REPORT FOR THE MIGRATION ADVISORY COMMITTEE

Jumping Someone Else's Train? Does Immigration Affect the Training and Hiring of Native-Born Workers (and Are There Different Effects From EEA and Non-EEA Migrants)? A Report for the Migration Advisory Committee

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Abstract

Firm based training is recognised as playing an important role in skill accumulation in developed economies and so in determining an economy's productivity level. The effect of immigration on firm based training is therefore an important question for UK policy makers and one which has been made especially relevant for current policy by the uncertainties of the Brexit process. However there is, as yet, very little evidence theoretical or empirical, on the possible effects of immigration on training. This project plans to increase the evidence base on this issue by analysing whether recent immigration has had a positive or negative effect on training of the extant workforce. We develop a simple theoretical model to show how immigration could influence the level of training depending on the skill of the migrant and the sector in which they are employed. We then test the predictions of the model with UK data to investigate whether training and hiring shares of UK-Born workers are falling in industries and occupations with rising shares of trained-immigrants from EEA and non-EEA countries.

Table of Contents

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1. Introduction

Training has become a key issue in the recent debate over cross-country differences in productivity performance. For example the OECD (2017) noted the UK's poor productivity levels compared to the rest of the G7 and argued that one reason for the UK's recent slow productivity growth was that over one quarter of UK workers were low skilled. Firm based training is recognised as playing an important role in skill accumulation in developed economies and so in determining an economy's productivity level, see e.g. Dustmann and Schonberg (2012). The effect of immigration on firm based training is thus an important question for UK policy makers and one which has been made especially relevant for current policy by the uncertainties of the Brexit process. However there is, as yet, very little evidence theoretical or empirical, on the possible effects of immigration on training. This project plans to increase the evidence base on this issue by analysing whether recent immigration has had a positive or negative effect on training of the extant workforce.

Recent studies on the effects of immigration have argued that skilled immigrants add to the human capital stock of an economy and thereby have a beneficial impact on an economy's aggregate productivity, [see e.g. Mountford and Rapoport (2011)]. Moreover the empirical evidence for countries like the UK suggests that rising immigration appears to have had little detrimental effect on the average wage or employment prospects of UK-born workers, whether less skilled or otherwise. [See e.g. Manacorda, Manning and Wadsworth (2012)]. However these findings do not exclude the possibility that migrants with an existing stock of human capital may crowd out the human capital formation of indigenous workers in certain sectors of the economy.

Intuitively, immigration may be a complement or a substitute for the training of the existing workforce. A positive training effect may arise if, for example, a skilled migrant is able to train more indigenous workers. A negative training effect could occur if firms source a ready supply of trained workers from abroad rather than undertake the expense of training a local workforce. If the latter effect dominates then although the aggregate employment of indigenous workers may not be affected by rising immigration, the sectoral composition in which native workers are found may be affected. Consequently if immigration causes native workers to find employment in sectors with lower levels of training then social mobility in the receiving economy, as well as the welfare of this group, could be reduced by skilled immigration.

Migrants differ in their skill sets and stocks of human capital and so their effects on the UK labour market will also differ. Empirically the skill sets and stocks of human capital of migrants to the UK from the EU may differ from those of migrants to the UK from outside the EU, and so there may be differential effects on training of native workers dependent on migrant area of origin. In what follows we estimate whether a training effect of immigration exist and whether there is any differential effect by area of origin.

We develop a simple theoretical model to show how immigration could influence the level of training in the UK and test the model with UK data to investigate whether training and hiring rates of indigenous workers are falling in industries and occupations with rising shares of trained-immigrants. We map and document the distribution of, and changes in, skilled and unskilled (EEA/non-EEA) migrant labour across sectors and occupations alongside the incidence, hiring and training rates of native workers. We then examine whether there is any evidence for differential training and hiring effects caused by migrants from the EU and elsewhere.

2. Why Might Immigration Affect Training And Productivity?

If people could borrow to invest in their training then it could be argued that, in a competitive world economy, the ability of labour to migrate to where it is most productive would increase productivity and wages and so raise the incentive to acquire productive skills. However people cannot easily borrow to finance training against the increased future earnings such training may bring about. There are many reasons for this, but one is the inability of lenders to recover the loan in the event that the training expenditure does not in fact lead to higher earnings. This consequently effects the incentives to take up a loan in the first place.

Since people cannot easily borrow to pay for training then only people who have high income or wealth will be able to purchase training outright, or provide sufficient collateral to borrow for training. Thus opportunities to gain skills are linked to one's family's wealth. Training is also linked to family circumstance in other ways. For example the tendency for children to follow into similar occupations to their parents may also indicate an intra-family or local transmission of skills. (See e.g. Lentz and Laband (1989) and Bell, A., Chetty, R., Jaravel, X., Petkova, N. and J. Van Reenen (2017)).

For these reasons and others it is commonly argued that the market provides an inefficiently low level of training and this argument is used to justify the public provision and subsidies of education and training, (Acemoglu and Pischke (1999) summarise the literature). Job based training allows people to gain skills, typically at minimal cost, whilst working - i.e. without the need for family wealth. In a world where training is sub-optimally low, this mechanism may be important for productivity [See e.g. Dearden, Reed and Van Reenen (2006)].

In this context it is interesting to ask under what circumstances it makes sense to say that an immigrant affects indigenous workers' access to job based training schemes i.e. "takes a good job" . [By a "good job" we mean a job with training which provides a chance for upward income mobility for their family.] In the theoretical model, described briefly below, we show that there may be different effects of immigrants on training in different sectors, in particular between traded and non-traded sectors. This is because when the demand for a good is determined on the world market then the employment of an immigrant by a firm need not reduce its ability to employ an indigenous worker. It may just mean that more of the world demand for the good is satisfied by domestic production. In contrast the demand for non-traded goods is limited by the size of the domestic economy. An immigrant, or indeed a native, working in the non-traded sector will produce more of the non-traded good than he or she will demand, (because income is not exclusively spent on non-traded goods). Thus following an increase in immigration into the non-traded sector this will push re-allocation of (unskilled) native workers from the non-traded into the traded sector and so will, other things equal, reduce the remaining demand for native workers in the non-traded sector below its pre migration level.[1] Thus it is much easier to argue that an immigrant takes a good job in a non-traded sector than in a traded sector. However, if hiring immigrant labour increases the profitability of the non-traded sector more firms offering training could enter the sector and increase the number of training positions available to native workers. Ultimately whether the positive or negative effects of immigration dominate is a matter for empirical verification.

The theoretical model in the Appendix shows that the impacts of immigrants on training and hiring will also differ across the characteristics of the immigrant. Immigrants with high wealth increase the demand for domestic non traded goods. Immigrants with high skill can increase the availability of training. As such both may have a positive effect on domestic training. Whereas those of similar skills

[1] Since the output produced by a worker in the non-traded sector is more than the amount consumed by the worker, someone else has to demand more of the non-traded good than they produce – which can only be done by someone working in the traded sector. We assume that migrants into the non-traded sector have a non-traded specific skill set.

to domestic trained workers and who work in the non-traded sector may have positive or negative effects on domestic training. Negative, because importing trained workers may displace natives. Positive, because trained migrants may be able to do more training. Thus the theoretical model shows that the popular concern that immigrant workers are taking "good jobs" does make theoretical sense, especially in non-traded sectors. However since there are also ways that immigrants could increase the number of good jobs in the economy then the issue is a matter for empirical verification.

EEA and Non-EEA Immigration

Migrants differ in their skill sets and stocks of human capital and so there may be differential effects on training of native workers dependent on migrant area of origin. It is conceivable that the pool of migrant labour from EEA countries differs from that from Non-EEA countries. UK Immigration policy toward Non-EEA workers has been tightened over the years, beginning with the ending of unrestricted migration from the Commonwealth in the early 1970s and the subsequent introduction of work permits for "skilled workers". The definition of skilled has also been tightened over the years so that it now covers only graduate-level jobs.[2] EEA migration, at least until the end of the Brexit transition period, is essentially unrestricted. So employers can choose over a wider pool of labour from the EEA than from outside the EEA. In what follows we estimate whether a training effect of immigration exists and whether there is any differential effect by area of origin.

