The Effect of Immigration on Robotisation: Evidence from the UK

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Declaration

I, Lydia Field, hereby declare that the work presented in this dissertation is my own original work. Where information has been derived from other sources, I confirm that this has been clearly and fully identified and acknowledged. No part of this dissertation contains material previously submitted to the examiners of this or any other university, or any material previously submitted for any other assessment.

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Classification

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Abstract

This paper analyses the impact of immigration on industrial robotisation in local UK labour markets using data from the British Labour Force Survey and the International Federation of Robotics. I use a Bartik instrument for immigration to identify causality, as well as dummies to remove industry, regional and year fixed effects. I find that on average, migration leads to a fall in the share of robots per worker, suggesting that robots and immigrants are substitutable to some degree. This negative relationship is particularly strong for immigrants working in low-skilled occupations.

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Contents

List of Figures

List of Tables

1 Introduction

1.1 Motivation and Policy Relevance

The fear that immigrants may displace native workers, thereby depressing wages and increasing unemployment, is a significant driver of the national debate on immigration in the UK. The European Social Survey (2014) found that 67% of British people think that immigrants take jobs away. Rather similar fears are associated with robots, automation and Artificial Intelligence(AI): robots are seen as competitors for jobs currently done by humans, and there are fears that increasing use of robotic technologies could lead to increased unemployment.

The ONS (2017) found that while only 7.4% of UK jobs were at high risk of automation, a full 64.9% were at medium risk. The latter category includes jobs where a number of the job tasks will be automated, such that the job will be significantly altered, but it will not be completely eliminated by automation. The employment effects of immigrants and robots are linked because firms optimising production decide between investment in robots, the employment of immigrant or native workers, or a combination of these inputs. An increase in immigration could therefore have different effects on the degree of robotisation depending on the complementarity or substitutability of immigrants and robots. If they are close substitutes as suggested in Clemens et al. (2018) and Lewis (2011), then an increased immigrant labour force will lead firms to put off installing robots. If they are complements, an increased immigrant labour force may lead firms to employ more robots. Policies to restrict immigration are often justified as job-protection for native workers. But if robots are a closer substitute for immigrants than native workers, then restrictions on immigration could hasten robotisation, rather than increasing native employment.

1.2 Aims and Methodology

In this paper, I use data from the UK Labour Force Survey and the International Federation of Robotics (IFR) to estimate the causal impact of immigration on industrial robotisation in the UK. I focus on multipurpose industrial robots, which the IFR defines as "automatically controlled, reprogrammable, multipurpose manipulator[s] programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (IFR 2018, p.29). These can be used for packaging, welding, painting, material handling, machine feeding or assembly, amongst other uses. These robots represent only part of the broader set of automated technologies with potential employment effects, including automation in the services sector.

To identify the causal effect of immigration, I instrument for the observed immigrant share using the predicted immigrant share based on the regional settlement patterns of immigrants in 1986. This resolves concerns about simultaneity of immigration and robot adoption, as well as concerns around measurement error of immigrants.

My analysis sheds light on the relative substitutability of industrial robots and immigrants. I find that on average an increase in the immigrant share of the workforce leads to a fall in the number of robots per worker. This negative relationship undermines the argument that reduced immigration will create jobs for native workers: if immigrants and robots are substitutes, then the jobs that would have been performed by immigrants would be performed by robots rather than by native workers. In the economic sectors such as the vehicle industry where industrial robotisation plays a major role, immigration restriction might therefore be less likely to raise wages and employment for those born in Britain, but instead hasten the trend of robotisation. Where meaningful, I distinguish between demographic groups for example by skill level and age. I will also point out the data-based and theoretical limitations of my work, and point to areas for further research.

This study adds to the existing literature by looking at the link between immigration and robotisation. There is a wide literature covering the effect of immigration on native employment and wages (see e.g. Altonji et al 1991, Borjas 2003, Card 2007, Dustmann, Frattini and Preston 2013). Recent papers have examined the effect of robotisation on native employment conditions (see e.g. Acemoglu and Restrepo 2020, Borjas and Freeman 2019, and Kariel 2021). But to the best of my knowledge, this is the first analysis of the effect of immigration on robotisation.

1.3 Structure

This paper is structured as follows. In Section 2 I cover the topic's background, discussing UK trends in both robots and migration, as well as surveying the relevant literature. In Section 3 I discuss the theory of how economies react to immigration, and how robots can be included in this analysis. In Section 4 I describe my data and its limitations, and give a descriptive account of the evolution of both immigration and robotisation in the UK between 1994 and 2018. In Section 5 I present my empirical strategy and address potential problems with estimating causal effects. In Section 6 I analyse the data and discuss my results. I conclude in Section 7.

2 Background

2.1 Context

2.1.1 Robots

In the course of the decade from 2007-2017, global orders for industrial robots tripled (IFR, 2018). These robots are changing global labour markets. Across the OECD, 14% of existing jobs are at high risk from automation, while 32% are at risk of significant change. The UK sits below this average, with 10% of jobs at risk of complete automation, and 25% at risk of significant change (OECD, 2018). But these risks do not affect all workers equally. The jobs at highest risk of automation tend to be in low-skilled and routine occupations, for example food preparation assistants, cleaners and helpers, or labourers in mining, construction, manufacturing and transport. The industries at highest risk are manufacturing and agriculture. Finally, younger people are more at risk, as entry-level jobs are more at risk of automation than jobs held by more senior and older workers(OECD, 2018). It is often easier not to hire someone than to fire someone.

2.1.2 Immigrants

The gross inflow of migrants to the UK has steadily increased over the past 25 years, with around 150,000 immigrants coming to the UK in 1995 compared to 486,000 in 2018 (International Migration Database, 2021). Total immigrant stocks have also been increasing. In 2006 there were 2.8 million immigrants in the UK, but by 2019, numbers were up to 9.5 million people, representing 14% of the population. The largest shares by countries of origin were immigrants from India and Poland, who make up 9.1% and 8.6% of British immigrants respectively. They are followed by immigrants from Pakistan, Romania, and the Republic of Ireland. In terms of pull factors, EU immigrants mainly came to the UK for work, while the most common reason amongst non-EU immigrants was family (The Migration Observatory, 2019). The effects of the withdrawal of the UK from the European Union on future migrant flows remain uncertain, as for example this may affect the trend by reducing the flow of European immigrants.

2.2 Review of the Literature

2.2.1 Who do immigrants compete with?

When considering the impact of immigration on a host economy, studies have taken different approaches in defining the labour markets affected. Card (2001) looks at regional labour markets, which he further divides along occupation lines. In this way he assumes that immigrants are competing with locals working in the same occupation in the same region. Borjas (2003) criticises the regional approach due to concerns that outmigration of natives and immigration will be correlated with labour market performance, creating endogeneity and biasing the estimated effects. Instead, he divides the national labour market along education and experience lines. In a later paper, David Card (2007) looks at cities and hourly-wage quartiles, therefore assuming that immigrants in the bottom wage quartile compete with locals with similar earnings. These studies all concern the United States. For the UK, Dustmann, Frattini and Preston (2013) look at immigration along the wage distribution, using a similar approach to Card (2007). They find significant evidence of immigrants taking jobs they are apparently overqualified for on arrival in the UK. This suggests that the assumption that immigrants compete with similarly skilled UK natives as in Borjas (2003) might be open to question.

2.2.2 Immigration in the UK

The first major study of the impact of immigration on UK native workers was Dustmann, Fabbri and Preston (2005). They found that immigration had a small and statistically insignificant effect on unemployment, and was associated with higher wage growth in the "currently resident" population. This matches the consensus in the US and European literature (see e.g. Card 1990, Altonji and Card 1991, Dustmann, Frattini and Preston 2013, Dustmann and Glitz 2015), that any negative effect of immigration on native wages and employment is small if it exists at all. Dustmann, Frattini and Preston (2013) look at the effects of immigration along the wage distribution, finding that immigration led to a slight decrease in wages below the 20th percentile, but increased wages above it. Overall, they show that an increase in the immigrant population equivalent to 1% of the native population leads to an increase in average wages of 0.25%.

