their geographic preferences, or the economic conditions of the Danish municipality. Thus, the Spatial Dispersal Policy generates variation in immigration across municipalities that is independent of local economic conditions. Furthermore, even after 1998, both via official family reunification policies and informal networks, subsequent waves of immigrants often settled in municipalities to which their countrymen were initially allocated (Foged and Peri, 2015).

Figure 2 shows the percent change in municipalities' non-Western immigrant share over our sample period. These is substantial variation across regions. Importantly, it is not the case that immigration increased more rapidly in urban areas, like Copenhagen, which would be concerning if automation was also more common in these municipalities for unrelated reasons.[13] The historical features of Danish immigration, including both the exogenous 'push factors' and this quasi-random geographic variation, represent a unique opportunity to examine the causal impact of immigration on firm-level automation decisions. Our subsequent instrumental variable approach more carefully isolates these useful sources of variation in the data.

By measuring the immigrant share across municipalities rather than at the firm level, we exploit the exogeneity of the Spatial Dispersal Policy and avoid the potential endogeneity of hiring decisions of firms. Both the time-series variation and the geographic variation in immigration will be useful for our empirical analysis.

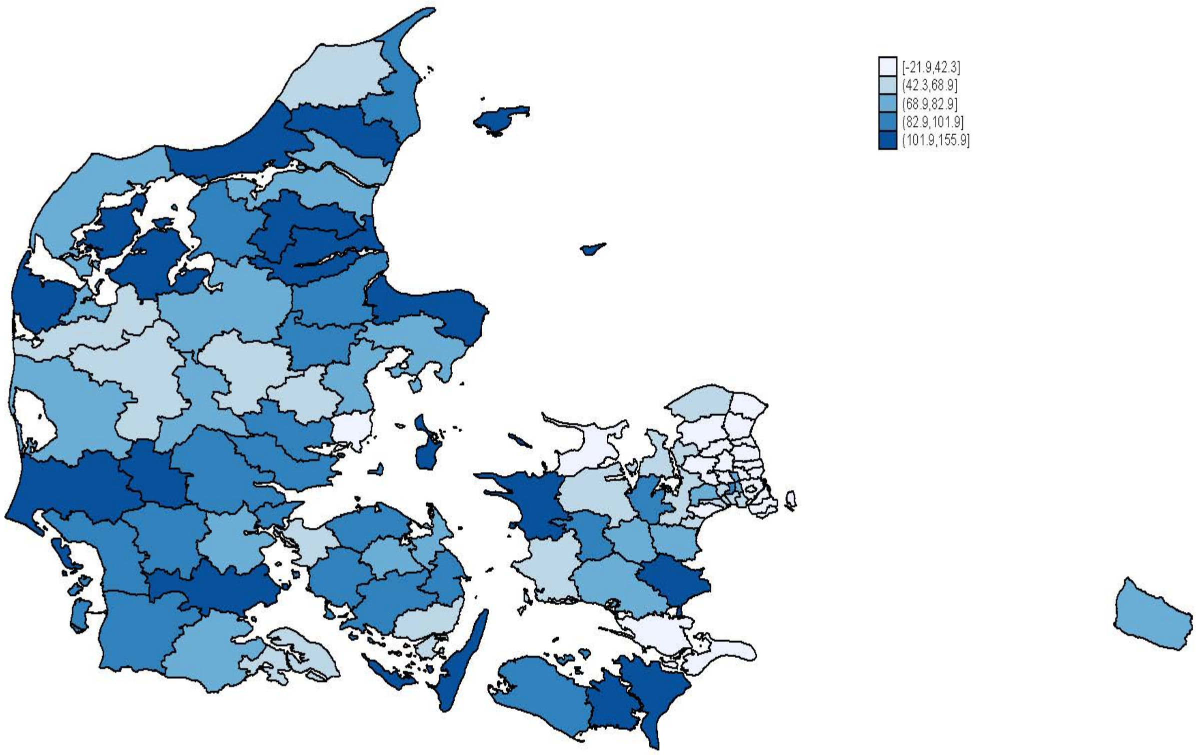
To provide preliminary insight into the relationship of interest, we plot in Figure 3 the share of non-Western immigrants against municipality adoption of robots at both the extensive margin (panel (a)) and intensive margin (panel (b)) after accounting for year fixed effects. A statistically significant negative relationship is evident. Consistent with the predictions from the labor supply effect, an increase in the share of non-Western immigrants is associated with a decline in the likelihood that a firm adopts a robot and the value of imported robots. It is interesting that significant negative relationships emerge in such raw cuts of the data. We examine whether these relationships hold in a more rigorous empirical specification in the next section.

2.4 Other variables

Descriptive statistics of the rest of the firm variables in the final dataset over the period 1995-2019 are presented in Table A2. Given the detailed employer-employee data set we are able to account for many relevant workforce and firm characteristics. Specifically, we include the firm-level share of females, college-educated and foreign workers as well as the share of workers employed in occupations that are intensive in routine tasks. As reported in Table A2, workers are on average 40% female, 6% foreigner and 18% employed in routine jobs. They have on average 18 years of work experience (measured as the number of years in the Danish labor market) and are on average 40 years old. We also account for a variety of firm characteristics, such as sales, size, multi-establishment status, and exporter status. Table A2 shows that the firms in our sample are

[13] Appendix Figure A.3 shows that this also holds when considering only Eastern European immigrants, who are less restricted in their choice of location than refugees.

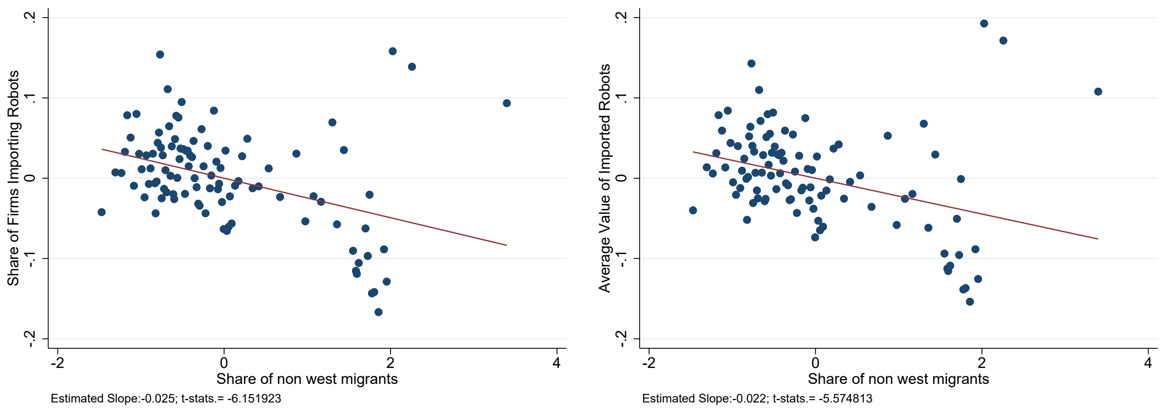
Figure 2: Percent Change (1995 to 2019) in the Share of Non-Western Immigrants by Municipality



Notes: Share of non-Western migrant workers calculated using data from the Danish Integrated Database for Labor Market Research.

Figure 3: Robot Adoption and Share of Non-Western Migrant Workers

(a) Extensive margin (b) Intensive margin



Notes: Vertical axes: residuals from regressing the share of firms that import robots on year dummies (left panel) and residuals from regressing the log of value of imported robots on year dummies (right panel). The residuals from regressing the share of non-Western migrant workers on year dummies is reported on the horizontal axis.

relatively big given our decision to work with firms with more than 50 employees. They in fact employ on average 130 workers and are 95% multi-establishment companies. Most of them are exporters and their average sales are 4 million Danish kroner.

3 Empirical Strategy

This sections outlines our main estimation approach and identification strategy. It also presents a number of tests performed in order to assess the validity of our strategy.