3. Data

The data used for the analysis comes from the UK Labour Force Survey (LFS). This dataset contains information on the incidence of on-the job training and hiring of individuals alongside their industry and occupation which are our main outcomes of interest.

[2] In reality many of the socio-demographic characteristics of EEA and Non-EEA adult migrants appear to be rather similar. Table A9 in the appendix shows that, for example, the average age at which an adult migrant left full-time education which was 20.2 in 1995 and 20.9 in 2017, according to the UK Labour Force Survey. The equivalent estimates for EEA migrants are also 20.2 and 20.9 respectively.

The training variable used is the response to the LFS question

"In the 3 months since [date] have you taken part in any education or any training connected with your job or a job that you might be able to do in the future?"

We can classify immigrants in the LFS by their age, education and country of origin and year of arrival and hence estimate the workforce share of trained immigrants in each industry and/or occupation and/or region. This information allows us to investigate whether the extent of migration or the degree of skill among migrants has affected the extent of training among the indigenous workforce.[3] The definition of skilled adult migrant used in this study is

anyone born outside the UK who arrived after the age of 21 and who finished full-time education sometime after the age of 18.[4]

Since the LFS can distinguish EU migrant workforce from the non-EU migrant workforce, we can also map and document the changing distribution of skilled and unskilled (EU/non-EU) migrant labour across sectors and occupations alongside the incidence and training of native workers and examine whether there is any differential effect of EU and non-EU migration on the levels of training among the indigenous workforce.[5] As on the job training can only occur after one has been hired it is also

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[3] The question is only asked to those in employment under the age of 70 and not to working students. See http://doc.ukdataservice.ac.uk/doc/7985/mrdoc/pdf/lfs_user_guide_vol2_questionnaire2016.pdf
This variable was used by Dearden et al. (2006) and shown by them to be positively associated with higher productivity.

[4]There is no information in the LFS to allow us to find what type/subject a migrant took before arriving

[5] The split used in this study is EEA/Non-EEA rather than EU/Non-EU. The LFS country of origin information allows a more precise classification of EEA from 2007 until 2016. Prior to that some dependencies are missing from the definition. The Republic of Ireland is included in the definition of non-immigrant. The ONS suppressed the country of origin data from the publically available data in 2017 q3, impeding timely analysis of immigration issues.

important to examine the incidence of hiring - which can also be measured in the LFS, that is by the proportion of the sectoral workforce who are UK-born and in a job for less than 12 months.

To boost the sample size in each sector we pool across all 4 LFS quarters in each year. We also produce a sector-level dataset, taking mean values of the variables used in the study in each occupation, industry and year. A sector is defined as the product of 1 Digit-SIC and 1 Digit SOC and Year, so that, for example we treat professionals (SOC 2) working in manufacturing (SIC 2-4) differently from professionals in working Health (SIC 12). Similarly professionals working in health will be treated differently from manual workers (SOC 8, 9) working in Health. This enables us to distinguish between the traded and on-traded sectors and between "good" jobs and other jobs. A "good" sector in the non-traded sector is defined here as any sector paying above the mean hourly wage of the sample in each year.[6]

One complication with LFS is that the occupational and industry codes were changed mid-sample (in 2008 for industries and in 2010 for occupations) which creates a problem for the consistency of the data across the sample period. We take a two tier approach to address this issue. First we attempt to create a consistent industry/occupation data at the level of the individual across the whole sample period using translation files provided by MAC.[7] Second, the principle variable of interest – the trained immigrant share - varies only at the occupation/industry level over time and to avoid any measurement errors associated with mapping across breaks in the SIC/SOC classifications, we also estimate the data at 3-digit occupation or industry level and split the analysis across periods which run consistently. [8] We aggregate the data from the LFS to a 3-digit level for occupations and industries.

[6] This is similar in spirit to the Goos and Manning (2007) definition of "lovely" jobs
[7] See also the MAC's Jennifer Smith's SIC mapping webpage
https://warwick.ac.uk/fac/soc/economics/staff/jcsmith/sicmapping/resources/direct/
The occupations are mapped across 4 digit SOC 2000 and SOC2010 using the ONS crossover
[8] This is 1995-2010 and 20011-2017 for industry and 2001-2010, 2011-2017 for occupation.

This generates a balanced panel of around 69 occupations and 141 industrial sectors in the first sub-period and 76 occupations and 111 industrial sectors in the second sub-period.

4. Trends in On-the Job-Training and Hiring

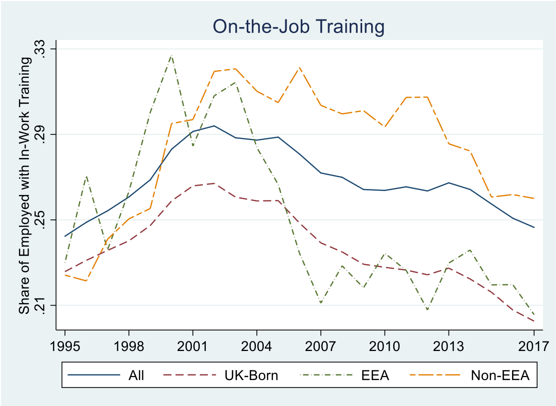
In this section we will highlight some broad characteristics of the data and motivate the statistical analysis described below. This section shows that there is significant heterogeneity across sectors in their training propensities and in their growth of immigrant and native employment. Nevertheless at the aggregate level there are clear trends towards increased immigration share and reduced rates of on the job training.

The aggregate trends in immigration share and on the job training are also shown by the following figures. Figure 1 graphs the incidence of in-work training over time. There has been a noticeable downward trend in training rates that began around 2002. By 2017, the share of the UK-Born workforce reported having had some in-work training in the last 3 months had fallen to around one in five, (a fall of around 6 percentage points).[9] Figure 1 also shows that this decline is shared by both immigrant and non-immigrant alike.[10] Indeed the decline among EEA migrant adults is largest of all. Non-EEA migrants do appear to be more likely to receive in-work training than others, though to what extent this is driven by demographic or job characteristics we explore in the estimation section below.

Figure 1. Trends in On-the-Job Training 1995-2017

[9] The fall in the training rate is even more pronounced among younger UK-Born workers, down 39% from in 2002 to 31% in 2017 for those under the age of 25.

[10] The group not shown in Figure 2 are immigrants who arrived before the age of 21.