2.2.3 Evidence of substitutability between automation and immigrants

Existing literature on the relationship between migration and automation yields some evidence that automated technologies may be a close substitute for immigrant labour. Clemens et al. (2018) find that, as a result of an expulsion of migrant farm workers in the U.S., production processes previously reliant on the migrant workers became heavily automated as a result of their expulsion, where this made business sense. For crops where no good automation option existed, farms stopped producing the same crops and switched to alternatives. The authors find no effect on native employment and wages, suggesting that the economy adjusted to the change in immigrant numbers through the use of technology, rather than via the wages and employment of the US-born. This supports the idea that automated technology is a closer substitute for immigrants than native workers. This conclusion is supported in Lewis (2011), where the author finds that in regions of the US where immigration led to faster growth in the relative supply of low-skilled labour, firms were slower to automate. In Germany, Dustmann and Glitz (2015) find that firms in the tradeable sector adapt to immigration through the use of technologies that employ immigrants more intensively (while firms in the non-tradable sector adapt via wages). Firms in the tradeable sector cannot set their output prices, so increasing wages is often not possible, pushing firms to adapt through alternative means. In the non-tradeable sector, firms have more price-making power and can push up their prices to remain profitable despite a wage increase.

2.2.4 Robots and labour markets

Studies investigating the impact of robots on labour markets have emerged very recently. Acemoglu and Restrepo (2020) find that commuting zones most exposed to robotisation have lower wages and employment than areas with less exposure to robots. Their results imply that an increase of one robot in a commuting zone leads to a fall in employment of 6.2 human workers. This is echoed by Borjas and Freeman (2019), who show that increased robotisation within an industry is linked to reduced wages and employment, particularly amongst those with the least education. They further compare the labour market effects of immigrants and robots and find that each robot displaces 2-3 times more human workers than each immigrant.

Both of these papers focus on the U.S., while European studies find more mixed results. Dauth et al. (2017) find that industrial robots in Germany have not led to reduced employment. They do find compositional effects, however, such that robots lead to fewer jobs in manufacturing but this is compensated by more jobs in services. They are able to use longitudinal data to show the reduction of employment in manufacturing is not due to current workers being displaced, but due to firms not hiring new young workers. A recent paper looking at the UK has more positive findings. Kariel (2021) analyses the impact of robot exposure on the UK labour market, employing a differences-in-differences strategy comparing local authorities with high and low robot exposure between 1993-2011. He finds that robots have actually raised employment in the UK, with one robot associated with 10 more workers over the period. Looking at the impact by industry, he finds that robots have reduced employment in the automobile sector, where robots are most concentrated, but led to increased employment in the services sector, similarly to Dauth et al. (2017). All of the above studies instrument for robotisation using other countries' robot installations, to avoid simultaneity between robot exposure and local demand conditions.

3 Theory

My analysis considers the causal impact of immigrants on robotisation. In this section I first discuss the theory behind immigrant competition in the labour market, and the three key channels through which an economy can adjust to immigration. For the purpose of presenting the theory I make various simplifying assumptions, some of which will be further explored and relaxed in my empirical analysis.

3.1 Who do immigrants compete with for jobs?

The research literature has considered *which native-born workers* are competitors to immigrants in the labour market. In principle, immigrants and natives could be perfect substitutes, conditional on their skill level, measured as educational attainment, work experience, or some combination of the two (see e.g. Altonji and Card 1991, Card 2001, or Borjas 2003). Alternatively, immigrants and natives might be inherently different input factors, due to differing language ability, local knowledge and networks (see Grossman 1982). Between these extremes, it might be that immigrants and natives are imperfect substitutes, implying that the competitive pressure of new immigrants is concentrated primarily on earlier immigrants, and only secondarily on natives (Ottaviano and Peri 2006). My analysis introduces a new competitor: robots. From a firm's perspective, robots, native workers and immigrants are three potential input factors. The relative substitutability between the three will determine where the effects of migration are seen. If immigrants are closer substitutes to robots than natives, then the competitive effects of migration will fall mainly on robots, rather than on native employment and wages. This is a simplified way of thinking about the link between the three input factors. In fact, robots are more like a production technology than a third kind of labour; they require an upfront investment that pays returns over years, and there may be more of a lag in obtaining them due to shipping and importing requirements. In my analysis, I consider robots as a production technique.

Since my data considers industrial robots, it seems likely that the most substitutable immigrants will be those of a low skill level, who would be more likely to work in manual or routine jobs that are replaceable by industrial robots. In the UK, there is evidence of significant downgrading by immigrants, who upon arrival work in jobs for which they are overqualified. Dustmann, Frattini and Preston (2013) find that while 26% of highly educated recent UK immigrants were employed in routine and semi-routine occupations, the figure was only 5% for natives with the same level of education. This suggests that there may be competition between more highly educated immigrants and industrial robots too. I will investigate this idea in my analysis by looking at the overall effect of migration on robots, but also the differing effects of low-, mid- and high-skilled immigrants.

3.2 How does an economy adjust to immigration?

[1] For the purpose of presenting the theory, let us assume that there are two skill levels, skilled and unskilled. In this section I will also assume that immigrants and natives are perfect substitutes by skill categories, and that robots are a production technique that requires a lag to implement. This is plausible given the time required to import and/or install robotic technologies. I assume that the economy is small and open to reflect the UK, so prices are set on the world market and are not influenced by the economy. I also assume that that capital is perfectly elastic, so the stock can be moved, increased or decreased immediately, which seems reasonable for a small open economy like the UK.

Under these assumptions, immigration will affect wages and employment of natives only if the skill-mix of the immigrants is different to that of the na-

[1] Section 3.2 borrows from the exposition of the theory in Dustmann, Fabbri and Preston (2005)

tive population, such that immigration leads to a change in the skill-mix of the host economy. Otherwise, a proportional increase in both the number of skilled and unskilled workers would not affect the equilibrium between labour supply and demand of either skill group in the host economy. The economy would expand, but equilibrium wages would be unaffected.

Assuming that the immigrant skill distribution differs from that of natives, there are three ways in which an economy can adjust to an immigration shock. First of all, wages and employment can adjust, which is what tends to be discussed in the media. An influx of unskilled immigrants will increase the relative supply of unskilled labour, leading to a fall in wages and, if the labour supply curve is upward sloping, also a fall in employment for unskilled workers. This is the only adjustment channel in a one good economy, but obviously no actual economies only have one good. Consider an economy which produces a variety of goods and includes different industries. While wages and employment may adjust in the short term, this economy will eventually adjust via a change in the output mix, or a change in the use of technology. As Rybczynski (1955) noted, the fall in unskilled wages will lead to a fall in the unit cost of production for goods that use unskilled labour. Since we assume that prices are set on the world market, and a small open economy cannot affect them, a lower cost leads to greater industry profits, so that the industry will expand in a competitive setting. This expansion will then lead to an increase in the relative demand for unskilled workers, and eventually wages will be bid up to their original level. Therefore, in the medium to long term, we won't see a wage or employment effect, but rather a change in the economy's industry structure.

In the medium to long term, the economy may also adjust through changes in production technology as the relative advantages of different production techniques change according to the changing skill mix of labour supply. An increase in the relative supply of unskilled workers makes the use of production techniques that are intensive in this kind of labour cheaper. Conversely, technologies that are intensive in skilled labour will be become relatively more expensive. Firms may therefore switch their technologies in response to immigration. One potential such change would be the use of robots. Suppose robots make relatively intensive use of high-skilled labour. Then immigration of low-skilled workers should lead to a reduction in the use of robots. (Given the evidence on immigrant downgrading, this may be true even for high-skilled immigrants in the UK if they are actually working in low-skilled occupations.) The relative importance of production technology adaptation is supported by the empirical literature: various studies find that most of the endogenous response to immigration happens through this channel, as opposed to the industry mix (see Hanson and Slaughter 2002, Lewis 2003, Dustmann and Glitz 2015).

4 Data and Descriptive Statistics

The International Federation of Robotics (IFR) provides data on new robot installations by country, industry and year. The data covers “multipurpose industrial robots”, which the IFR defines as an “automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications” (IFR 2018, p.29). My analysis is limited to industrial robots, which are concentrated in the manufacturing industry. This will bias my analysis toward finding a greater impact of migration in manufacturing industries, as opposed to services for example. The IFR has begun to produce data on service robots, which will eventually provide the basis for an important extension to my analysis. The IFR data covers the global robot market, as it is collected from the majority of suppliers worldwide (IFR, 2018). While the IFR constructs an estimate of robot stocks, I will be constructing my own estimate of the number of productive robots. The IFR’s “Operational Stock” variable is created assuming “an average service life of 12 years with an immediate withdrawal from service afterwards” (IFR 2018, p.28). I will follow Borjas and Freeman (2019) in assuming that the current stock is equal to the sum of previous installations. This is justified on the basis that the depreciation of older robots is roughly equal to the appreciation of newer robots due to technological improvements, so my stock variable is a fair reflection of robotic productive capacity. The IFR data for the UK covers the period 1993-2018. I will be using the sample from 1994-2018 to match the period of my labour force data. The IFR data is not region specific, so I will be imputing the regional distribution of robots based on regional shares of employment by industry, following Acemoglu and Restrepo (2020). This introduces potential measurement error which will decrease the precision of our estimates, but will not introduce bias since robotisation is the dependent variable.