3.1 Specification

Our goal is to examine how a firm's decision to adopt a robot is impacted by the share of non-Western immigrants within the municipality. We estimate the following equation:

$$Robot_{ijmt} = \beta_0 + \beta_1 Img_{mt}^{non-west} + X'_{ijmt}\delta_1 + W'_{ijmt}\delta_2 + \gamma_i + \gamma_j + \gamma_t + \epsilon_{ijmt} \quad (1)$$

where the dependent variable, $Robot_{ijmt}$, is robot adoption at firm i, in industry j, located in municipality m, and in year t. Our analysis initially focuses on robot adoption based on the firms' imports at both the extensive and intensive margin, and then uses a variety of other measures of robot adoption in the robustness checks section.

Our key independent variable $Img_{mt}^{non-west}$ is the non-Western immigrant share of the workforce in municipality m and year t, $Img_{mt}^{non-west} = F_{mt}^{non-west} / P_{mt}$, where $F_{mt}^{non-west}$ is the stock of immigrant workers of non-Western origin and P_{mt} is total employment in municipality m and year t.[14] If low-skill migrant workers and robots are substitutes, we should see $\beta_1 < 0$.

The vectors X_{ijmt} and W_{ijmt} contain the firm and workforce characteristics that were described in the previous section. Since some of them could be endogenous, we report findings with and without these controls.[15] We incorporate a comprehensive set of fixed effects including firm fixed effects (γ_i), 2-digit industry fixed effects (γ_j) and year fixed effects (γ_t). Finally, the standard errors are clustered at the municipality level.

3.2 Identification

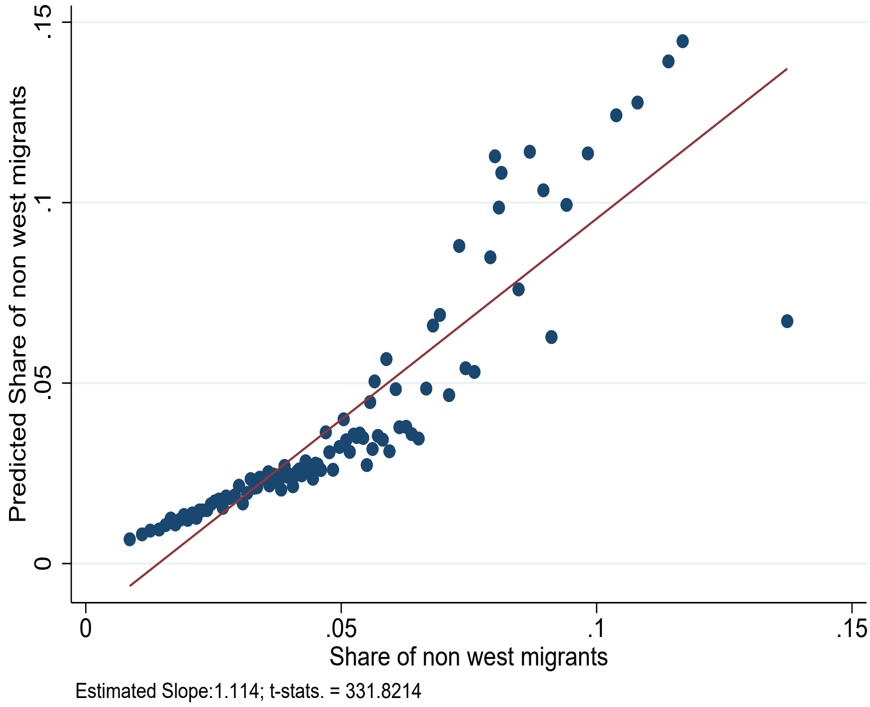
Unobserved municipality-specific shocks could be correlated with both immigration and robot adoption. For instance, municipalities that host many successful firms that can afford to invest in automation technologies may at the same time experience an influx of immigrants. While this type of endogeneity would introduce a positive bias and attenuate the anticipated negative immigration coefficient, we nevertheless pursue an instrumental variable approach addressing endogeneity concerns.

As discussed above, the Danish Spatial Dispersion Policy provides a natural experiment that allows us to isolate plausibly exogenous variation in immigration, and in this way identify the causal effect of immigration on firm-level automation. The instrument takes advantage of the

[14] Our results are similar if we lag the independent variable by one, two and three years or assume a non-linear impact of immigration on robot adoption (see Section 4.4).

[15] As detailed in Appendix A.3, there is reason to assume that the coefficients on these variables – but not the coefficient on the immigrant share – will be biased. Therefore we do not report the coefficient estimates.

Figure 4: Immigration and the Immigration Instrument



Notes: The share of non-Western migrant workers in a given municipality and year is reported on the vertical axis. The predicted share (IV) of non-Western migrant workers in a given municipality and year is reported on the horizontal axis.

fact that foreign political shocks led to an exogenous increase in the number of non-Western immigrants arriving in Denmark in each year. The instrument then allocates these immigrants to municipalities where previous immigrants from the same country lived in 1993, when immigrant location decisions were often determined by the Spatial Dispersal Policy.[16] More specifically, the predicted non-Western immigrant share is calculated as follows:

$$ImgIV_{mt}^{non-west} = \sum_{d} \frac{F_{dt} * (F_{md93}/F_{d93})}{P_{m93}} \tag{2}$$

where F_{dt} is the national stock of migrant workers from a non-Western country d in year t. These immigrants are allocated to municipalities based on the share of migrants from country d in year 1993 (i.e., F_{md93}/F_{d93}). This product is then normalized by total employment in the municipality in 1993 (P_{m93}) and summed across all foreign countries d to generate predicted immigration at the municipality-year level.

To assess the strength of our instrument, Figure 4 plots the actual share of non-Western immigrants within a municipality against predicted immigration. A significant positive relationship is evident

[16]The dispersal policy did not apply to all immigrants but only to refugees; refugees comprised 30% of non-Western immigrants in 1993. However, for our identification strategy the more important point is that this initial distribution was random and the subsequent growth in refugees was sizable. Immigrant location decisions that were determined by this program are more exogenous than is typically assumed by the common 'shift share' instrument.

Table 2: Pre-Sample Trends and Long-Run Changes in Automation

	Δ robot users (broad)	Δ imports	Δ exports	Δ capital stock
	(1)	(2)	(3)	(4)
Δ Non West Img IV (in sample)	0.446	0.288	-0.283	-0.378
	(0.717)	(0.296)	(0.518)	(0.255)
N	97	97	97	97
R-sq	0.361	0.150	0.059	0.262

Notes: In column 1 the dependent variable is the pre-sample trend (i.e. the change from 1993 to 1995) in the share of firms that use robots according to our main definition. In column 2, 3 and 4 the dependent variable is the pre-sample trend (i.e. the change from 1993 to 1995) in respectively the average levels of imports, exports and capital stock. The explanatory variable in all regressions is the long-run change (1995 to 2019) in the immigration instrument. Regressions also include the following firms' average characteristics at the municipality in 1993: value-added, workers' education, workers' work experience, workers' age and share of female workers, managers, middle managers and part-time workers. Regressions are weighted by the local labor force in 1993. Robust standard errors in parentheses. Significance levels: ***1%, **5%, *10%.

which verifies that our instrument is correlated with immigration within a municipality. This provides preliminary visual confirmation of the standard first-stage IV results reported later.

The common threats to this 'shift share' instrumental variable approach (Goldsmith-Pinkham et al., 2020) are less relevant in the Danish context. First, typically there are concerns that the national stock of immigrants from country d, F_{dt}, could be driven by domestic conditions that are endogenous. However, in Denmark the large inflow of non-Western immigrants during this period was largely driven by instability and policy changes in foreign countries (Olney and Pozzoli, 2021). Second, there are often concerns that the initial distribution of immigrants across municipalities in the pre-sample year could have been driven by endogenous economic conditions that have persisted over time. In Table 2 we find that long-run changes in our immigration instrument are uncorrelated with pre-sample trends in robot adoption within a municipality. In particular, the change in the instrument from 1995 to 2019 is unrelated to the pre-1995 trend in the share of robot users. We find that long-run changes in our immigration instrument are also uncorrelated with pre-sample trends in other economic conditions within the municipality such as imports (column 3), exports (column 4) and capital stocks (column 5), consistent with the stated goals of the Spatial Dispersal Policy.