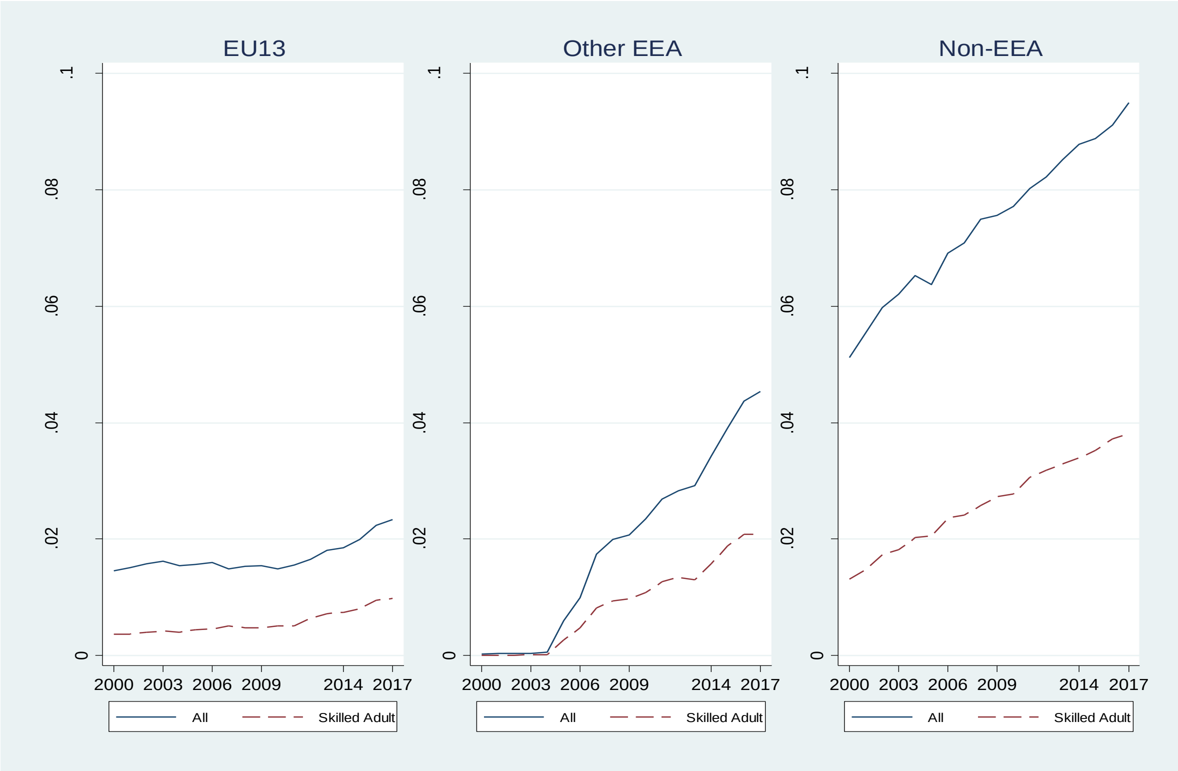


Source: LFS, authors' calculation

The analysis focuses on the effects of skilled adult migrants on training. Figure 2 plots the shares of all immigrants and skilled adult immigrants in the UK employed population of working age over time. Skilled-adult migrants form about one half of the (employed) migrant population.[11] Non-EEA migrants are the majority of all immigrants and the skilled adult immigrant population. There are more skilled adult EEA migrants from outside the EU13 than from the EU13 countries.

Figure 2. Trends in Immigrant Shares of the Population by Area of Origin

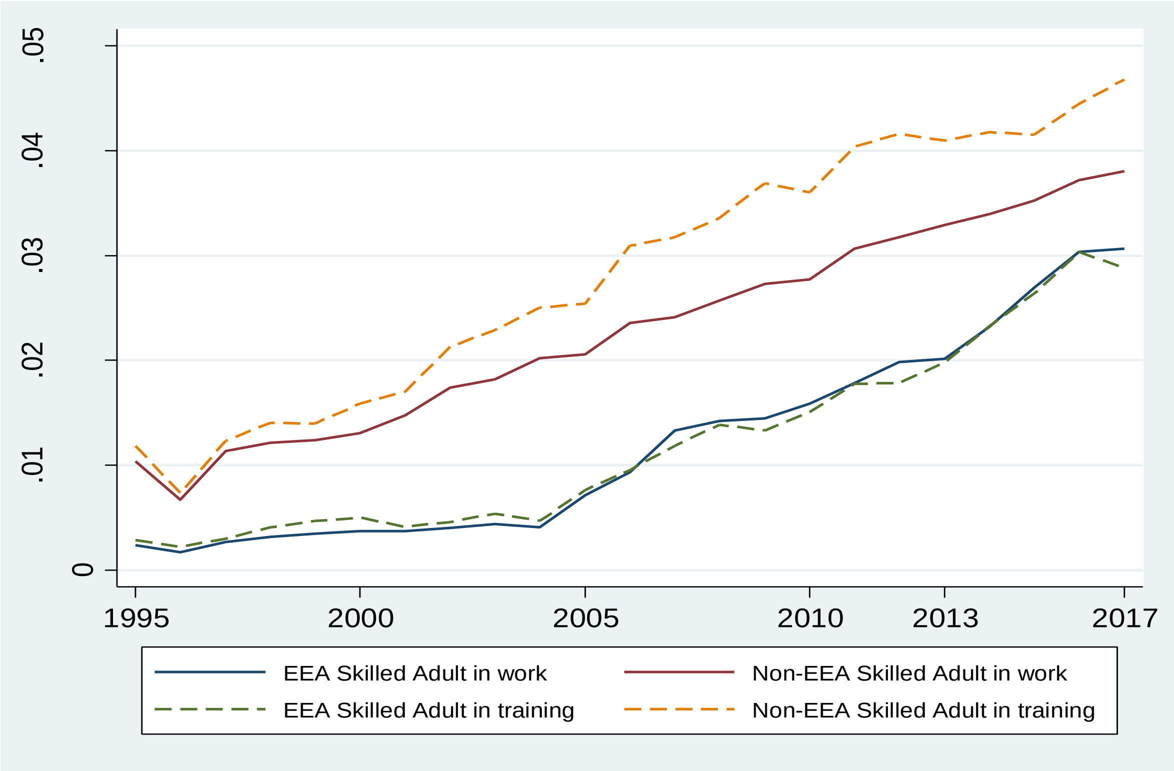
[11] One fifth of the employed immigrant population arrived in the UK before the age of 10 and so were schooled predominantly in the UK



Source: LFS, author calculation.

To help see whether migrants are increasing their share among newly hired workers or among workers with training, Figures 3 plots Immigrant shares among the workforce and the share of in-work trainees among each migrant group. There are times when the share of skilled adult EEA migrants does appear to be more than proportionate to their share in the workforce, but this corresponds to periods, like from 2004 to 2007, when the share of new arrivals among migrants is rising. To quantify this difference it is necessary to control for other factors that influence hiring that may vary across migrant populations. This is explored below.

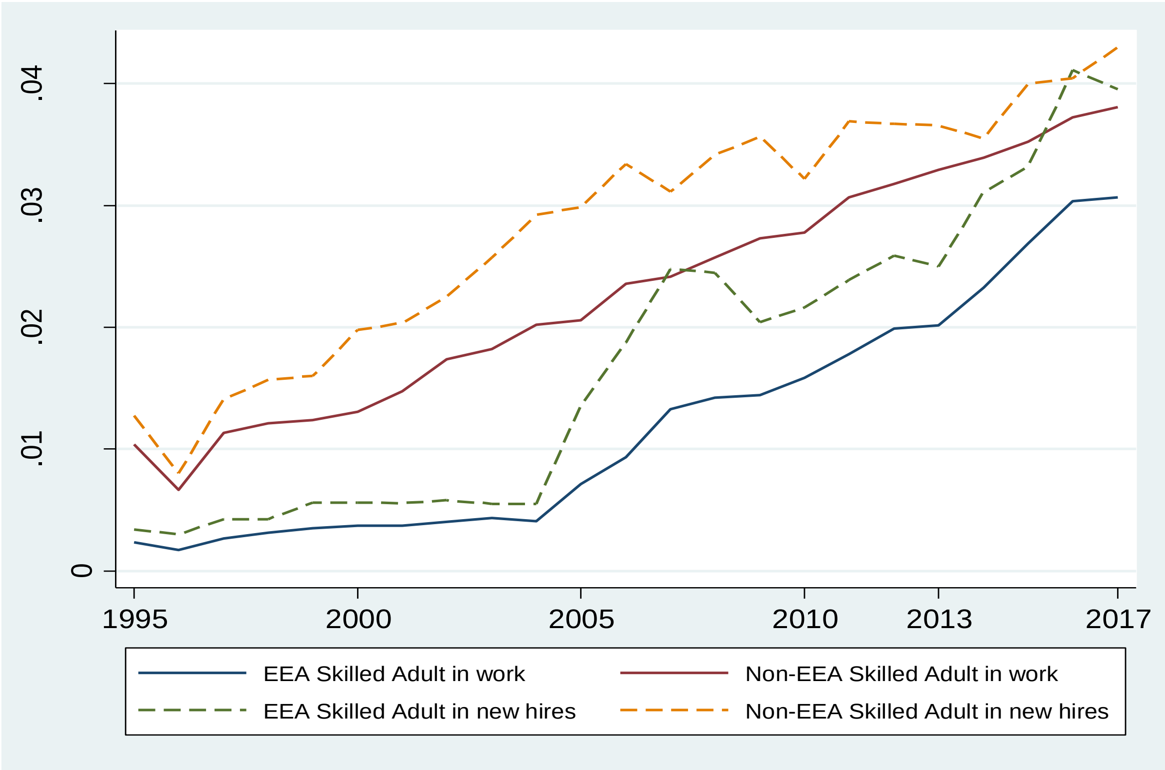
Figure 3. Skilled Adult Immigrant Shares Among Workforce and in-Work Trainees



Source: LFS, authors' calculation

Figure 4 plots immigrant shares, specifically those of EEA and Non-EEA skilled adult migrants, of the workforce alongside immigrant shares of hiring. Adult immigrants are broadly represented in the share of new hires as in the workforce as a whole. There are times when the share of skilled adult EEA migrants does appear to be more than proportionate to their share in the workforce, but this corresponds to periods, like from 2004 to 2007, when the share of new arrivals among migrants is rising. To quantify this difference it is necessary to control for other factors that influence hiring that may vary across migrant populations.