The UK Labour Force Survey is a household survey that has been collected quarterly since spring 1992. Between 1984 and 1991, it was collected annually. Since 1992, it has been a rotating quarterly panel, such that each household is interviewed in five consecutive quarters. The sample covers 40,000 households and 100,000 individuals each quarter. It aims to be representative of the UK population. From 1994 it began to include Northern Ireland in the same quarterly cycle, so from 1994 onwards covers the whole UK. I will therefore be using the period 1994-2018. It mainly covers demographics, employment, education and income data (Office for National Statistics, 2015). The LFS geographical data covers the twenty standard regions of the UK, according to usual residence of respondents. While the use of region of residence instead of region of work could lead to some measurement error due to commuting, the breadth of the regions should mitigate this concern. Industry classifications change throughout the survey from Standard Industrial Classification (hereafter SIC) 80, to SIC92, to SIC07. I have therefore developed a crosswalk between them and industry categories specified by the IFR, which broadly follow the International Standard Industrial Classification of All Economic Activities (ISIC), revision 4 (see Appendix). I define an immigrant as someone whose country of birth is not the UK. In order to determine an individual's skill level I use the age at which they completed full time education. This is principally for ease of comparison between immigrants and the UK-born, as immigrants might have qualifications that are hard to compare.

The following descriptive statistics concern the sample that I use in my regressions. Since my analysis concerns the labour market, I drop those over 65 or under 16. As I define labour markets according to industry-region-year cells, I drop all individuals who do not declare a region or an industry. This latter omission means that I drop most of those who are unemployed, and this is important to note for the rest of my analysis, since I effectively exclude unemployed immigrants from my sample. Though this might seem paradoxical given that this paper is partially motivated by concerns about the effects of migration on employment, it is appropriate because the analysis focuses on the effects of immigrants in the labour force on robotisation.

Migrants make up an increasing proportion of the UK workforce, as can be seen in figure 1. In 1994, those born outside the UK made up 0.07% of the Labour Force Survey sample. This increases fairly linearly, doubling to 0.16% by 2018. These are not representative of the true immigrant share of the UK population, but do reflect the increasing trend. The total number of immigrants in our sample increased from 18,000 to 26,000 over the period. An even starker transition can be observed regarding robot intensity, as shown in figure 2. National robots per sampled worker increased exponentially, from essentially zero in 1994 to 2.6 in 2018. In these ratios the denominator is the number of sampled workers in the Labour Force Survey, and not total UK workers (for which the robot ratio would be much lower). Since my analysis uses the variation in these figures rather than absolute levels, it does not matter that the sampled number of UK workers is considerably smaller than the national worker count in any given year.

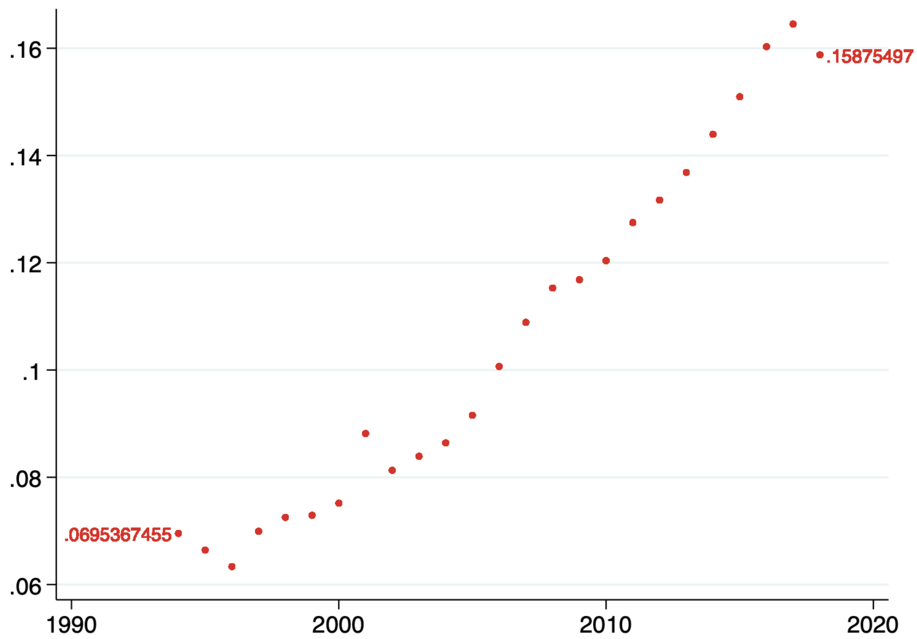

Figure 1: Migrants per sampled UK Worker

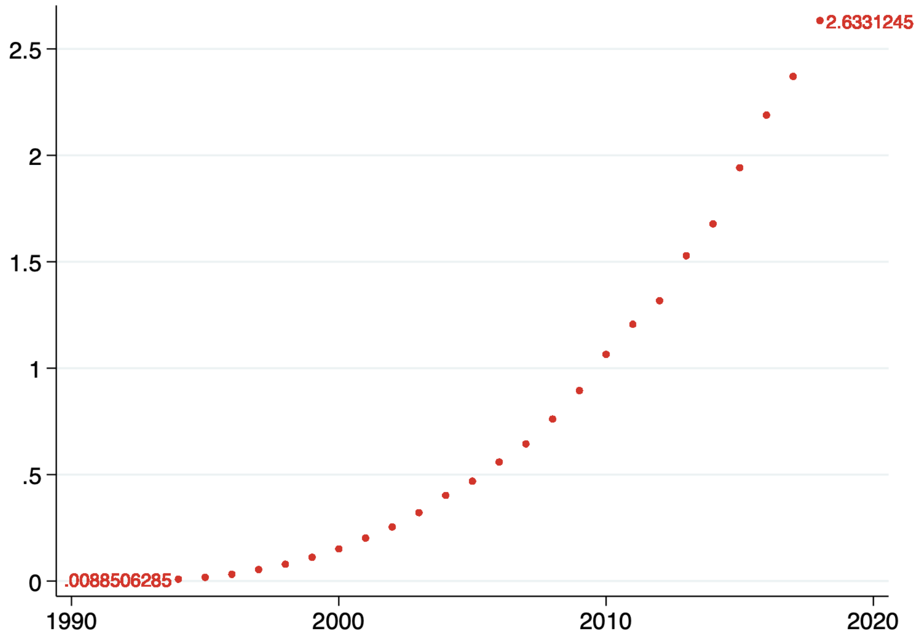

Figure 2: Robots per sampled UK Worker

Table 1 presents descriptive statistics for the immigrant and robot data that I use in my analysis. I present the means, minima, maxima and standard deviations for the numbers of immigrants and robots in industry-region cells, as well as immigrant shares, expressed as the number of immigrants in an industry-region-year cell divided by the total workforce in an industry-region-year cell, and robot intensity, expressed as robot stock in an industry-region-year cell divided by the total workforce in an industry-region-year cell. The denominator for these intensity variables is taken from 1994, which is why the share can be greater than one. On average there are 1,250 immigrants in a local market in our sample, with immigrant numbers ranging from zero to 29,250. There is significant variation in the immigrant share of an industry-region-year workforce, from none of the workforce in some industry-region-year cells, to 3.8 times 1994 employment in others. Robot stocks vary from zero to 4,400 , with a mean value of 18 robots in a local market represented by an industry-region-year cell. Robots per worker range from zero to 7.6, but the average is just under 0.05.

Table 1: Immigrant and Robot Numbers and per Worker Shares

	mean	sd	min	max
Immigrant Number	1243.865	2679.741	0.000	29246.000
Immigrants per Worker	0.096	0.114	0.000	3.750
Robot Stock	18.380	124.799	0.000	4384.054
Robots per Worker	0.043	0.338	0.000	7.651

This table presents immigrant and robot statistics at the level of the industry-region-year cells I will later use in my regressions. The first row presents immigrant numbers. The second row presents immigrant numbers divided by the total labour force in that industry-region-year cell in 1994. I use 1994 numbers throughout rather than year-by-year estimates to avoid any denominator endogeneity in my regressions. The third row presents robot stock statistics. The final row presents statistics for robot stocks deflated by the labour force in that industry-region-year cell in 1994.