4 Empirical Results

This section presents our findings on the labor supply effect on robot adoption. First, we examine whether an influx of non-Western migrants decreases the likelihood that firms import robots (i.e. the extensive margin). Second, we focus on whether immigration decreases the value of robot imports, conditional on the firm importing a robot (i.e. the intensive margin). Then, we explore the sensitivity of the main results by using alternative definitions of robot adoption and immigration. We also test the robustness of our main results by estimating the impact of immigration for specific sub-samples and by using alternative specifications and econometric approaches. We conclude this section by providing empirical evidence of the economic mechanisms behind our main results.

4.1 Main Results

Table 3 presents our main results. We start off by estimating the impact of non-Western immigration on robot adoption with a parsimonious specification of equation (1), in which we control for only firm, industry and year fixed effects (column 1). This simple specification shows that the share of non-Western immigration is negatively related to the probability that a firm within that municipality imports at least one robot. The estimated coefficient of -0.2 implies that a one percentage point increase in our share variable is associated with a 0.002 decrease in the probability of robot adoption, which corresponds to approximately a 5% decline.[17]

Columns 2 and 3 add respectively workforce characteristics and firm characteristics. The coefficients estimated on the share of non-Western migrant workers is fairly similar to the one reported in column 1 (i.e. -0.23 in both columns 2 and 3).

We proceed in column 4 with our instrumental variable approach to overcome endogeneity concerns. The results from the first stage are reported at the bottom of column 4. The F-statistic well above 10 shows that the instrument is strongly related to our endogenous variable, confirming our earlier results reported in Figure 4. In the second stage we find that non-Western immigration has a negative causal impact on the probability of robot adoption. Specifically, a one percentage point increase in the share of non-Western migrant workers triggers a 0.003 decline in the probability that a firm within that municipality imports at least one robot. This estimate corresponds to a 7% decline, which is around 40 percent larger than the non-instrumented coefficient. This is consistent with a spurious positive bias in the OLS estimations discussed in the previous section. When addressing this endogeneity issue, the causal impact of non-Western immigration on robot adoption is therefore more negative.[18]

In the second panel of Table 3, we examine the impact of immigration on the intensive margin of robot adoption. Columns 5, 6, 7 and 8 use as the dependent variable the logarithm of robot import values (in 2015 Danish kroner), conditional on adoption over the sample period. In column 5 we find that an increase in the share of non-Western immigrants in a municipality significantly reduces the values of robot imports, after accounting for only industry and year fixed effects. Columns 6-7 sequentially include firm fixed effects, firm characteristics, and workforce characteristics. In all of these specifications, the results show that immigration significantly reduces the intensive margin of robot adoption. While the numerous controls and fixed effects reduce endogeneity concerns, they do not eliminate them entirely and thus we now turn to our instrumental variable approach in Column 8. The IV results show that immigration has a significant negative impact on the intensive margin. An increase in immigration by one percentage point decreases the intensive margin of robot adoption by 15 percent. The immigration coefficient in the IV specification (column 8) is larger than the analogous OLS coefficient (column 7), which is again consistent with a spurious positive bias in the OLS coefficient. Once this source of endogeneity is accounted

[17] The immigration variable is a share variable between 0 and 1. We therefore interpret the coefficient of 0.2 as a 0.002 decrease, which corresponds to a 5% decline relative to the mean of the dependent variables (0.041) reported at the bottom of Table 3.

[18] Additional results available upon request from the authors show that firms localized in a municipality with a large influx of migrant workers indeed hire them. Specifically, a one percentage point increase in our share variable is correlated with a 0.001 increase in the share of non-Western migrant worker at the firm level, which corresponds to approximately a 2.3% increase.

Table 3: Immigration and Robot Adoption

	Robot Adoption (extensive)			
	OLS (1)	**OLS (2)**	**OLS (3)**	**IV (4)**
Non West Immigrant Share_t	-0.213***	-0.230***	-0.227***	-0.291**
	(0.071)	(0.069)	(0.066)	(0.114)
Industry and Year Fixed Effects	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes
Workforce Variables	no	yes	yes	yes
Firm Variables	no	no	yes	yes
Mean Y	0.041	0.041	0.042	0.042
First Stage F-stat on Instrument	.	.	.	156.87
First Stage- Non-west Img IV Coeff.	.	.	.	0.403*** (0.032)
R-sq	0.401	0.402	0.403	0.002
N	61,257	61,257	61,257	61,257
	Robot Adoption (intensive)			
	OLS (5)	**OLS (6)**	**OLS (7)**	**IV (8)**
Non West Immigrant Share_t	-11.107**	-13.578***	-13.201***	-14.500*
	(4.283)	(4.352)	(4.106)	(7.555)
Industry and Year Fixed Effects	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes
Workforce Variables	no	yes	yes	yes
Firm Variables	no	no	yes	yes
Mean Y	2.330	2.330	2.335	2.335
First Stage F-stat on Instrument	.	.	.	111.03
First Stage- Non-west Img IV Coeff.	.	.	.	0.426*** (0.040)
R-sq	0.315	0.319	0.324	0.013
N	12,397	12,397	12,351	12,351

Notes: In the first panel, the dependent variable is a binary variable indicating whether the firm adopts at least one robot in year *t* according to our main definition. In the second panel, the dependent variable is log of robot import values in year *t* according to our main definition conditional on robot adoption. The non west immigrant share is the share of non western foreign workers within the municipality in year *t*. Workforce composition variables include the share of female, college and foreign workers, the share of workers employed in routine intensive occupations and workers' average work experience and age. Firm variables include firm-level log of sales, whether the firm exports, as well as the firm size a multi-establishment dummy. Robust standard errors clustered at the municipality level in parentheses. Significance levels: ***1%, **5%, *10%.

for with our instrumental variable approach, we find a more negative impact of immigration on robot adoption.

Overall, Table 3 confirms that immigration has a significant negative impact on robot adoption along the extensive and intensive margin. These findings indicate that firms located in municipalities that experience an exogenous influx of foreign workers have fewer incentives to automize their production processes. As shown in Table 1, non-Western immigrants are often low-skilled workers who perform routine tasks, which are more prone to be replaced by robots. Immigration and robot adoption can thus be considered substitutes. In the next sub-section we explore the robustness of the main results to a number of refinements and tests before providing an explicit support of the substitution hypothesis.

4.2 Robustness Checks of the Robot Adoption Measure

In Table 4, we test the robustness of our IV results with respect to alternative ways of measuring robot adoption. For sake of brevity and given that the results obtained on the intensive margin are very similar, we focus on the extensive margin. In column 1, we construct the dependent variable by including only imports of industrial robots narrowly defined by HS code 847950. Naturally, the effect is smaller than in the baseline regressions as we are measuring a subset of automation technology, but it is still negative and significant.

In column 2, we identify cases of robot adoption by alternatively looking at workers' occupation. The International Standard Classification of Occupations ISCO-88 (Danish version DISCO-88) contains two occupational codes related to robots: i) Automated assembly line operators (3123) and ii) Industrial robot operators (8170). We can interpret the share of workers in one of these occupations as a proxy for robot adoption. However, there are two caveats to using this measure. First, the set of robot-using firms is much narrower according to this measure than according to any of our other measures, which suggests that some robot adopters do not employ specific robot operators. Second, the two codes disappear in a reclassification of occupations in 2009 (DISCO-08), which implies that we can run the analysis using these occupational categories only up until 2009. Still, we find a negative and significant coefficient. A one percentage point increase in the share of non-Western migrant workers induces a 17.5 % decrease in the share of workers employed in automation-related occupations.

In column 3, we measure the dependent variable by focusing exclusively on cases of robot adoption which are validated in the VITA survey (see Appendix Section A.3 for details). For the purpose of this robustness check, we only use true positives (firms that import robots according to the trade register and report in the survey that they use robots) and true negatives (non-importers that report not using robots).[19] The survey covers the years 2017-2019, which implies that the sample size shrinks to about 3,000 observations. Nevertheless, the coefficient is negative and significant and even slightly larger than in the baseline regressions. Specifically, a one percentage point increase in the share of non-Western migrant workers triggers a decrease of approximately 8% in the probability that a firm within that municipality adopts at least one robot in a given year.