Figure 4. Skilled Adult Immigrant Shares Among Workforce and New Hires



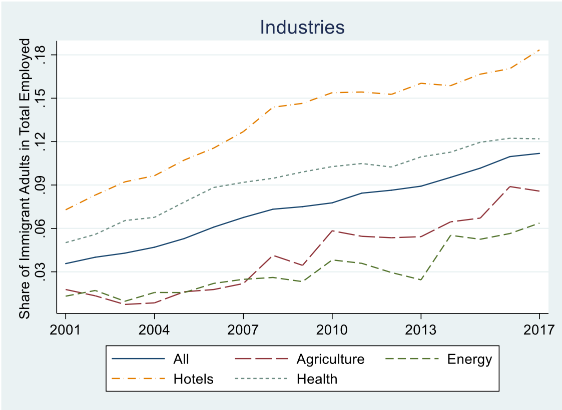
Source: LFS, authors' calculation

This does not however mean that migrants have no role to play in sectoral allocation of native labour. If the migrant share is rising differentially across sectors this could mean that native workers are under-represented in training or hiring in these sectors. It is certainly true that some sectors and occupations have made greater use of trained migrant labour than others.

Figure 5 shows that sectors like Health and Hotels & Hospitality have long made use of migrant labour. The shares of adult migrants in their workforces are above the UK average. Conversely other sectors, like Energy and Agriculture do not appear to drawn on relatively large amounts of adult migrant labour.[12] Similarly occupations like nursing and IT working have long employed larger shares of adult migrants than the UK average. It is also the case that other occupations, for example architecture or hairdressing are not large users of adult migrant labour, (see Figure 6).

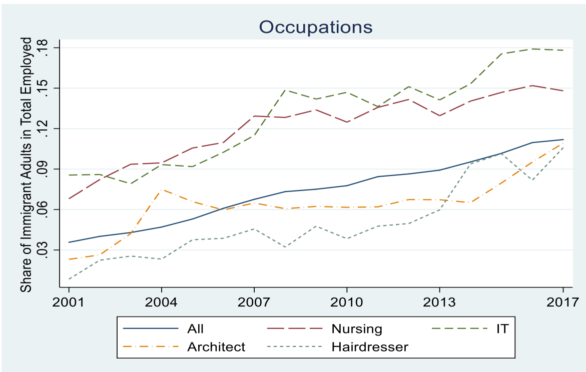
[12] There is the possibility that the LFS does not sample seasonal agricultural workers living in temporary accommodation which may account for agriculture's low migrant share.

Figure 5. Industry Shares of Adult Migrant Labour



Source: LFS, authors' calculation

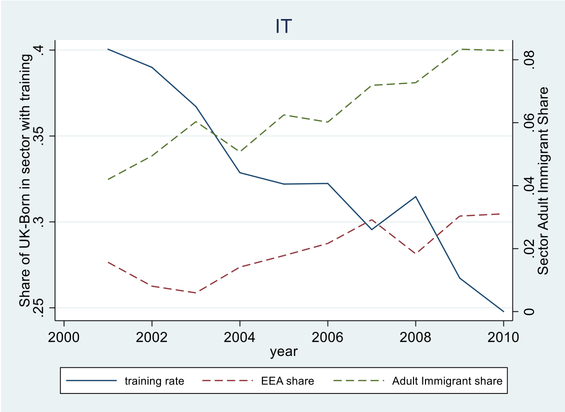
Figure 6. Occupation Shares of Adult Migrant Labour

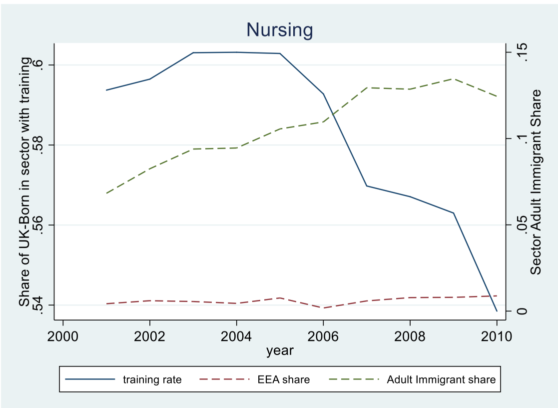


Source: LFS, authors' calculation

As an example of what, at face value, may seem to be an issue of concern are the patterns sketched out in Figure 7 below for two sectors. The Figure plots the incidence of on-the-job training for all UK-Born workers in two sectors, that arguably belong to the categories of "good" jobs, IT working and Nursing. The former is part of the traded sector, the latter the non-traded sector. The graphs show a fall in the share of workers receiving in-work training over the period 2001 to 2010, alongside a rise in each occupation's workforce share of immigrants who arrived in the UK as (trained) adults. The Figure shows that much of the rise in immigrant workforce shares in these two sectors over the period was from Non-EEA countries.

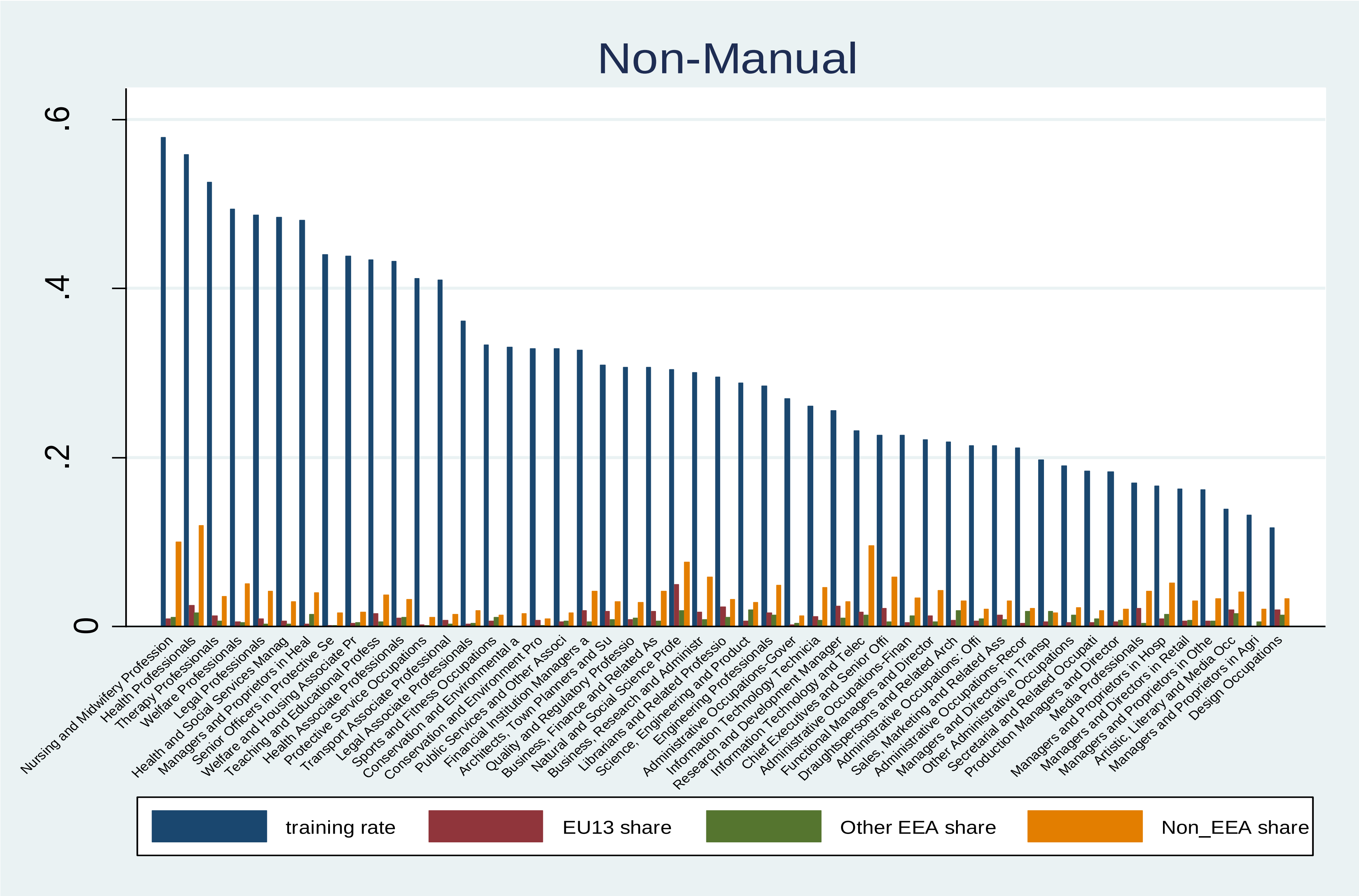
Figure 7. Training Rates and Workforce Share of Immigrants in Nursing and IT