Table 2 presents the industry concentrations of both robots and immigrants per worker. Across the sample, immigrants make up the highest fraction of workers in the industry sectors of Food and Beverage Manufacturing, Textile Manufacturing, Other non-Manufacturing Industries and Automotive Manufacturing. Robots are used most intensively in Automotive Manufacturing (by a huge margin), followed by Plastic and Chemical Product Manufacturing, Wood and Furniture Manufacturing and Food and Beverage Manufacturing. Automotive and Food and Beverage Manufacturing are relatively intense in both robots and immigrants, but there is no obvious pattern across industries, in that immigrants and robots don't seem to be concentrated in the either the same or in markedly different industries.

Table 2: Immigrants and Robots per Worker, means by industry across years

	Immigrants per Worker	Robots per Worker
Agriculture, forestry, fishing	0.046	0.006
Mining, quarrying	0.083	0.037
Utilities	0.060	0.010
Construction	0.067	0.008
Education, R+D	0.092	0.011
Other non-manufacturing	0.111	0.000
Food and beverages	0.153	0.225
Textiles	0.139	0.013
Wood and furniture	0.055	0.390
Paper	0.070	0.010
Plastic and chemical products	0.082	0.629
Non-metal mineral products	0.060	0.146
Metals (basics, products, machines)	0.064	0.172
Electronics	0.083	0.166
Automotive	0.094	5.509
Other vehicles	0.056	0.128
All other manufacturing branches	0.083	0.199

This table presents immigrants per worker and robots per worker at the level of the industry-year cell. The statistics shown are averages across years by industry.

Table 3 shows the regional concentration of both robots and immigrants per worker. Given that the regional distribution of robots is imputed from the regional distribution of employment by industry, the regions we measure as robot-intense will be those with high levels of employment for industries that are robot intensive. The most robot intense regions are the West Midlands (Met County), the Rest of the West Midlands, and Tyne and Wear. Immigrants make up by far the greatest share of the Inner and Outer London workforce, followed by the West Midlands (Met County). As with the industry shares, there is some overlap in the high-robot and high-migrant regions, but there isn't a clear pattern overall.

Table 3: Immigrants and Robots per Worker, means by region across years

	Immigrants per Worker	Robots per Worker
Tyne and Wear	0.082	0.076
Rest of North Region	0.064	0.053
South Yorkshire	0.088	0.035
West Yorkshire	0.111	0.037
Rest of Yorks+H'side	0.079	0.050
East Midlands Region	0.106	0.051
East Anglia Region	0.116	0.038
Inner London	0.410	0.009
Outer London	0.320	0.018
Rest of SE England	0.127	0.037
South West	0.093	0.034
West Midlands Met.	0.158	0.128
Rest of West Mid.	0.079	0.094
Greater Manchester	0.116	0.031
Merseyside	0.079	0.053
Rest of North West	0.081	0.054
Wales	0.076	0.050
Strathclyde	0.066	0.024
Rest of Scotland	0.090	0.022
Northern Ireland	0.118	0.038

This table presents average immigrants per worker and robots per worker by region. I take the ratios by industry-region-year cell, then average them across industries and years to get the mean robots or immigrants per worker by region.

Table 4 covers the mean demographic characteristics of immigrants and natives. It shows age, sex, age at which full time education was completed, as well as frequencies in each education category. Education categories are defined according to the age at which an individual left full time education. Those who left at age 16 or before are defined as low-skilled, those who left between 17 and 19 are mid-skilled, and those who left at 20 or later are defined as high-skilled. Across the whole sample, immigrants are better educated than natives, finishing school at age 20 compared to 17.6 for natives. The distribution across education groups is very different for immigrants and natives. Among immigrants, 60% are in the highest education category, 23% in the medium skill group, and 17% are low-skilled. Among natives, 53% are in the lowest educational group, 25% are in the intermediate category, and 22% are highly educated. Immigrants tend to be slightly younger, with an average age of 39.6 compared to 40.2. Sex distributions are similar, with females making up 50% of UK-born and 47.4% of immigrants.

Table 4: Mean Age, Gender Share, and Education of Immigrants and Natives

	Native	Immigrant
Age	40.23	39.59
% Female	47.96	47.40
Age Left Full Time Education	17.58	19.99
Education		
% Low	52.60	17.18
% Mid	25.11	22.66
% High	22.29	60.16

This table presents demographic statistics on immigrants and natives in my sample. It shows average age, percentage female, average age they left full time education, and the percentage in each education category, for immigrants and natives. I define education groupings according to the age at which a immigrant left full time education. The low-skilled are those who left education at age 16 or before. The mid-skilled left full time education between 17 and 19. Those who left education at age 20 or later are defined as high-skilled.

5 Empirical Strategy

In order to identify the causal impact of immigration on robotisation, I will be exploiting variation across labour markets, defined as region-industry cells, and across time. I will measure immigration as the share of immigrants in employment for each industry-region labour market, and robot intensity by the number of robots per worker. Since the robot data is country-wide, I assign robots to regions using the regional share of an industry's employment, following Acemoglu and Restrepo (2020). I therefore assume that if 20% of car manufacturing employment is in Merseyside, then 20% of car manufacturing robots will be in Merseyside. So as long as the regional distribution of robots follows that of employment, the measurement error associated with this imputation should be limited. In order to avoid endogenous changes in the weighting variable, I use the regional distribution of employment from 1994 for all years of robot data.

5.1 OLS specifications

Essentially, I regress robots per worker in each industry-region-year cell on immigrants per worker in each industry-region-year cell, and control for fixed effects. I run an OLS regression of the form

$$\lambda_{ir}^{1994}\frac{S_{it}}{L_{ir,1994}} = \beta\frac{M_{irt}}{L_{ir,1994}} + \theta_i + \theta_r + \theta_t + \epsilon_{irt}$$

, where $\lambda_{ir}^{1994} = \dfrac{L_{ir,1994}}{L_{i,1994}}$ is our regional assignment variable, such that $\lambda_{ir}^{1994}\dfrac{S_{it}}{L_{ir,1994}}$ captures robot intensity, measured as robot stock per worker, $\dfrac{M_{irt}}{L_{ir,1994}}$ is the immigrant share of employment, $\theta_i, \theta_r, \theta_t$ are industry, region and time fixed effects and i denotes industry, r denotes region and t denotes year. Since industry, region and year are observed, I can run this regression using dummy variables. I divide by $L_{ir,1994}$ rather than L_{irt} to avoid endogeneity through the denominator, for example if migration affects total employment in a labour market.

I also run a first-differenced specification, which removes industry and region fixed effects, and where time fixed effects can still be controlled for using year dummies. This essentially regresses the change in robots per worker in each industry-region-year cell on change in immigrants per worker in each industry-region-year cell. This specification would be

$$\lambda_{ir}^{1994}\frac{S_{it}-S_{it-1}}{L_{ir,1994}}=\beta\frac{M_{irt}-M_{irt-1}}{L_{ir,1994}}+\Delta\theta_t+\Delta\epsilon_{irt}$$

This specification reduces the amount of variation in the data, which can lead to issues with identification.

Both of the above specifications are vulnerable to simultaneity bias. If a local market is growing, then immigrants may choose to move there. It also seems reasonable that firms in a growing local labour market would install more robots than a stagnant market. The simultaneous links between strong aggregate demand, demand for robots, and an attractive market for immigrants creates an endogeneity problem, meaning the estimate for β will not pick up the causal effect of immigration on robotisation. If I am correct in guessing a positive simultaneous relationship, this could lead to overestimation of the true effect, β. Error in measurement of the immigrant stock presents a second empirical issue. This is a particular concern due to the small number of immigrants in some region-industry cells. Measurement error is exacerbated by first differencing, and can lead our estimates for β to be biased towards zero.

5.2 Instrumental Variables Estimation

To address both the concern of simultaneity bias and of measurement error, I instrument for migration using a "Bartik" instrument. As Bartel (1989) noticed, immigrants from country X tend to cluster in regions where previous immigrants from X have settled. This kind of instrument is used widely in the literature, for example in Card (2001) or Lewis (2003). Thus, we can construct a predictor of migration flows which is plausibly exogenous, if we use immigrant settlement patterns from long enough prior to the study that they are not correlated with current market conditions. The key balance is to have a recent enough year that the instrument is relevant, but a distant enough year that the instrument satisfies the exclusion restriction.

In practice, let $\theta_{rc} = \dfrac{M_{rc,1986}}{M_{c,1986}}$ be the share of immigrants from origin country c living in region r in 1986. Let M_{cit} be the number of new immigrants from country c working in industry i in year t. Then $\theta_{rc}M_{cit}$ is the predicted number of immigrants from origin country c working in region r in industry i in year t. Summing over origin countries, $\sum_c \theta_{rc}M_{cit}$ is the expected number of immigrants in each industry/region cell. I can therefore instrument for $\dfrac{M_{irt}}{L_{ir,1994}}$ with $\dfrac{\sum_c \theta_{rc}M_{cit}}{L_{ir,1994}}$. In first differenced specifications, I instrument for $\dfrac{M_{irt} - M_{irt-1}}{L_{ir,1994}}$ with $\dfrac{\sum_c \theta_{rc}M_{cit} - \sum_c \theta_{rc}M_{cit-1}}{L_{ir,1994}}$.