[19]Since VITA does not include information on the year of robot adoption, we cannot construct an adoption variable solely using the survey.

It has been shown (Graetz and Michaels, 2018; Bonfiglioli et al., 2020; Koch et al., 2021) that certain firm characteristics like size and sales respond endogenously to robot adoption, which is why it is common in the literature on the effects of robot adoption to focus on first-time adopters. While this should be less of a concern in the case of (exogenous) migrant population, it is possible that e.g. native workers reallocate in response to robots being installed at their workplace. In column 4, we therefore focus on first-time adopters among robot importers. With the caveat that this variable may be right censored for firms that existed and adopted their first robot before 1995[20], we can use this alternative definition to study the relationship between migration and first adoption observed in the sample period. According to our instrumented coefficient, a one percentage point increase in the share of non-Western migrant workers triggers a 0.002 decline in the probability that a firm within that municipality imports the first robot over the sample period. This translates into a 2% decline in the probability of first adoption. The coefficient is smaller than the one reported in Table 3, column (4), which suggests that while this margin is relevant, an important part of the adjustment to a positive labor supply shock goes through existing robot users scaling up their technology by less.

In column 5 we re-run our estimation on the extensive margin using the main definition of robot adoption but dropping firms that are located in the postal codes where robot integrators and distributors operate.[21] This is done in order to exclude companies that are involved in the production and the installation of robots. The results are fairly similar to the ones obtained in the baseline sample.

Finally, column 6 represents a placebo test, in which we estimate the impact of immigration on the total capital stock, measured as the log of total fixed assets in a given year. According to the hypothesis put forward in this paper, human workers are substitutable to robots because robots are able to carry out the same tasks as (low-skill) human workers. The same argument should not apply to non-automated capital such as other types of equipment or structures. Therefore, this regression serves as a test of the substitutability hypothesis. Indeed, we do not find a significant effect of immigration on the overall capital stock.

[20] Robot adoption before 1995 was, however, very low. For example, the IFR reports that in total, only 35 robots were adopted in Denmark in 1993.

[21] We obtained the complete list of robot integrators and distributors through an internet search and by looking at the list of exhibitors at the most important fair on robotics held in Denmark (Automatik).

Table 4: Immigration and Robot Adoption, Using Alternate Adoption Variables

	Robot Adoption	Robot Adoption	Robot Adoption	Robot Adoption	Robot Adoption	Capital Stock
	narrow definition	**occupation based def.**	**VITA validation**	**first-time adopters**	**excl. integrator locations**	**log of total fixed assets**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Non-West Immigrant Share_t	-0.038*	-0.007*	-0.437**	-0.159***	-0.243**	-2.852
	(0.022)	(0.004)	(0.186)	(0.048)	(0.110)	(1.813)
Industry and Year Fixed Effects	yes	yes	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	no	yes	yes	yes
Workforce Variables	yes	yes	yes	yes	yes	yes
Firm Variables	yes	yes	yes	yes	yes	yes
Mean Y	0.004	0.0004	0.053	0.111	0.039	17.437
First Stage F-stat on Instrument	153.87	162.18	88.85	173.29	240.36	124.96
First Stage- Non-west Img IV Coeff.	0.402*** (0.032)	0.450*** (0.035)	0.416*** (0.044)	0.402*** (0.031)	0.406*** (0.026)	0.414*** (0.037)
R-sq	0.000	0.002	0.04	0.001	0.002	0.099
N	61,257	31,852	2,982	46,421	50,716	44,696

Notes: In column 1, the dependent variable is a binary variable indicating whether the firm adopts at least one robot in year t according to our narrow definition that excludes the product code Machines and mechanical appliances having individual functions (847989). In column 2, the dependent variable is the share of workers employed in the occupational codes Automated assembly line (3123) and Industrial-robot Operators (8170). In column 3, the dependent variable is defined using the VITA survey (2017-2019) and in which we only include cases of robot adoption validated in the survey. In column 4, the dependent variable is based on our main definition of robot adoption and the sample includes only first-time adopters over the sample period among robot importers. In column 5, the dependent variable is a binary variable indicating whether the firm adopts at least one robot in year t according to our main definition and we exclude postal codes in which robot distributors and integrators are located. In column 6, the dependent variable is the log of total fixed assets.The non-West immigrant share is the share of non-Western foreign workers within the municipality in year t. Workforce composition variables include the share of female, college and foreign workers, the share of workers employed in routine intensive occupations and workers' average work experience and age. Firm variables include firm-level log of sales, whether the firm exports, as well as the firm size a multi-establishment dummy. Robust standard errors clustered at the municipality level in parentheses. Significance levels: ***1%, **5%, *10%.

4.3 Robustness Checks of the Immigration Measure

For the reasons discussed in the previous section, our baseline analysis has focused on non-Western immigration. This section examines whether our results are sensitive to using other definitions of the immigrant share. In column 1 of Table 5 we use as our key independent variable the share of non-Western immigrants at core working age (ages 25-55) and instrument this using predicted immigration of working-age workers. In this way, we exclude workers who are either in schooling or at retirement age and concentrate on a segment of immigration population that is employed on a more stable basis. However, note that this measure is potentially more endogenous to the hiring and consequently adoption decisions at the firm-level than the one used in the main analysis because it includes only employed immigrants with a strong attachment to the labor market. The results, including both the first-stage and second-stage results, are similar to the baseline findings from Table 3.

The remaining specifications focus on even narrower immigrant groups. First, we examine how Danish firms respond to low-skilled immigration, defined as immigrants without secondary education. Second, we concentrate on migrant workers employed in occupations strictly related to production activities by using the classification developed in Bernard et al. (2017). We see in columns 2 and 3 that exogenous inflows of either low-skilled or production workers significantly reduce the likelihood that Danish firms within that municipality adopt at least one robot. These refinements allow us to corroborate the interpretation of the negative coefficient as indicative of a substitution relation between immigration and automation, given that it is especially low-skilled and production workers that are substitutable by robots. In fact, when we construct our immigration variable by focusing on Western migrant workers the coefficient becomes insignificant, as this type of immigration often mainly includes highly skilled and non-production workers which are complements and not substitutes to robots (see Table 1). Note that we do not instrument the share of Western migrant workers because the first stage is not precisely estimated given that our instrument has a strong predictive power only for the share of non-Western migrant workers. In column 5, we look exclusively at immigrants from either the mid-1990 refugee countries or the ten Eastern European countries that joined the EU in 2004 and 2007, respectively.[22] This more carefully identifies foreign workers that immigrated to Denmark due to plausibly exogenous home country shocks, however it narrows the set of immigrants within the municipality that potentially could influence a firm's robot adoption. The numbers reported in column 5 confirm that the results are unchanged when this alternative definition of immigration is used. In the last column of Table 5, we use the average share of non-Western migrants over the period between 1993 and 1999 as the base in order to construct our instrumental variable. This is done in order to cover several and more recent years in order to determine the spatial distribution of migrants across municipalities. We then estimate our main regression for the extensive margin for the period between 2000 and 2019. The IV coefficient obtained using this alternative IV approach is almost identical to the one reported in the main analysis.

[22]We follow the same refugee classification as Foged and Peri (2015) and the ten new EU countries are again Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, the Slovak Republic and Slovenia, as well as Cyprus and Malta.