To get a sense of the economy wide use of on-the-job training, Figure 8 graphs the on-the-job 3 month training incidence for UK-born workers across approximately 85 three-digit occupations in 2017, alongside the share of (skilled) adult immigrants in each sector. Figure 9 repeats the exercise across three-digit industries. These Figures suggest that the measure of training used in this study is positively associated with the level of skill. Training incidence, of UK-Born workers, is generally higher in more skilled occupations (as ranked by 3 digit SOC code). This gives us some confidence that the variable we use in our estimation is positively correlated with productivity enhancing tasks. The occupational distribution of immigrants also varies by area of origin. EU13 skilled adult immigrants are concentrated in professional non-manual occupations. Other EU migrants, while educated beyond secondary school, tend to be working in manual occupations. Non-EEA workers can be found in both professional and manual occupations. This reflects the history of immigration controls which over time have changed the sectors in which non-EEA migrants can work. It is harder to classify industrial sectors as skilled, but the rate of training appears to be higher in the personal service sector (particularly health and social care) rather than manufacturing.

Figure 8. Training Rates of UK-Born Workers by Occupation: 2017



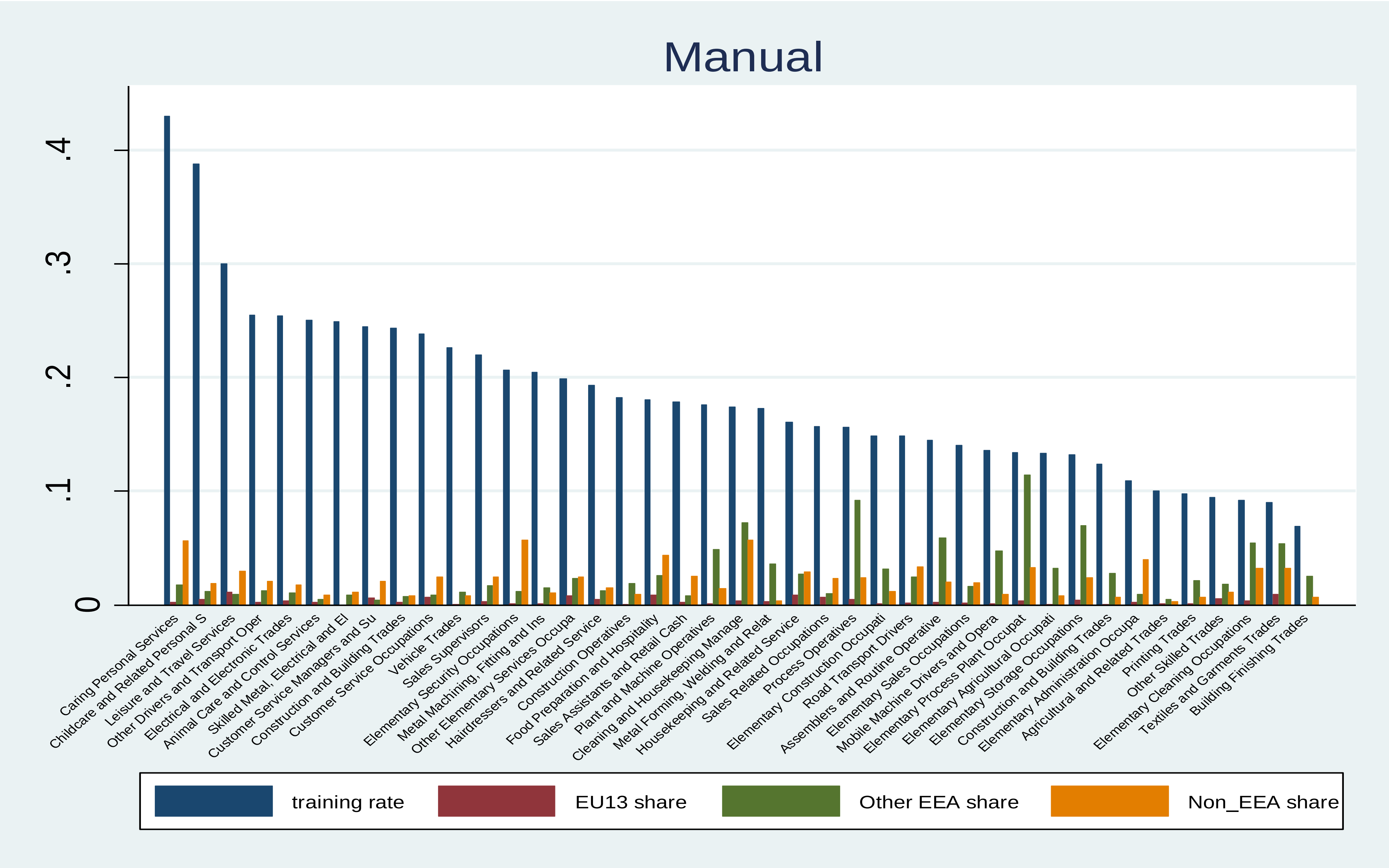
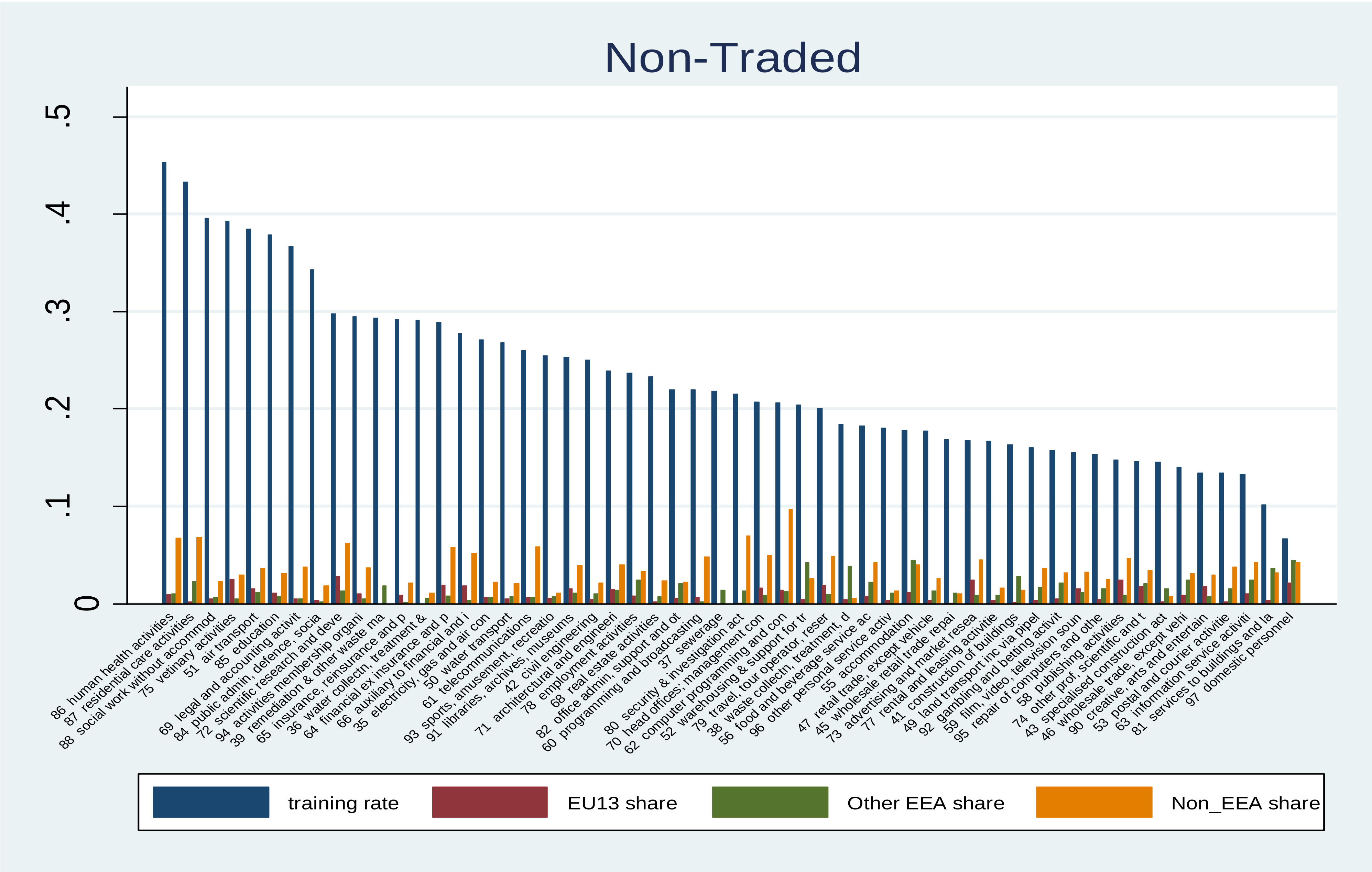