The instrumental variable (IV) estimate recovers the causal effect on immigration on robotisation if the instrument is exogenous, i.e. if the predicted immigrant number is unrelated to local demand conditions in year t. This cannot be tested, but is arguable if we believe that local economic conditions are not too persistent. The standard in the literature is to use settlement patterns a decade prior to the base year (see e.g. Lewis 2011 or Dustmann and Glitz 2015). My instrument is based on data from only eight years prior to the first year in my sample, as 1986 is the earliest year in which the Labour Force Survey records regions in the same way as they do in my sample. The relevance of my instrument can be tested in a first stage regression. The instrument will not only resolve the simultaneity issue, but also the measurement error as long as the measurement error in the predicted immigrant share is uncorrelated with the measurement error in the observed immigrant share.

5.3 Controls

In addition to the dummy variables I add to control for industry, region and year fixed effects, I control for the demographics of a labour market. I include controls for the average age of immigrants and natives in each industry-region-year cell, since I expect that a younger population may be more substitutable for robots, based on the finding that young people are at higher risk from automation than older workers (OECD, 2018).

I also control for the skill-composition of the native population. I am concerned that if e.g. regional immigration of low-skilled migrants causes out-migration of low-skilled natives, then the measured effect on robotisation will be capturing both that of immigration and of a change in the native skill composition. I therefore control for the number of high- and mid-skilled native workers as a fraction of the number of low-skilled workers in order to isolate the effect of immigration.

5.4 Extensions

To further investigate how the effect of immigration on robotisation varies according to immigrant characteristics, I run two further specifications. First, I run a specification which differentiates between immigrants according to skill group. I define a skill group according to the age at which a immigrant left full time education. The low-skilled are defined as those who left education at age 16 or before. The mid-skilled left full time education between 17 and 19. Those who left education at age 20 or later are defined as high-skilled. My specification is

$$\lambda_{ir}^{1994}\frac{S_{it}}{L_{ir,1994}} = \beta_l\frac{M_{irt,low}}{L_{ir,1994}} + \beta_m\frac{M_{irt,mid}}{L_{ir,1994}} + \beta_h\frac{M_{irt,high}}{L_{ir,1994}} + \theta_i + \theta_r + \theta_t + \epsilon_{irt}$$

The different β_{skill}'s therefore identify how the effect varies by skill category. Based on the research provided in the background section, I would expect $\beta_l < \beta_m < \beta_h$, i.e. the lower skilled immigrants have a more negative effect on the robot stock. I also expect that β_l will be negative, but potentially all three estimates will be negative, especially if immigrants are downgrading.

I also run a specification to look at how the effect varies by occupation. Due to the evidence of immigrant downgrading in the UK, I am concerned that skill level may not proxy the skill requirements of the jobs done by immigrants. Occupation may better help to differentiate those immigrants who work as managers or professionals from those who work routine occupations requiring low skills, who therefore may be more substitutable for robots. The Labour Force Survey defines 9 occupation categories, that I subdivide into "high" occupations that have high skill requirements and "low" occupations that have have low skill requirements. High occupations include managers and administrators, professional occupations and associate professional occupations. Low occupations include clerical and secretarial occupations, craft and related occupations, personal and protective service occupations, sales occupations, plant and machine operatives, and other occupations. My specification is as follows:

$$\lambda_{ir}^{1994}\frac{S_{it}}{L_{ir,1994}} = \beta_{highocc}\frac{M_{irt,highocc}}{L_{ir,1994}} + \beta_{lowocc}\frac{M_{irt,lowocc}}{L_{ir,1994}} + \theta_i + \theta_r + \theta_t + \epsilon_{irt}$$

I expect $\beta_{highocc} > \beta_{lowocc}$, with β_{lowocc} being negative to reflect the substitutability of immigrants in "low" occupations and robots.

To run an IV specification for either of the above extensions, I would instrument $\frac{M_{irt,group}}{L_{ir,1994}}$ using $\frac{\sum_c \theta_{rc} M_{cit,group}}{L_{ir,1994}}$.

6 Results

Table 5 presents estimates of the effect of immigration on robotisation. Column 1 is the OLS specification without any controls other than the dummy variables used to eliminate fixed effects. Column 2 adds controls for the skill composition of the native population as well as the average ages of immigrants and natives. Columns 3 and 4 are the corresponding 2SLS Instrumental Variables specifications. An increase in the immigrant share has a negative impact on the degree of robotisation. This supports our hypothesis that immigrants and robots are substitutes. As expected, the coefficient on immigrant share is more negative in the IV specifications. Since attenuation bias due to measurement error would push the estimate towards zero, and simultaneity would push the estimate upwards, this suggests that one or both of these is at work in the OLS specification. Reassuringly, the controls do not hugely change the estimate or adjusted R-squared. Adding controls reduces the magnitude of the OLS coefficient, but increases that of the IV estimate. The IV estimate of -1.24 implies that if the immigrant share of the total 1994 workforce increases by one standard deviation (or 0.114), then robots per worker will decrease by -0.141, or 0.42 standard deviations.

It is also notable that the mean age of natives and immigrants have small but opposite effects on robotisation. This reinforces the hypothesis that natives and immigrants interact differently with robots. An older native population is associated with less robotisation, which is supported by the OECD (2018) evidence that older workers are less at risk of robotisation. An older immigrant population, on the other hand, is associated with a greater degree of robotisation, which goes against the OECD (2018) research. Perhaps this has to do with reduced job stability for immigrants - if they are more likely to be replaced than natives due to discrimination, or greater participation rates in informal work where worker protections are limited. This disparity could be an interesting area for further research.

Controls for native skill composition reveal that a greater relative number of high-skilled natives is associated with fewer robots per worker, while a greater relative share of mid-skilled natives is associated with more robots per worker. This is surprising given the OECD (2018) research that higher-skilled workers tend to less at risk from automation, and therefore presumably more complementary to robots.

For robustness, I run the regressions looking at the effect of immigrants on robotisation, first without the most immigrant-heavy region (inner London) and then without the most immigrant intensive industry (food and beverage manufacturing). The results are reported in tables 6 and 7. Though the estimated effect is smaller, it remains significant and negative.

Table 5: Effect of Immigration on Robotisation, specifications in levels

	(1) OLS	(2) OLS	(3) IV	(4) IV
Immigrants per Worker	-0.0840*	-0.0804*	-1.090***	-1.238***
	(0.034)	(0.035)	(0.127)	(0.146)
H/L Skill Natives		-0.0203*		-0.0177
		(0.010)		(0.011)
M/L Skill Natives		0.0268*		0.0440**
		(0.013)		(0.014)
Mean Age of Natives		-0.00315		-0.00408*
		(0.002)		(0.002)
Mean Age of Immigrants		0.00000474		0.00214***
		(0.000)		(0.000)
Constant	-0.264***	-0.140	0.354***	0.469***
	(0.042)	(0.079)	(0.044)	(0.092)
Observations	8491	8334	8491	8334
Adjusted R^2	0.753	0.751	0.727	0.719

Standard errors in parentheses

The left hand side is always robots per worker, by industry, region and year, where the denominator is from base year 1994. The right hand side variable of interest is the ratio of immigrant to total workers by industry, region and year, where again the denominator is from 1994. The first two columns are least squares regressions, that also include year, region and industry dummies to control for fixed effects. The first column is the simplest specification, while the second column includes controls for the proportions of natives of each skill group: I construct the number of mid- and high-skilled natives as a share of low-skilled natives in each industry-region-year cell. I also include controls for the mean ages of immigrants and natives. The third and fourth columns are the corresponding 2SLS regressions where the number of immigrants in an industry-region-year cell is instrumented by predicted immigrant numbers, based on 1986 settlement patterns by area of birth.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Robustness Checks: excluding London

	(1) OLS	(2) IV
Immigrants per Worker	-0.0491	-0.806***
	(0.037)	(0.150)
H/L Skill Natives	-0.0347*	-0.0272
	(0.014)	(0.015)
M/L Skill Natives	0.0300*	0.0398**
	(0.015)	(0.015)
Mean Age of Natives	-0.00173	-0.00258
	(0.002)	(0.002)
Mean Age of Immigrants	0.000102	0.00147**
	(0.000)	(0.000)
Constant	-0.199*	0.419***
	(0.083)	(0.095)
Observations	8013	8013
Adjusted R^2	0.754	0.740