Table 5: Immigration and Robot Adoption, Using Alternate Immigration Variables

	Robot Adoption (extensive)					
	(1)	(2)	(3)	(4)	(5)	(6)
Non-West Immigrant Share_t (only working age pop.)	-0.299**					
	(0.146)					
Non-West Immigrant Share_t (only low-skilled)		-0.107**				
		(0.044)				
Non-West Immigrant Share_t (only production)			-0.245**			
			(0.101)			
West Immigrant Share_t				-0.025		
				(0.060)		
Refugee and Eastern EU Immigrant Share_t					-1.010**	
					(0.442)	
Non-West Immigrant Share_t						-0.242**
						(0.098)
Industry and Year Fixed Effects	yes	yes	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes	yes	yes
Workforce Variables	yes	yes	yes	yes	yes	yes
Firm Variables	yes	yes	yes	yes	yes	yes
Mean Y	0.042	0.042	0.042	0.042	0.042	0.041
First Stage F-stat on Instrument	134.25	793.24	20.71	-	99.27	169.36
First Stage- Img IV Coeff.	0.375*** (0.032)	0.793*** (0.028)	0.611*** (0.134)	-	0.111*** (0.011)	0.400*** (0.031)
R-sq	0.002	0.002	0.002	0.002	0.002	0.002
N	61,257	61,257	61,257	61,257	61,257	54,967

Notes: The dependent variable is a binary variable indicating whether the firm adopts at least one robot in year t according to our main definition. In column 1, the endogenous explanatory variable is the share of non-Western immigrants in the age between 25 and 55 in the municipality at time t, while the instrument is the predicted share of non-Western immigrants in the same age group. In column 2 the endogenous explanatory variable is the share of non-Western low-skilled immigrants in the municipality at time t, while the instrument is the predicted share of non-Western low-skilled immigrants (where low-skilled immigrants are defined as those with less than a secondary education). In column 3 the endogenous explanatory variable is the share of non-Western immigrants employed in production in the municipality at time t, while the instrument is the predicted share of non-Western immigrants employed in production. In column 4 the endogenous explanatory variable is the share of Western immigrants in the municipality at time t, while the instrument is the predicted share of Western immigrants. In column 5 the endogenous explanatory variable is the share of refugee or new-EU immigrants in the municipality at time t, while the instrument is the predicted share of refugee and new-EU immigrants. In column 6 we only keep the sample period from 2000 through 2019 and the endogenous explanatory variable is the share of non-Western foreign workers within the municipality in year t, while the instrument is the predicted share calculated using the municipality share of non-Western foreign workers by country of origin averaged over the period from 1993 through 1999. Workforce composition variables include the share of female, college and foreign workers, the share of workers employed in routine intensive occupations and workers' average work experience. Firm variables include firm-level log of sales, whether the firm exports, as well as the firm size a multi-establishment dummy. Robust standard errors clustered at the municipality level in parentheses. Significance levels: ***1%, **5%, *10%.

4.4 Further Robustness Checks

We proceed the set of robustness checks and refinements in Table 6, in which we first assess whether our main results change if we include in the analysis firms with fewer than 50 employees. Column 1 shows that the estimated effect of immigration is slightly lower (around 4 percent) and imprecisely estimated. This is consistent with the fact that smaller firms tend to feature lower rates of robot adoption. We then explore the existence of non-linearities in the effects discussed so far by considering an additional specification in which we add the squares of the immigration variable. The results from this extension are reported in column 2 of Table 6 and show that the relationship between immigration and the probability of robot adoption is an inverted u-shaped one, i.e. the impact of immigration is negative only for values of the share of migrant workers exceeding 4 percent. In columns 3, 4 and 5 of Table 6, we look at whether our results change by lagging our variable of interest by one (column 3), two (column 4) and three (column 5) years as it may take time for companies to adjust robot adoption in response to changing economic conditions. The coefficients estimated on the first and third lags are negative, precisely estimated and in line with the baseline results reported in Table 3. In the last column we exclude from the main sample firms that moved from one municipality to another within Denmark. This refinement ensures that changes in the share of non-Western immigrants captures variation over time within the same municipality and does not reflect the possibility that the firm has relocated. We continue to estimate a negative coefficient on the immigrant share. However, the impact of immigration on robot adoption is now around four times as large as the one estimated in the main analysis.

To further check the importance of firms' lagged responses to the immigration shocks, we finally re-estimate equation (1) with a stacked specification by taking long differences of the dependent and explanatory variables over the following fixed reference years: 1995, 2000, 2005, 2010, 2015 and 2019. Given that this specification is less obvious with a dummy as a dependent variable, we replace it with the cumulative sum of robot imports in each point of time. This is equivalent to the change in a firm's stock of robots over a five-year period. The results of this alternative specification are reported in Table 7. Columns 1, 2, 3 report the estimated coefficient obtained with OLS in which we progressively include the whole battery of fixed effects, workforce variables and firm variables. Note that the firm fixed effects in the stacked specification are accounted for by taking the long difference. In the last column we instrument the long difference in the endogenous variable with the long difference in predicted immigration obtained from the shift-share approach. All of these columns show that immigration negatively affects robot adoption even in this long difference specification. Specifically, an increase of one percentage point in the share of non-Western migrant workers decrease the cumulative sum of the number of imported robots by 4 percent over a five-year period.

Table 6: Immigration and Robot Adoption, Additional Results

	Robot Adoption (extensive)					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Non-West Immigrant Share_t	-0.016*	1.001***				-1.586**
	(0.010)	(0.329)				(0.978)
(Non-West Immigrant Share_t)^2		-8.618***				
		(2.115)				
Non-West Immigrant Share_$t-1$			-0.243**			
			(0.126)			
Non-West Immigrant Share_$t-2$				-0.091		
				(0.122)		
Non-West Immigrant Share_$t-3$					-0.250***	
					(0.093)	
Industry and Year Fixed Effects	yes	yes	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes	yes	yes
Workforce Variables	yes	yes	yes	yes	yes	yes
Firm Variables	yes	yes	yes	yes	yes	yes
Mean Y	0.004	0.042	0.042	0.043	0.044	0.041
First Stage F-stat on Instrument	157.16	355.98; 166.76	196.74	214.91	222.71	60.53
First Stage- Non-west Img IV Coeff.	0.419*** (0.033)	0.679*** (0.047); 0.051*** (0.009)	0.407*** (0.029)	0.412*** (0.028)	0.418*** (0.028)	0.213*** (0.027)
R-sq	0.001	0.001	0.002	0.001	0.001	0.002
N	1,619,221	61,257	53,469	48,838	44,497	27,287

Notes: The dependent variable is a binary variable indicating whether the firm adopts at least one robot in year t according to our main definition. The non-West immigrant share$_t$ is the share of non-Western foreign workers within the municipality in year t. Workforce composition variables include the share of female college and foreign workers, the share of workers employed in routine intensive occupations and workers' average work experience and age. In column 1 we include firms with fewer than 50 employees in the estimation sample. Columns 2, 3, 4 and 5 includes our main sample, i.e. only firms with more than 50 employees. Column 6 excludes from the main sample firms that change their location at least once over the sample period. Firm variables include firm-level log of sales, whether the firm exports, as well as the firm size a multi-establishment dummy. Robust standard errors clustered at the municipality level in parentheses. Significance levels: ***1%, **5%, *10%.

Table 7: Immigration and Robot Adoption, Stacked Regressions

	Δ Cumulative Sum of Robot			
	OLS (1)	**OLS (2)**	**OLS (3)**	**IV (4)**
Δ Non West Immigrant Share	-3.845***	-3.897***	-3.117**	-3.441*
	(1.666)	(1.671)	(1.723)	(1.882)
Industry and Year Fixed Effects	yes	yes	yes	yes
Workforce Variables	no	yes	yes	yes
Firm Variables	no	no	yes	yes
Mean Y	0.510	0.510	0.530	0.530
First Stage F-stat on Instrument	.	.	.	301.82
First Stage- Non-West Img IV Coeff.	.	.	.	0.415*** (0.024)
R-sq	0.117	0.118	0.121	0.004
N	8,815	8,815	8,815	8,815

Notes: The dependent variable is the first difference in the cumulative sum of robot imports according to our main definition over the 5-year window. Δ Non-West Immigrant Share is first difference in the share of non-Western foreign workers within the municipality over the 5-year window. Workforce composition variables include the share of female and foreign workers, the share of workers employed in routine intensive occupations and workers' average work experience and age. Firm variables include firm-level log of sales, whether the firm exports, as well as the firm size a multi-establishment dummy. All control variables are taken in first difference over the 5-year window. Robust standard errors clustered at the municipality level in parentheses. Significance levels: ***1%, **5%, *10%.