Manual
0
.1
.2
.3
.4
Caring Personal Services
Childcare and Related Personal S
Leisure and Travel Services
Other Drivers and Transport Oper
Electrical and Electronic Trades
Animal Care and Control Services
Skilled Metal, Electrical and El
Customer Service Managers and Su
Construction and Building Trades
Customer Service Occupations
Vehicle Trades
Sales Supervisors
Elementary Security Occupations
Metal Machining, Fitting and Ins
Other Elementary Services Occupa
Hairdressers and Related Service
Construction Operatives
Food Preparation and Hospitality
Sales Assistants and Retail Cash
Plant and Machine Operatives
Cleaning and Housekeeping Manage
Metal Forming, Welding and Relat
Housekeeping and Related Service
Sales Related Occupations
Process Operatives
Elementary Construction Occupati
Road Transport Drivers
Assemblers and Routine Operative
Elementary Sales Occupations
Mobile Machine Drivers and Opera
Elementary Process Plant Occupat
Elementary Agricultural Occupati
Elementary Storage Occupations
Construction and Building Trades
Elementary Administration Occupa
Agricultural and Related Trades
Printing Trades
Other Skilled Trades
Elementary Cleaning Occupations
Textiles and Garments Trades
Building Finishing Trades
training rate
EU13 share
Other EEA share
Non_EEA share

Figure 9. Training Rates of UK-Born Workers by Industry: 2017



Non-Traded
0
.1
.2
.3
.4
.5
training rate
EU13 share
Other EEA share
Non_EEA share

An alternative way to address the issue is to think of the pool of all UK-born workers in each year as allocated to a given sector. If there were trends against a particular occupation we might expect it to be losing out in the occupation's share of hires of UK-Born workers over time, H_{ON}/H_n. Again the trends for both IT and Nursing (Figure 11) over the period 2001-2010 show a fall in the occupation share of hiring for UK-born workers alongside a rise in the workforce shares of immigrant adults (primarily Non-EEA immigrants) One such illustration of where this appears to be true is Nursing over the period 2001-2010.

This does not of course demonstrate causality between the two trends or that these trends are replicated across other sectors and time periods. We attempt to address these issues in the empirical section below.

Sectoral Changes in Employment of UK-Born and Immigrants

A more comprehensive picture of trends in employment can be gleaned from Figure 12 which plots changes in employment for the UK-born against changes in employment of immigrants in each occupation between 2001 and 2010 and between 2011 and 2017 respectively.[13] Each dot in the graph represents a specific 3-digit occupation. The full list of changes in employment by migrant status is given in Appendix Table A1. The backward sloping 45 degree line separates occupations that are growing overall in these periods from those that are declining. Any occupation that lies above and to the right of this line is growing. The forward sloping 45 degree line separates occupations that are growing because of immigration from those that are growing because of growth in UK-born employment. Any occupation above and to the left of this line is growing primarily because of immigration.

[13] The sample split coincides with the change in the Standard Occupation Classifications codings

Clearly there is much heterogeneity across occupations over the sample periods. The first period is one of net decline in aggregate employment in the run-up to and the beginning of the latest recession. Yet some occupations are growing in this period (Figure 12) primarily because of hiring immigrants, (Eg 611 Care Homes), others are growing primarily, but not exclusively, because of hiring UK-born workers (Eg 231 Teachers). Some occupations are declining overall but losing native-born workers while gaining immigrants (eg 913 Processing). Other occupations are declining because of falls in both UK-born and immigrant numbers (eg 421 Secretarial), while a few are growing overall but with falling numbers of immigrants

The second period is characterised by net aggregate growth in employment encompassing the ending of the recession and the subsequent upturn. Despite this a few occupations declined (eg 411 Government Admin.) with falls in both UK-born and immigrant numbers over the period. Other occupations (eg 421 secretarial) show net overall decline in employment alongside rising immigrant numbers. Most occupations however grow over this second period. Some grow (Eg 531 Construction Trades) exclusively because of rising immigrant numbers while numbers of UK-born employed fall. Others (Eg 223 Nursing & Midwifery) grow over this period through approximately equal numbers of immigrants and UK-born. Others (Eg 231 Teaching) grow primarily through rising numbers of UK-born workers.

Table 1 looks at the individual chances of receiving on-the-job training. The sample is pooled individual data over the period 2001 to 2017. The estimated coefficients reported in the Table are linear probability estimates of the likelihood an individual has received on-the-job training in the 3 months before being surveyed in the LFS. The estimates for immigrant workers represent the differences in training probabilities relative to UK-born workers. The basic associations, column 1, show that immigrants – by around 1 percentage point – less likely to receive on-the-job training than UK-Born workers – but skilled immigrants who arrived as adults are around 0.6 points more likely to receive on-the-job training. [14] Demographic and job controls generally reduce these associations, but the inclusion of occupation and industry fixed effects strengthens the positive estimate for immigrants. The further inclusion of occupation/industry trends then makes little difference to the fining that however reduce the statistical significance of the immigrant adult estimates. So conditional on the occupation demographic and job characteristics, immigrants who arrived as adults with more than high school education appear to receive around 2 to 4% more training than UK-born workers.[15]

This overall immigration training effect appears to be driven by a greater chance of training among NON-EEA workers, (panel B) consistent with the pattern seen in
Figure **3**. EEA adult migrants, skilled or otherwise, appear to have training rates comparable or lower to those of UK-born workers. This seems to hold when EEA migrants are split into EU13 countries of origin and elsewhere from within the EEA.

[14] This is because the overall effect for skilled migrants is the sum of both estimated coefficients on both immigrant dummies (1=immigrant and 1= skilled adult arrival immigrant).
[15] If the mean training rate is 25% then a 1% point differential is around 4% more training.