Standard errors in parentheses

The left hand side is always robots per worker, by industry, region and year, where the denominator is from base year 1994. The right hand side variable of interest is the ratio of immigrant to total workers by industry, region and year, where again the denominator is from 1994. The first column is a least squares regression, that also includes year, region and industry dummies to control for fixed effects. The second column is the corresponding 2SLS regression where the number of immigrants in an industry-region-year cell is instrumented by predicted immigrant numbers, based on 1986 settlement patterns by area of birth. I also control for the proportions of natives of each skill group: I construct the number of mid- and high-skilled natives as a share of low-skilled natives in each industry-region-year cell. I also include controls for the mean ages of immigrants and natives.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Robustness Checks: excluding Food Manufacturing

	(1) OLS	(2) IV
Immigrants per Worker	-0.0877*	-1.311***
	(0.040)	(0.154)
H/L Skill Natives	-0.0205*	-0.0169
	(0.010)	(0.011)
M/L Skill Natives	0.0272	0.0471**
	(0.014)	(0.015)
Mean Age of Natives	-0.00320	-0.00389*
	(0.002)	(0.002)
Mean Age of Immigrants	0.00000902	0.00238***
	(0.000)	(0.001)
Constant	-0.146	0.465***
	(0.083)	(0.096)
Observations	7839	7839
Adjusted R^2	0.751	0.720

Standard errors in parentheses

The left hand side is always robots per worker, by industry, region and year, where the denominator is from base year 1994. The right hand side variable of interest is the ratio of immigrant to total workers by industry, region and year, where again the denominator is from 1994. The first column is a least squares regression, that also includes year, region and industry dummies to control for fixed effects. The second column is the corresponding 2SLS regression where the number of immigrants in an industry-region-year cell is instrumented by predicted immigrant numbers, based on 1986 settlement patterns by area of birth. I also control for the proportions of natives of each skill group: I construct the number of mid- and high-skilled natives as a share of low-skilled natives in each industry-region-year cell. I also include controls for the mean ages of immigrants and natives.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The first stage of the instrumental variable specification is presented in table 8. If predicted immigrants per worker increases by 1 unit, the observed number of immigrants per worker increases by 1.02. The instrument is therefore strongly predictive.

Table 8: IV First Stage: Immigrants per Worker

	Immigrants per Worker
Predicted Immigrants per Worker	1.018***
	(0.027)
Constant	0.0590***
	(0.002)
Observations	8491
Adjusted R^2	0.146

Standard errors in parentheses

Regression of observed immigrants per worker on the proposed instrument, predicted immigrants per worker. The number of predicted immigrants is constructed using the regional settlement patterns of immigrants in 1986. I assume that immigrants from the same areas of birth will settle in similar regions to 1986 immigrants throughout the period of study. I multiply the regional shares of 1986 immigrants by areas of birth by the observed number of immigrants from that area, in an industry and year. By region, I sum across origin countries to get the total predicted immigrant number in an industry-region-year cell. Both observed immigrants and predicted immigrants are deflated by the observed number of workers in an industry-region cell in base year 1994.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

I also run the specifications in differences, as described in Section 5. The results are presented in table 9. These results are much less informative, as all estimates except for the constant are small and insignificantly different from zero. By comparing the adjusted R-squared with table 5, it is clear that the specifications in differences lose much of the explanatory power of the specifications in levels. From here on, I will only analyse the regressions in levels, but regressions in differences are reported in the appendix.

Table 9: Effect of Immigration on Robotisation, specifications in differences

	(1) Diff. OLS	(2) Diff. OLS	(3) Diff. IV	(4) Diff. IV
Diff. Immigrants per Worker	0.00263 (0.0065)	0.00279 (0.0071)	-0.0445 (0.0246)	-0.0626 (0.0339)
Diff. H/L Skill Natives		-0.000816 (0.0018)		-0.000696 (0.0018)
Diff. M/L Skill Natives		0.00173 (0.0019)		0.00213 (0.0019)
Diff. Mean Native Age		-0.0000455 (0.0003)		-0.000000653 (0.0003)
Diff. Mean Immigrant Age		0.0000310 (0.0001)		0.000131 (0.0001)
Constant	0.0150*** (0.0044)	0.0151*** (0.0044)	0.0406*** (0.0044)	0.0393*** (0.0046)
Observations	8144	7929	8144	7929
Adjusted R^2	0.016	0.015	0.009	0.005

Standard errors in parentheses

The left hand side is the first difference of robot stocks by industry, region and year, normalised by the total number of workers in 1994. The right hand side variable of interest is the difference of immigrant numbers, normalised by the number of workers by industry and region in 1994. The first column is the first differenced OLS regression, that includes year dummies to absorb aggregate time-trends.The second column is the corresponding 2SLS regression, where the difference in immigrant numbers is instrumented for using the predicted difference in immigrant numbers. I also control for the change in proportions of natives of each skill group. I construct the number of mid- and high-skilled natives as a share of low-skilled natives in each industry-region-year cell, then first difference these to get the change. I also include controls for the change in mean ages for both immigrants and natives in each industry-region-year cell.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To investigate the substitutability of immigrants and robots further, I split the immigrants into low, medium and high-skilled groups according to the age at which they completed their education. This allows me to look at whether low-skilled immigrants are particularly substitutable for robots, as predicted based on the previous research presented in Section 2. Table 10 presents the results of these specifications. It is notable that the estimate for the impact of low-skilled immigrants is much more negative than for other skill groups. Since the low-skilled immigrant share variable has a standard deviation of 0.02899, an increase in the low-skilled immigrant share by one standard deviation will lead to an fall in robots per worker by -0.114, or 0.34 standard deviations (according to the IV estimate). Although the estimate is more negative than for all immigrants, the relative effect by standard deviations is less powerful for the low-skilled immigrant share than the overall immigrant share. This is surprising given the general evidence that lower skilled occupations are more highly automatable. The estimates for mid-skill immigrants and high-skill immigrants are negative, but small and statistically indistinguishable from zero. As in the regressions in table 5, the IV estimates are more negative than the OLS ones, implying that attenuation bias, simultaneity or both are pushing the OLS estimates up towards zero. The first stages for all three skill-specific instruments, show that all the instruments are relevant (see appendix).

Table 10: Effect of Immigration on Robotisation, by Skill Group

	(1) OLS	(2) IV
Low Skill Immigrants per Worker	-0.275**	-3.927***
	(0.092)	(0.404)
Mid Skill Immigrants per Worker	-0.0890	-0.272
	(0.082)	(0.422)
High Skill Immigrants per Worker	0.0341	-0.0689
	(0.074)	(0.195)
H/L Skill Natives	-0.0227*	-0.0398***
	(0.010)	(0.012)
M/L Skill Natives	0.0267*	0.0293
	(0.013)	(0.016)
Mean Age of Natives	-0.00313	-0.00337
	(0.002)	(0.002)
Mean Age of Immigrants	0.0000833	0.00294***
	(0.000)	(0.001)
Constant	-0.140	0.392***
	(0.079)	(0.096)
Observations	8334	8334
Adjusted R^2	0.751	0.700

Standard errors in parentheses

The left hand side is robots per worker, by industry, region and year. These regressions look at how the effect varies by immigrant skill group. The right hand side variables of interest are the ratios of immigrants from each skill group to the total number of workers by industry and region in 1994. The first column is a least squares regression, that also includes year, region and industry dummies to control for fixed effects. The second column is the instrumented version of the first column, where immigrant numbers from each skill category are instrumented by predicted immigrant numbers in that group, based on 1986 settlement pattern by area of birth. For the skill-specific instruments, I multiply regional shares by country of origin by the number of immigrants in a specific skill category, rather than all immigrants in that industry-region-year cell. I also control for the proportions of natives of each skill group: I construct the number of mid- and high-skilled natives as a share of low-skilled natives in each industry-region-year cell. I also include controls for the mean ages of immigrants and natives.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Given the strong negative estimated effect of low-skilled immigrants and the statistically insignificant estimate for other skill groups, I want to check if the negative relationship estimated overall is being solely driven by low-skilled immigrants. I therefore run the regression of robots per worker on immigrants per worker, but excluding low-skilled immigrants. Table 11 shows a smaller but still significantly negative relationship. The standard deviation for the immigrant share excluding the low-skilled is equal to 0.093. This allows us to say that if the share of these immigrants increases by one standard deviation, then robots per worker fall by -0.0405, or 0.12 standard deviations. The effect is therefore cut by over two-thirds once we exclude the low-skilled immigrants. But there is still a significant negative effect, which we might not expect from more highly skilled immigrants. One clue to this puzzle may be in the evidence of downgrading in the UK documented by Dustmann, Frattini and Preston (2013). If immigrants tend to work in positions for which they are overqualified, the age at which they left full time education may not be a very good proxy for the kinds of jobs they tend to work in. Highly educated immigrants may be working in low-skilled, routine or manual occupations, and therefore be good substitutes for robots.