4.5 Mechanisms

This section explores the mechanisms behind the observed negative relationship between immigration and robot adoption. If low-skilled workers and robots are substitutes, then a firm's decision whether to adopt a robot instead of employing a human worker will depend on relative factor prices (Zeira, 1998). The inflow of migrants should put downward pressure on wages, with the result that the cost advantage obtained from adopting robots gets smaller. Thus, fewer robots get installed.[23] To support this hypothesis, we examine first the impact of immigration on wages, before studying the relationship between the wage level and the value of imported robots.

Immigration of low-skilled workers could influence domestic labor costs in different ways. First, through an impact on equilibrium low-skill wages (Borjas, 2003). Column 1 of Table 8 examine this possibility by estimating the impact of non-Western immigration on the average wage of low-skilled workers. The results show that immigration reduces low-skilled workers' wages. Second, immigrants typically earn more than they did in their country of origin, but they may earn less than similarly qualified workers in their host country.[24] If so, an influx of immigrants can lower domestic labor costs and therefore reduce incentives for local firms to invest in robots. Consistent with this idea, column 2 shows that an exogenous influx of non-west immigrants decreases

[23]Dechêzlepretre et al. (2021) show that the same argument applies to automation innovation.

[24]The previous literature has shown that part of the migrant pay gap is not explained by differences in observable characteristics, such as education and work experience (Longhi et al., 2012). Employer discrimination against migrant workers due to factors such as prejudice or mistrust may account for part of this unexplained wage gap (Solé and Parella, 2003). Other possible reasons include differences in returns to foreign-acquired skills and education of migrant workers, as employers may not fully recognize these (Barrett et al., 2012), possibly due to the fact that skills recognition systems are not prevalent.

the average wage of non-Western workers in the municipality. To test this hypothesis more carefully, column 3 regresses individual log hourly wages on a binary variable indicating whether the worker is a non-Western immigrant. The results show that conditional on a variety of factors (including industry, occupation, firm, gender, age, and education) immigrants are paid 1% less than similar native workers.

In column 4, we then show that the average value of imported robots within a municipality is indeed positively correlated with immigrant workers' average wages.[25] This result corroborates the idea that when foreign workers' wages increase there are larger incentives for companies to import more robots and vice versa.

We finally replicate the analysis on wages for the sample period that precedes the large increase in robot adoption rates among Danish firms, i.e. the period from 1995 through 1999. The coefficients estimated on the share of non-Western immigrant workers are larger for all of the outcome variables at the municipality level (see second panel of Table 8). These findings allow us to dismiss the concern that the analysis reported in the first panel is driven by simultaneity issues and corroborate the notion that immigration tends to decrease wages even before the widespread adoption of automation technology.

[25]Additional results available on request show that also the share of firms that adopt robots is positively related to the immigrant workers' average wages and that both margins of adoption are also related to the average low-skilled wages.

Table 8: Immigration and Robot Adoption: Mechanisms

	Whole Sample			
	Avg. Low-Skill Wage (Mun.-Level)	Avg. Non-West Wage (Mun.-Level)	Log of Hourly Wage (Worker-Level)	Log of Robot Values (Mun.-Level)
	(1)	(2)	(3)	(4)
Non-West Immigrant Share	-1.846***	-2.241***		
	(0.324)	(0.464)		
Non-West Immigrant			-0.010***	
			(0.000)	
Non-West Immigrant Wage				0.065***
				(0.010)
Year Fixed Effects	yes	yes	yes	yes
Municipality Fixed Effects	yes	yes	no	yes
Industry, Firm, Occupation, and Gender Fixed Effects	no	no	yes	no
Age and Education Variables	no	no	yes	no
Mean Y	4.914	5.079	5.184	0.030
First Stage: F-stat on Instrument	15.37	15.37	.	15.38
First Stage: Non West Img IV Coeff.	0.089*** (0.023)	0.089*** (0.023)	.	0.089*** (0.023)
R-sq	0.868	0.854	0.580	0.511
N	2,352	2,352	48,228,116	2,352
	1995-1999			
	Avg. Low-Skill Wage (Mun.-Level)	Avg. Non-West Wage (Mun.-Level)	Log of Hourly Wage (Worker-Level)	
	(6)	(7)	(8)	
Non-West Immigrant Share	-3.387	-7.171		
	(3.261)	(5.999)		
Non-West Immigrant			-0.017***	
			(0.001)	
Year Fixed Effects	yes	yes	yes	
Municipality Fixed Effects	yes	yes	no	
Industry, Firm, Occupation, and Gender Fixed Effects	no	no	yes	
Age and Education Variables	no	no	yes	
Mean Y	4.785	4.933	5.184	
First Stage: F-stat on Instrument	15.38	15.37	.	
First Stage: Non-West Img IV Coeff.	0.089*** (0.023)	0.089*** (0.023)	.	
R-sq	0.938	0.764	0.582	
N	485	485	7,157,464	

Notes: In column 1 and 2 the dependent variable is the natural log of the average hourly wages respectively for low skill and non-Western workers at the municipality level at time t. In column 3, the dependent variable is the log of hourly wages at the worker level and the independent variable is a binary variable indicating whether the worker is a non western immigrant. In column (4), the dependent variable is the log of the value of total robot imports at the municipality level at time t. The first panel includes the results obtained using the whole sample period. The second panel includes the results obtained using the sample period from 1995 through 1999. Robust standard errors in parentheses in all columns and clustered at the worker level in columns 3 and 8. Significance levels: ***1%, **5%, *10%.

5 A Simple Model of Low-Skill Immigrants and Robots

In the following, we formalize the intuition behind our results in a partial equilibrium model. We keep the model as simple as possible to highlight the main mechanism. The model considers a local labor market as a small open economy. Interpreting the local labor market as a commuting zone (Moretti, 2011) implies that capital is mobile whereas labor is immobile. In the first step, we consider how the presence of immigrants affects low-skill wages and the skill premium in the absence of any robot technology. In the second step, we model the adoption of robot technology, which, mirroring the situation in Denmark, gets imported from abroad with an exogenous rate of return.

5.1 Model without robots

There is a large number of competitive firms that operate a Cobb-Douglas production technology with two types of tasks as input: high-skill (H) and low-skill (L),

$$Y = H^{\alpha} L^{1-\alpha} \tag{3}$$

where H and L are denoted in efficiency units and $\alpha \in (0, 1)$. Profit maximization leads to the first-order conditions

$$(1-\alpha)\left(\frac{H}{L}\right)^{\alpha} = w_L; \qquad \alpha\left(\frac{H}{L}\right)^{\alpha-1} = w_H. \tag{4}$$

Labor is supplied exogenously by two types of workers, immigrants and natives. Immigrants of size $\bar{L}$ can only perform low-skill tasks. Their efficiency is 1, so that $\bar{L}$ is also total immigrant labor supply in efficiency units. There is a unit mass of natives allocated on an interval $j \in [0, 1]$ who all have the same efficiency at carrying out low-skill tasks (identical to the immigrants) but differ in their efficiency at high-skill tasks, $\Gamma(j) = 2j^{1/2}$, such that higher-indexed natives are more productive. Natives sort into the task which pays them the higher wage. The wages paid to native j are $\mu_{Hj} = w_H \Gamma(j)$ and $\mu_{Lj} = w_L$. There exists a threshold native $\tilde{j} = \left(\frac{w_L}{2w_H}\right)$ who is indifferent between carrying out low-skill or high-skill tasks. Anyone to the left (right) of $\tilde{j}$ works in low-skill (high-skill) jobs.