Table 1: Training Probability of UK Born Relative to Immigrants (pooled individual data 2001-2017)

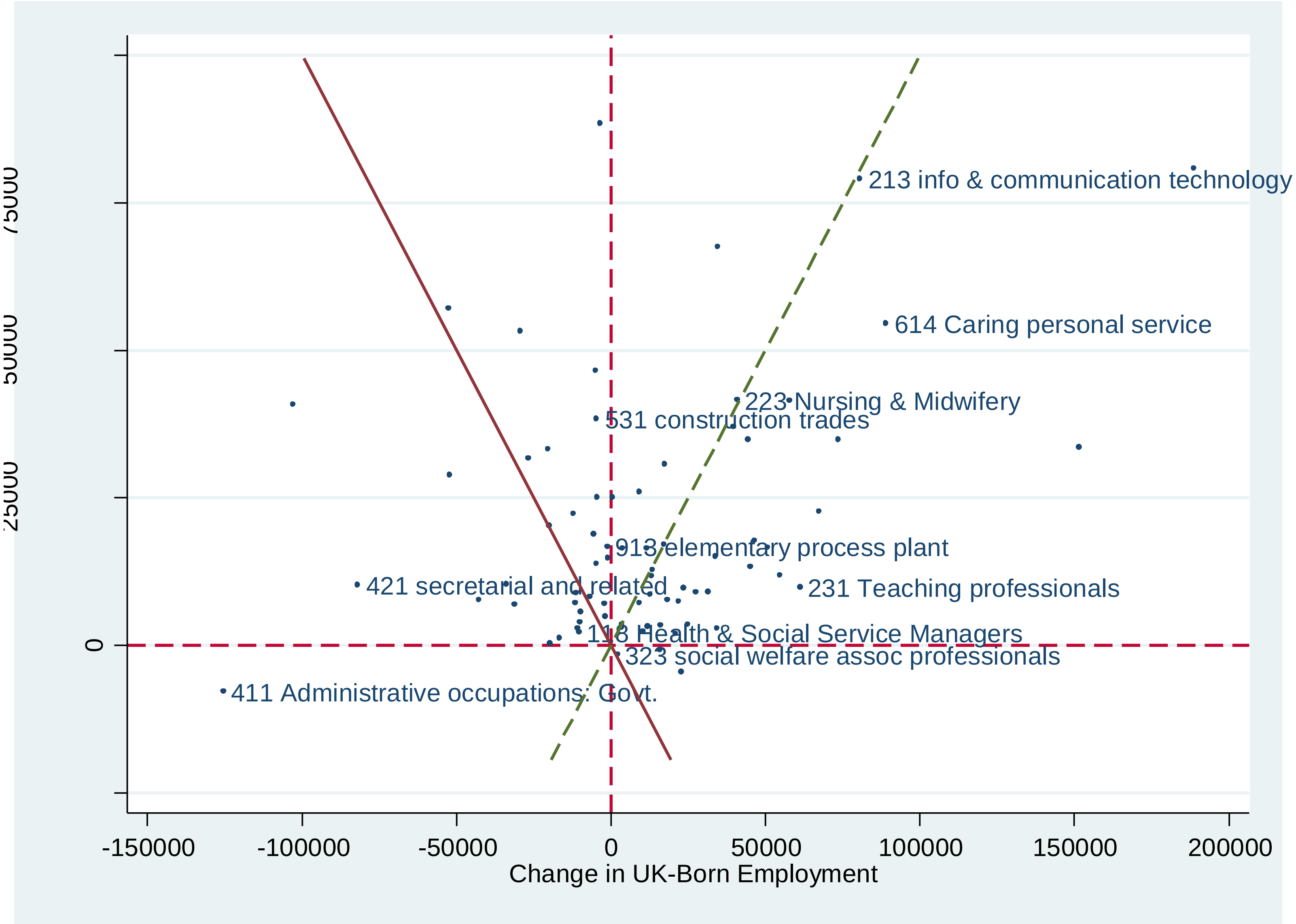
	coe1	coe2	coe3	coe4
	b/se	b/se	b/se	b/se
Immigrant	-0.016** (0.002)	-0.016** (0.002)	-0.004** (0.002)	-0.006** (0.002)
Skilled Immigrant Adult	0.061** (0.003)	0.012** (0.003)	0.016** (0.004)	0.016** (0.004)
Panel B				
Immigrant	-0.014** (0.002)	-0.014** (0.002)	-0.004** (0.002)	-0.005** (0.002)
EEA Adult Skilled	0.010 (0.005)	-0.030** (0.005)	-0.006 (0.005)	0.004 (0.005)
Non-EEA Adult Skilled	0.080** (0.004)	0.029** (0.005)	0.018** (0.004)	0.019** (0.004)
Panel B				
Immigrant	-0.014** (0.002)	-0.014** (0.002)	-0.004** (0.002)	-0.005** (0.002)
EU13 Adult Skilled	0.066** (0.008)	0.010 (0.008)	0.006 (0.009)	0.009 (0.009)
Other EEA Adult Skilled	-0.027** (0.006)	-0.056** (0.007)	0.006 (0.009)	-0.008 (0.011)
Non-EEA Adult Skilled	0.080** (0.004)	0.029** (0.005)	0.018** (0.004)	0.019** (0.004)
Demographic	No	Yes	Yes	Yes
Job	No	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Occupation	No	No	Yes	Yes
Occ. Trends	No	No	No	Yes

In short, it is possible to hire both immigrants and UK-born at the same time, so that we should not automatically conclude that occupations or industries which employ more immigrants necessarily hire or train fewer UK-born workers. Our theoretical framework suggests we might expect to see differences in training and hiring behaviour between the traded and non-traded sectors and also between jobs with differing skill requirements. Ultimately this is an empirical issue, which we address in the next section

Figure 12. Changes in employment of UK born and Adult Immigrant workers by occupation 2001-2010

s s

Figure 13. Changes in employment of UK born and Immigrant workers by occupation 2010-2017



5. Empirical Estimation of Immigration Effect on Training and Hiring of UK-Born Workers.

We aim to estimate two model specifications that look to establish the effect of immigrant workforce shares on training of UK-Born workers. A sector-level analysis and individual level analysis.

Sectoral/occupational level analysis

The predictions of the model could be tested using a panel of industrial sectors and/or occupations over T years afforded by the dataset. The estimation is thus of the type

$$N\_OJT_{it} = \beta_0 + \beta_1 EU_{it-1} + \beta_2 NEU_{it-1} + \gamma X_{it} + \alpha_i + d_t + \varepsilon_{it} \qquad (1)$$

i = 1, 2,…I   industries/occupations

t = 1, 2…T   years

N_OJT is then the share of all UK-born workers in sector i at time t who are in receipt of on-the-job training. EU and NEU are the shares of EEA and non-EEA workers respectively in the sector workforce at time t-1 .

β_1 and β_2 are the parameters of interest – the effects of migrant shares of the sector workforce - X are a set of sector and time-varying controls that can include a lagged dependent variable and the α_i and d_t are sector and year fixed effects (and possibly their interaction).

It is far from clear what the appropriate measure of trained migrant pressures at the workforce should be. One method common in the immigration literature is to estimate the sector share of (skilled adult) migrants,

$$M_{s,t}/(M_{s,t}+N_{s,t}) = M_{s,t}/(M_{s,t}+ N_{ojt,s,t} + N_{other,s,t}) \approx M_{s,t}/(N_{ojt,s,t} + N_{other,s,t})$$

Clearly these measures are contemporaneously correlated with numbers of UK-born workers in receipt of training. One way to try to address this is to lag the measure by one year. While this will reduce endogeneity concerns caused by simultaneity, eg so that causality is more likely to run from the existing migrant stock of the workforce to subsequent decisions to hire or train, the measure is still open to other concerns that affect endogeneity such as measurement error (caused in this instance by the sample size of migrants in each sector) or by the correlation between workforce share and any relevant variables omitted from the model.