Table 11: Effect of Immigration on Robotisation, excluding Low-Skilled Immigrants

	(1) OLS	(2) IV
M+H Skill Immigrant Share	-0.0509	-0.436**
	(0.044)	(0.148)
H/L Skill Natives	-0.0201*	-0.0174
	(0.010)	(0.010)
M/L Skill Natives	0.0263	0.0315*
	(0.013)	(0.014)
Mean Age of Natives	-0.00313	-0.00341
	(0.002)	(0.002)
Mean Age of Immigrants	-0.0000892	0.000323
	(0.000)	(0.000)
Constant	-0.139	0.471***
	(0.079)	(0.087)
Observations	8334	8334
Adjusted R^2	0.751	0.749

Standard errors in parentheses

The left hand side is always robots per worker, by industry, region and year, where the denominator is from base year 1994. The right hand side variable of interest is the ratio of mid and high-skilled immigrants to total workers by industry, region and year, where again the denominator is from 1994. The first column is a least squares regression, that also includes year, region and industry dummies to control for fixed effects. The second column is the corresponding 2SLS regression where the number of immigrants in an industry-region-year cell is instrumented by predicted immigrant numbers, based on 1986 settlement patterns by area of birth. I also control for the proportions of natives of each skill group: I construct the number of mid- and high-skilled natives as a share of low-skilled natives in each industry-region-year cell. I also include controls for the mean ages of immigrants and natives.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To investigate this idea further, I run a regression where I divide immigrants according to their occupations rather than their education levels. I first divide occupations into two categories, according to jobs with high skill requirements and those with fewer skill requirements. The high-skilled grouping includes managers and administrators, professional occupations, and association professional and technical occupations. The lower skilled occupations includes clerical and secretarial occupations, craft and related occupations, personal or protective occupations, sales occupations, plant and machine operatives and other occupations. Table 12 shows that the estimate for the more managerial occupations is insignificant, while that for the lower paid occupations is negative. An increase in the share of "Low" occupation immigrants per worker by one standard deviation (or 0.0813) leads to a fall in robots per worker by -0.187, or 0.55 standard deviations. This represents the greatest impact in terms of standard deviations of all the estimates we have considered. Its relative impact compared to the effect from the specification which differentiated by skill-level further suggests that the education level of immigrants is a poor predictor for the jobs they will have. Moreover, the strong effect reinforces the idea that immigrants in more routine or manual jobs, for which the skill-requirements are lower (even if the immigrants are skilled) are substitutable with robots. Table 13 breaks occupations down further into the 9 occupation categories. Though this breakdown gives few significant estimates, the estimate for the effect of immigrants working as Plant and Machine Operatives is negative and significant. An increase in the share of these immigrants by one standard deviation leads to a fall in robots per worker by 0.41 standard deviations. The strong substitutability between industrial robots and immigrants working as plant and machine operatives is intuitive: industrial robots can best replace those working routine tasks in industrial settings.

Table 12: Effect of Immigration on Robotisation, differentiating by Occupation Grouping

	(1) OLS	(2) IV
High Occ. Immigrants per Worker	0.0266	0.177
	(0.100)	(0.229)
Low Occ. Immigrants per Worker	-0.105*	-2.303***
	(0.041)	(0.233)
H/L Skill Natives	-0.0220*	-0.0488***
	(0.010)	(0.012)
M/L Skill Natives	0.0269*	0.0540***
	(0.013)	(0.016)
Mean Age of Natives	-0.00310	-0.00363
	(0.002)	(0.002)
Mean Age of Immigrants	-0.0000242	0.00270***
	(0.000)	(0.001)
Constant	-0.141	0.463***
	(0.079)	(0.101)
Observations	8334	8334
Adjusted R^2	0.751	0.664

Standard errors in parentheses

The left hand side is robots per worker, by industry, region and year, where the denominator is from base year 1994. These regressions look at how the effect varies by immigrant occupation group. The right hand side variables of interest are the ratios of immigrants from each occupation grouping to the total number of workers by industry and region in 1994. The first column is a least squares regression, that also includes year, region and industry dummies to control for fixed effects. The second column is the instrumented version of the first column, where immigrant numbers from each occupation category are instrumented by predicted immigrant numbers in that group, based on 1986 settlement pattern by area of birth. For the occupation-specific instruments, I multiply regional shares by country of origin by the number of immigrants in a specific occupation category, rather than all immigrants in that industry-region-year cell. I also control for the proportions of natives of each skill group: I construct the number of mid- and high-skilled natives as a share of low-skilled natives in each industry-region-year cell. I also include controls for the mean ages of immigrants and natives.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Effect of Immigration on Robotisation, differentiating by Occupation

	(1) OLS	(2) IV
Manager Immigrants per Worker	0.0263	0.741
	(0.179)	(0.486)
Prof. Immigrants per Worker	-0.200	-0.106
	(0.181)	(0.444)
Assoc. Prof. Immigrants per Worker	0.267	0.124
	(0.222)	(1.115)
Clerical Immigrants per Worker	0.312	1.605
	(0.308)	(0.964)
Craft Immigrants per Worker	-0.0662	0.373
	(0.094)	(0.416)
Protective Immigrants per Worker	0.126	-3.208*
	(0.719)	(1.587)
Sales Immigrants per Worker	0.709	-0.908
	(0.492)	(1.338)
Machine Immigrants per Worker	-0.189*	-4.069***
	(0.077)	(0.370)
Other Immigrants per Worker	-0.112	-0.529
	(0.147)	(0.635)
H/L Skill Natives	-0.0219*	-0.0380**
	(0.010)	(0.013)
M/L Skill Natives	0.0262	0.0425**
	(0.013)	(0.016)
Mean Age of Natives	-0.00297	-0.00223
	(0.002)	(0.002)
Mean Age of Immigrants	-0.0000458	0.00164**
	(0.000)	(0.001)
Constant	-0.147	0.360***
	(0.079)	(0.103)
Observations	8334	8334
Adjusted R^2	0.751	0.661

The left hand side is robots per worker, by industry, region and year, where the denominator is from base year 1994. These regressions look at how the effect varies by immigrant occupation. The right hand side variables of interest are the ratios of immigrants from each occupation to the total number of workers by industry and region in 1994. The first column is a least squares regression, that also includes year, region and industry dummies to control for fixed effects. The second column is the instrumented version of the first column, where immigrant numbers from each occupation are instrumented by predicted immigrant numbers in that group, based on 1986 settlement pattern by area of birth. For the occupation-specific instruments, I multiply regional shares by country of origin by the number of immigrants in a specific occupation, rather than all immigrants in that industry-region-year cell. I also control for the proportions of natives of each skill group: I construct the number of mid- and high-skilled natives as a share of low-skilled natives in each industry-region-year cell. I also include controls for the mean ages of immigrants and natives.

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7 Discussion and Conclusion

In principle, the arrival of immigrants in a labour market may lead to an increase in the number of robots if they are complementary, a fall if they are substitutable, or no change at all if the economy adjusts to immigration through wages and employment of native-born workers. I have shown that in the UK, immigrants cause a fall in the share of robots per worker, within a labour market defined as an industry/region/year cell.

On average, an increase in the immigrant share by one standard deviation leads to a fall in the robot share by just under half (0.42) of a standard deviation. This supports the idea that immigrants and robots are substitutes, and that firms that have these robots available to them adapt to immigration by using fewer robots, and to a reduced immigrant population by using more robots. Coupled with the previous literature which finds a negligible effect of immigration on native employment and wages in the UK (see e.g. Dustmann, Fabbri and Preston 2005), this suggests that many firms in the industrial sector adapt to immigration through changing their use of technology, specifically robots, rather than by adjusting native employment and wages. This also fits with the evidence in Dustmann and Glitz (2015) that German firms in the tradeable sector tend to adjust through technology rather than wages. Industrial robots are concentrated in Manufacturing and Agriculture, which are both in the tradeable sector.

Extensions looking at this effect according to immigrants' occupations or skill levels reveal that some immigrants are more substitutable with robots than others. An increase in the low-skilled immigrant share by one standard deviation leads to a fall in the robot share by only 0.34 standard deviations. An increase in the share of immigrants working in low-skilled occupations by one standard deviation leads to a fall in the robot share by 0.55 standard deviations. This supports the hypothesis that immigrants are particularly substitutable with robots due to their concentration in low-skilled occupations. The stronger negative relationship between immigrants in low-skilled occupations rather than whose education suggests they are themselves low-skilled reinforce the evidence of immigrant downgrading in the UK identified by Dustmann, Frattini and Preston (2013).