Labor supply of natives in efficiency units is

$$\tilde{L} = \int_0^{\tilde{j}} 1 dj = \tilde{j} = \frac{w_L}{2w_H}; \qquad \tilde{H} = \int_{\tilde{j}}^{1} 2j^{1/2} dj = 1 - \left(\frac{w_L}{2w_H}\right)^2 = 1 - \tilde{L}^2 \tag{5}$$

Market-clearing for high- and low-skill tasks implies

$$L = \bar{L} + \tilde{L}; \qquad H = \tilde{H} \tag{6}$$

In equilibrium, firms maximize profits, natives choose their tasks optimally, markets clear. Combining eq.s (4), (5) and (6), the inverse skill premium is

$$\frac{w_L}{w_H} = \left(\frac{2\alpha}{1+\alpha}\right)\left(-\bar{L} + \sqrt{\bar{L}^2 + \frac{1}{\alpha^2} - 1}\right) \tag{7}$$

Taking the derivative with respect to $\bar{L}$,

$$\frac{\partial \frac{w_L}{w_H}}{\partial \bar{L}} = \frac{2\alpha}{1+\alpha}\left(-1 + \frac{\bar{L}}{\sqrt{\bar{L}^2 + \frac{1}{\alpha^2} - 1}}\right) < 0$$

where the inequality follows from $\sqrt{\bar{L}^2 + \frac{1}{\alpha^2} - 1} > \bar{L}$. As the inverse of the skill premium decreases in $\bar{L}$, the skill premium itself increases in the number of immigrant workers in the labor market. From eq.(5), it immediately follows that $\tilde{L}$ decreases in $\bar{L}$ whereas $\tilde{H}$ increases. Intuitively, When the supply of low-skill workers is larger, a higher skill premium incentivizes natives to move into high-skill jobs.

Denoting $\sqrt{\bar{L}^2 + \frac{1}{\alpha^2} - 1} \equiv \xi$, the level of wages are

$$w_H = \alpha\left(\frac{1 - \left(\frac{\alpha}{1+\alpha}\right)^2(\xi - \bar{L})^2}{\left(\frac{1}{1+\alpha}\right)\bar{L} + \left(\frac{\alpha}{1+\alpha}\right)\xi}\right)^{\alpha-1} \qquad w_L = (1-\alpha)\left(\frac{1 - \left(\frac{\alpha}{1+\alpha}\right)^2(\xi - \bar{L})^2}{\left(\frac{1}{1+\alpha}\right)\bar{L} + \left(\frac{\alpha}{1+\alpha}\right)\xi}\right)^{\alpha} \tag{8}$$

Both w_L and w_H decrease in $\bar{L}$ (but w_L more strongly).

5.2 Model with robots

We now introduce a third production factor, robots K, which is a perfect substitute to low-skill human tasks[26],

$$Y = H^\alpha (L+K)^{1-\alpha} \tag{9}$$

Robots are imported from abroad and offer an exogenous and fixed return $\bar{r}$; they fully depreciate after one period. The first-order conditions are

$$(1-\alpha)\left(\frac{H}{L+K}\right)^\alpha = w_L; \qquad \alpha\left(\frac{H}{L+K}\right)^{\alpha-1} = w_H. \tag{10}$$

Eq.(9) replaces eq.(3). Eq.(10) replaces eq.(4). The rest of the model stays the same.

There are two possible scenarios: (a) $\bar{r} \geq w_L$. In this case, the firms will not use any robots and the equilibrium is the same as in Section 5.1. As w_L is a negative function of $\bar{L}$ in eq.(8), this scenario is more likely if there are many immigrants in the labor market. So on the extensive margin, robot adoption depends negatively on the size of the immigrant population. (b) $\bar{r} < w_L$. In this case, robots get imported. As labor supply is exogenous and immigrants can only work in L-tasks, w_L converges to r. Then, the firms will employ a mix of human workers and robots at the low-skill

[26] The results will qualitatively be the same if robots and low-skill workers are imperfect substitutes. See Abeliansky and Prettner (2020) for a similar setup and discussion.

tasks. The amount of robots employed will depend on the presence of migrants. In the following, we focus on scenario (b).

Using $\bar{r} = w_L$ in eq.(10),

$$\bar{r} = (1-\alpha)\left(\frac{H}{K+L}\right)^{\alpha}; \qquad w_H = \alpha\left(\frac{\bar{r}}{1-\alpha}\right)^{\frac{\alpha-1}{\alpha}} \tag{11}$$

With eq.(5), labor supply by natives is

$$\tilde{L} = \left(\frac{\bar{r}}{1-\alpha}\right)^{\frac{1}{\alpha}}\frac{1-\alpha}{2\alpha}; \qquad \tilde{H} = 1 - \left[\left(\frac{\bar{r}}{1-\alpha}\right)^{\frac{1}{\alpha}}\frac{1-\alpha}{2\alpha}\right]^2 \tag{12}$$

Finally, we derive the demand for K from eq.(10),

$$K = \left(\frac{\bar{r}}{1-\alpha}\right)^{-\frac{1}{\alpha}}\left[1 - \left(\frac{\bar{r}}{1-\alpha}\right)^{\frac{2}{\alpha}}\frac{1-\alpha^2}{4\alpha^2}\right] - \bar{L} \tag{13}$$

K depends negatively on $\bar{L}$. Thus, more robots get adopted the fewer the number of immigrants (intensive margin).

The model outcomes are in line with the empirical findings shown in Section 4. Substitutability between robots and low-skill workers can thus rationalize these findings.

6 Conclusion

This paper examines the impact of a labor supply shock driven by immigration on firm-level robot adoption. We use a detailed employer-employee data set covering the universe of large firms over the period 1995-2019. A number of features of the Danish immigration experience during this period provide a unique opportunity to identify the causal impact of exogenous immigration shocks on subsequent firm-level robot adoption decisions. Our results show that an exogenous influx of immigrants leads to a significant decrease in robot adoption. This suggests that low-skill labor and robot adoption are substitutes. We rationalize this finding in a model where output is produced using high-skill and low-skill tasks.

Our findings carry important policy implications at a time when many countries have restrictive immigration policies in place and are experiencing labor shortages (especially in terms of low-skilled workers) due to the retiring of large baby boomer cohorts. Our key finding that immigration and robot adoption are substitutes suggest that we will see more automation over the next decades in response to labor shortages. It is therefore important to implement policies ensuring that young worker entering the labor force can collaborate, rather than compete with robots. Retraining measures should also be designed in order to help older workers' transition into non-automizable tasks.

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APPENDIX

A Data appendix

A.1 Additional tables

Table A1: Number of observations in the dataset

	Total obs.	**Robot obs.**
Merged employer-employee-dataset	3,674,768	14,650
Drop wholesale	3,610,730	10,973
Drop robot integrators	3,552,659	10,310
Drop small firms	79,926	4,154
Drop short-duration firms	64,503	3,615

Notes: The number of observations used in the regressions is lower because of some missing data for other variables.

Table A2: Descriptive Statistics

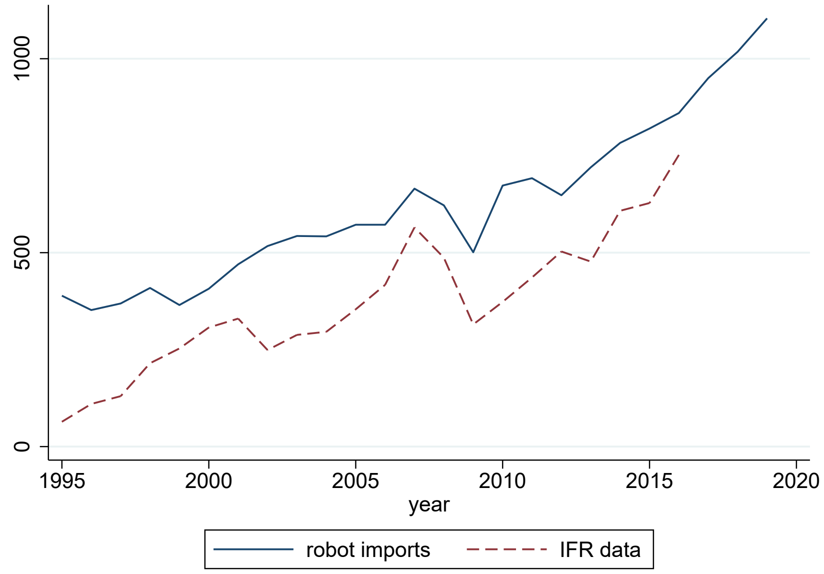
Variables	**Definition**	**Mean**	**Sd**
Robot variables			
Robot adoption (extensive margin)	1, if the firm imports a robot (product code=847950; 847989)	0.042	0.199
Robot adoption (intensive margin)	log of robot values, conditional on adoption	2.331	4710.000
Workforce variables			
Non Western immigrant share	foreigners from non-Western countries, municipality level	0.049	0.025
Female	female emloyees as a proportion of all employees	0.404	0.231
Foreign	foreign employees as a proportion of all employees	0.064	0.081
Routine	employees with routine intensive occupations as a proportion of all employees	0.175	0.183
Tertiary	tertiary educated workers as a proportion of all employees	0.231	0.235
Work Experience	average employees' work experience	18.312	5.235
Age	average employees' age	40.959	5.957
Firm variables			
Sales	log of sales	14.922	8.017
Size	log of number of employees	4.872	0.952
Multi-establishment	1, if the firm is a multi-establishment company	0.947	0.222
Exporter	1, if the firm exports	0.543	0.498
N		61,257	
Number of firms		5,589	

Notes: All descriptive statistics are calculated as averages over the period 1995-2019. Trade and accounting variables are in real Danish Kroner (using 2015 as the base year).

A.2 Additional figures

Figure A.2 shows the change in the share of foreign-born workers in Denmark by area of origin. All of the increase in immigration over this period is driven by an influx of foreign workers from non-Western countries, while Western immigration has remained relatively flat. Almost half (44%) of the growth in non-Western immigration comes from the eight refugee countries, while new EU member countries constitute 9% of this growth. Refugee countries include Afghanistan, Somalia,

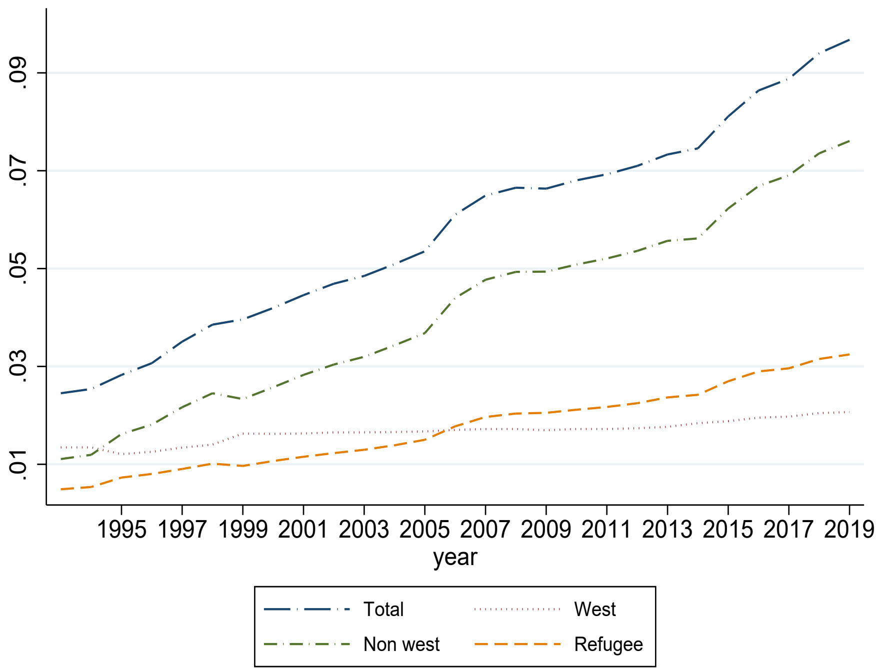
Figure A.1: Comparison of import data with IFR data



Notes: The graph shows the number of imported robots according to data from Statistics Denmark as used in this paper and according to data by the International Federation of Robotics (IFR).

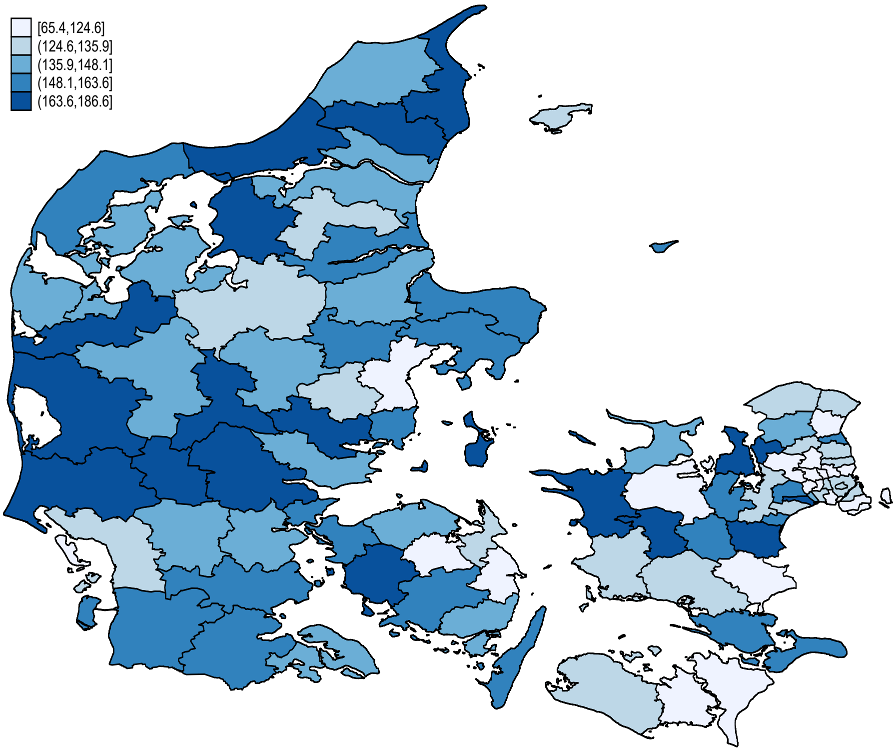
Iraq, Iran, Vietnam, Sri Lanka, Lebanon, and the former Yugoslavia (following Foged and Peri, 2015) and the new EU countries include Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, the Slovak Republic, Slovenia, Cyprus, and Malta who joined the EU in 2004 and Bulgaria, and Romania who joined in 2007.

Figure A.2: Share of Foreign-Born Workers in Denmark by Area of Origin



Notes: Share of migrant workers by area of origin calculated using data from Danish Integrated Database for Labor Market Research.

Figure A.3: Percent Change (1995 to 2019) in the Share of New EU Immigrants by Municipality



Notes: Share of new EU migrant workers calculated using data from the Danish Integrated Database for Labor Market Research.

A.3 Comparison with VITA

To validate our robot measure, we use a survey on robot adoption (VITA) that was carried out by Statistics Denmark in 2018 and subsequent years. Firms in the survey were given a definition of (industrial or service) robots and were asked whether they are using any of these. The survey covers Danish firms with 10 or more employees in all private sectors except the primary industry and the financial industry. It works as a form of rotating panel: Large firms get included every year, smaller firms only at irregular intervals. Overall, about 4,000 firms participate in the survey each year. The response rate is about 95%.

Table A3 summarizes the performance of the robot imports data on the sample of firms participating in VITA. The false positive rate is 2.6%, the false negative rate 87.4%, accuracy: 87.5%. These numbers are weighted statistics using survey weights provided by Statistics Denmark.

Table A4 compares true positive and false negative observations along key firm and employee characteristics. Differences between true positives and false negatives leads to a bias of coefficient estimates for several of the control variables. However, they are not statistically different when it

Table A3: External validity of the robot import data

		VITA		
		Yes	**No**	**Total**
	Yes	424	409	833
Imports	**No**	1,666	8,616	10,282
	Total	2,090	9,025	11,115

Table A4: Comparison of true positives and false negatives

	TP	FN	pval (TP=FN)
log(value-added)	18.537	17.055	0.00
log(capital stock)	18.489	16.681	0.00
log(sales)	19.646	18.123	0.00
log(productivity)	14.845	14.608	0.00
size	458.502	81.832	0.00
exporter	0.970	0.743	0.00
manufacturing share	0.733	0.634	
college share	0.193	0.161	0.00
highschool share	0.589	0.603	0.10
share of non-West immigrants in municipality	0.044	0.045	0.92
average age	45.574	43.514	0.00
share of female	0.313	0.341	0.74
share of machine operators	0.114	0.083	0.75
routine-task intensity	0.321	0.321	0.22
number of obs.	424	1,666	

comes to the share of refugees, based on which we conclude that the main coefficient of interest will not be biased.