The particular substitutability of industrial robots and immigrants working in low-skilled occupations has some interesting policy implications. Active labour market policies which focus on reducing the flow of low-skilled immigrants and those who would work in low-skilled occupations, like the new points-based immigration policy enacted after the UK's withdrawal from the European Union, may lead to large increases in the degree of industrial robotisation, rather than improving the employment conditions of UK natives working in the manufacturing and agricultural sectors (UK Government, 2020).

My analysis raises various avenues for future research. I have focused on industrial robots, which are only a small part of the automated technologies changing global labour markets. Since 2009, the IFR has been producing reports on service robots alongside their annual industrial robots reporting. This data is not yet available for analysis. Once this data becomes accessible through their portal, a natural extension to this paper would be to analyse the effects of immigration on service robots. This is of particular interest in a country like the UK where the service industry is much larger than the manufacturing industry, and often has made extensive use of immigrant labour - for example in hospitality and care services. It would also be useful to consider how these effects vary by country. For example, immigrants in the UK are more highly-skilled than the native-born, unlike immigrants in the US, so it would be interesting to conduct similar analysis for the US to see if immigrants in the US are even more substitutable with robots.

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9 Appendix

9.1 Regression Tables

Table 14: IV First Stage: Differenced Immigrants per Worker

	Change in Immigrants per Worker
Predicted Change in Immigrants per Worker	0.949***
	(0.039)
Constant	0.00230
	(0.001)
Observations	8144
Adjusted R^2	0.069

Standard errors in parentheses

Regression of first differenced observed immigrants per worker on the proposed instrument, first differenced predicted immigrants per worker. The number of predicted immigrants is constructed using the regional settlement patterns of immigrants in 1986. I assume that immigrants from the same areas of birth will settle in similar regions to 1986 migrants throughout the period of study. I multiply the regional shares of 1986 immigrants by areas of birth by the observed number of immigrants from that area, in an industry and year. By region, I sum across origin countries to get the total predicted immigrant number in an industry-region-year cell. I then take the first difference of that predicted immigrant number. Both differenced observed immigrants and differenced predicted immigrants are deflated by the observed number of workers in an industry-region cell in 1994.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: IV First Stage: Low-Skilled Immigrants per Worker

	Low Skill Immigrants per Worker
Predicted Low-Skilled Immigrants per Worker	0.977***
	(0.035)
Constant	0.0193***
	(0.001)
Observations	8491
Adjusted R^2	0.084

Standard errors in parentheses

Regression of observed low-skilled immigrants per worker on the proposed instrument, predicted low-skilled immigrants per worker. The number of predicted low-skilled immigrants is constructed using the regional settlement patterns of immigrants in 1986. I assume that immigrants from the same areas of birth will settle in similar regions to 1986 immigrants throughout the period of study. I multiply the regional shares of 1986 immigrants by areas of birth by the observed number of low-skilled immigrants from that area, in an industry and year. By region, I sum across origin countries to get the total predicted low-skilled immigrant number in an industry-region-year cell. Both observed low-skilled immigrants and predicted low-skilled immigrants are deflated by the observed number of workers in an industry-region cell in 1994.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: IV First Stage: Mid-Skilled Immigrants per Worker

	Mid-Skilled Immigrants per Worker
Predicted Mid-Skilled Immigrants per Worker	2.526***
	(0.098)
Constant	0.0201***
	(0.001)
Observations	8491
Adjusted R^2	0.073

Standard errors in parentheses

Regression of observed mid-skilled immigrants per worker on the proposed instrument, predicted mid-skilled immigrants per worker. The number of predicted mid-skilled immigrants is constructed using the regional settlement patterns of immigrants in 1986. I assume that immigrants from the same areas of birth will settle in similar regions to 1986 immigrants throughout the period of study. I multiply the regional shares of 1986 immigrants by areas of birth by the observed number of mid-skilled immigrants from that area, in an industry and year. By region, I sum across origin countries to get the total predicted mid-skilled immigrant number in an industry-region-year cell. Both observed mid-skilled immigrants and predicted mid-skilled immigrants are deflated by the observed number of workers in an industry-region cell in 1994.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: IV First Stage: High-Skilled Immigrants per Worker

	High Skill Immigrants per Worker
Predicted High-Skilled Immigrants per Worker	2.681***
	(0.043)
Constant	0.0195***
	(0.001)
Observations	8491
Adjusted R^2	0.317

Standard errors in parentheses

Regression of observed high-skilled immigrants per worker on the proposed instrument, predicted high-skilled immigrants per worker. The number of predicted high-skilled immigrants is constructed using the regional settlement patterns of immigrants in 1986. I assume that immigrants from the same areas of birth will settle in similar regions to 1986 immigrants throughout the period of study. I multiply the regional shares of 1986 immigrants by areas of birth by the observed number of high-skilled immigrants from that area, in an industry and year. By region, I sum across origin countries to get the total predicted high-skilled immigrant number in an industry-region-year cell. Both observed high-skilled immigrants and predicted high-skilled immigrants are deflated by the observed number of workers in an industry-region cell in 1994.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: Effect of Immigration on Robotisation, by Skill Group, specifications in differences

	(1) Diff. OLS	(2) Diff. IV
Diff. Low-Skilled Immigrants per Worker	0.00137	-0.381
	(0.0137)	(0.3723)
Diff. Mid-Skilled Immigrants per Worker	0.00643	-0.261
	(0.0130)	(0.4821)
Diff. High-Skilled Immigrants per Worker	0.000478	-0.920
	(0.0118)	(0.6149)
Diff. H/L Skill Natives	-0.000809	0.00144
	(0.0018)	(0.0030)
Diff. M/L Skill Natives	0.00171	0.00309
	(0.0019)	(0.0037)
Diff. Mean Native Age	-0.0000449	0.000446
	(0.0003)	(0.0005)
Diff. Mean Immigrant Age	0.0000315	0.000800
	(0.0001)	(0.0006)
Constant	0.0151***	0.0336***
	(0.0044)	(0.0086)
Observations	7929	7929
Adjusted R^2	0.015	.

Standard errors in parentheses

The left hand side is the first difference of robots, normalised by the number of workers in base year 1994. These regressions look at how the effect varies by immigrant skill group. The right hand side variables of interest are the ratios of immigrants from each skill group to the total number of workers by industry, region and year. I difference the number of immigrants in a skill group before deflating by workers in 1994. The first column is a first differenced regression, that includes year dummies to absorb aggregate time-trends. The second column is the correspondonding 2SLS specification, where the difference in immigrant numbers is instrumented for using the predicted difference in immigrant numbers. For the skill-specific instruments, I multiply regional shares by country of origin by the number of immigrants in a specific skill category, rather than all immigrants in that industry-region-year cell. I also control for the change in proportions of natives of each skill group. I construct the number of mid- and high-skilled natives as a share of low-skilled natives in each industry-region-year cell, then first difference these to get the change. I also include controls for the change in mean ages for both immigrants and natives in each industry-region-year cell.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

9.2 Industry Code Crosswalk

Industry	My Code	ISIC rev.4 code	INDCLM	INDD92M	INDD07M
Agriculture, forestry, fishing	1	A-B	1-3	1-3	1-3
Mining and quarrying	2	C	4,6,11,12	4-8	5-9
Manufacturing	3	D			
Food and beverages	31	10-12	24	9-10	10-12
Textiles	32	13-15	25-27	11-13	13-15
Wood and furniture	33	16	28	14	16
Paper	34	17-18	29	15-16	17-18
Plastic and chemical products	35	19-22	5,7,8,15,30	17-19	19-22
Glass, ceramics, stone, mineral products (non-auto)	36	23	14	20	23
Metal	37	24, 25, 28	12,17-18	21-23	24, 25, 28
Electrical/electronics	38	26-27	19-20,23	24-27	26-27
Automotive	39	29	21	28	29
Other vehicles	40	30	22	29	30
All other manufacturing branches	41	91	31	30-31	31-33
Electricity, gas, water supply	5	E	9-10,16	32-33	35-39
Construction	6	F	32	34	41-43
Education/research/development	7	P	53-54	50,53	72, 85
All other non-manufacturing branches	8	90	33-52,55-60	35-49,51-52,54-60	45-71,73-84,86/99
Unspecified	.	99	61-63	61-63, -8	-8

INDCLM, INDD92M and INDD07M are the LFS variable names for the industry class variables for SIC80, SIC92 and SIC07 classifications respectively.