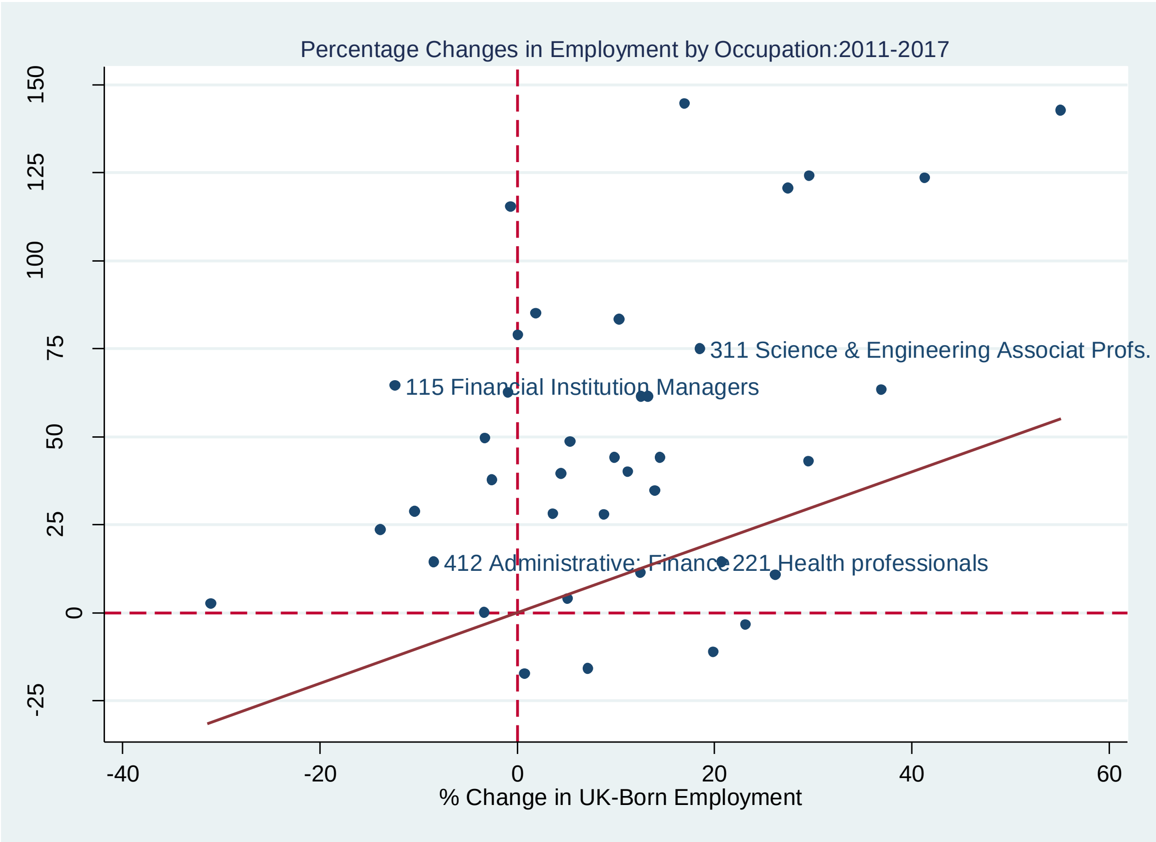
Measures of the workforce share such as the above can also change over time because of changes in the number of migrants (the numerator in the measure above) or the numbers of UK-born workers – the denominator in the measure above - (or both). Hence a given change in the migrant share may be due to very different factors. A rise in the number of immigrants or a fall in the numbers of native workers in the workforce will both give a similar change in the migrant share variable. [16]

Figure 14 illustrates this point. The figure plots the percentage change in (skilled adult) immigrants in each 3-digit non-manual occupation between 2011 and 2017 against the percentage change in UK-born workers in the same occupations. Each dot represents a particular 3 digit occupation. Health professionals (soc 221) have experienced a similar percentage rise in the number of immigrants working in the sector as Administrative Finance sector (soc 412), but the percentage change in the number of UK-born workers in the sectors is very different, rising in soc221 by around 20% and falling in soc412 by around 10% over the period. Consequently the migrant share measure will have risen in soc412 but fallen in soc221 even though immigrant numbers rose by the same percent.[17] One way to control for this is to include the percentage change in the workforce alongside the migrant workforce share in the set of explanatory variables. We present estimates with and without this control in what follows.

[16] The same change if migrant numbers increase by αM or UK-born numbers fall by $(1/\alpha)N$ since $\alpha M/(\alpha M+N) = M/(M+(1/\alpha)N)$ Note that the change is similar but not identical if comparing $\alpha M/(\alpha M+N) \neq M/(M+(1-\alpha)N)$

[17] The migrant share will have fallen in soc221 because – as shown in the Figure – soc221 lies below the 45 degree line which traces out equi-proportionate changes in immigrant and UK-born numbers. Any occupation above the 45 degree line has migrant numbers rising proportionately faster than UK-born numbers. This will raise a measure of migrant share such as $M_{s,t}/(M_{s,t}+N_{s,t})$ or M_{st}/N_{st}. Any occupation below the 45 degree line has UK-born workforce numbers rising proportionately faster

Figure 14. Percentage Changes in Immigrant and UK-Born Workforce Shares



Source LFS, author calculation

The variance of the error term can contain a group (sector) specific component but also could be influenced by the different sized populations in each sector as well as possible unobserved spillovers across groups. We can therefore estimate the model that uses HAC error robustness, that is robust to heteroskedasticity of unknown form and also allow for unknown autocorrelation, (see Cameron and Millar (2013)). Equally we can choose to cluster the standard errors by groups. The obvious cluster is at the level of the treatment, (industry/occupation/year), though this ignores cross-cluster and within-cluster correlations caused by autocorrelation. Angrist and Pischke (2013) suggest clustering at the higher level of aggregation (industry/occupation) to address the cross-time correlation within clusters.[18] In what follows the standard errors in the individual and sector-level regressions are

[18] Though this does not deal with cross-cluster correlations at a point in time unlike the HAC approach.

clustered at different levels of aggregation to examine the sensitivity of the estimates to different assumptions.

Individual Level Estimation

Equally the model could be estimated at the level of the individual. Equation (1) then becomes a probit or linear probability estimation of the probability that a UK-Born individual is a) observed in receipt of on the job training b) in a new job.[19] The advantage of this approach is that it enables us to control for more individual variation that may be associated with training or hiring probability. Demographic controls include gender, 6 age, 4 education and 19 region dummy variables. Job controls include dummy variables for self-employment, part-time working, job tenure, temporary job and public sector. The disadvantage is that the level of variation of the principle variable of interest – the workforce share of immigrants – is only available at the industry/occupation/year level. This requires multi-level clustering of the standard errors.

We are agnostic as to the best approach and so present results using both levels of analysis.

Analysis at either level of aggregation may also suffer from the problem of endogeneity i.e. that the variation in the explanatory variable of interest – the migration share of employment in the sectoral workforce - is not exogenous, due to some (inherently unknown) combination of reverse causality or omitted variable bias or measurement error. We aim to take account this potential endogeneity by lagging the explanatory variable or instrumenting the immigration variables using the "shift-share" instrument for instrumenting sectoral migration demand by interacting the historical sectoral migration employment shares with national growth rates in migration employment, (see for example Altonji Card (1991) and the recent critique by Jaeger, Stuhler and Ruist (2018). This will provide a measure for the increased supply of migrants in each sector that is not influenced by sectoral labour

[19] A new job is proxied by anyone in work with job tenure below 12 months.

demand shocks and which may be more robust to measurement error caused by year to year sampling variation of the migrant variables. The instrument for sector s is built as $\sum_{i=1}^{N} s_{i0} M_{it} \Big/ \sum_{i=1}^{N} b_{i0} P_{it}$ where s_{i0} is the base year share of migrant group i working in sector s among all migrants of type i, M_{it} is the aggregate (UK-wide) count of all migrants of type i at time t, b_{i0} is the base year share of group I in sector s among all workers, and P_t is the aggregate count of workers at time t.[20]

[20] Note the variant on the "Bartik" instrument which uses $\sum_a s_{ar} g_a$ as a proxy for $\sum_a s_{ar} g_{ar}$ ie replaces the local area level of migrant group a with the national area level of group a weighted by the share of group a in area r. The Altonji-Card instrument uses the count of migrant group a in area r as a share of all migrants of type a

6. Findings Training: Individual level analysis

If, as Table 1 suggests, UK-born workers receive less training, on average, than some adult migrants does this then mean that as the workforce share of migrants rises the incidence of training among UK-Born workers falls? Not necessarily since the theoretical framework suggests there may be both positive and negative effects of skilled immigration on training of UK-born workers.

To illustrate the basic association between immigration and on-the-job training, Figure 15 plots the change in the training rate of UK-born workers for each of 110 one-digit occupations/2-digit industry combinations used to define traded and non-traded sectors against the change in the occupation workforce share of skilled adult immigrants over the same period. Each dot gives the change for a given sector. The sectors are split into traded and non-traded and within the non-traded sector the sectors are split further into “good” – paying above the mean hourly wage - and other non-traded sectors. The association is weakly positive. Consistent with the analysis above most dots are below the zero change line indicating a fall in the training rate of UK-born workers within the sector over this period. The dots are also distinguished by sector. Notably all the dots in the non-traded “good” job sector indicate a fall in training rates of UK-born workers over this period. This is not the case for the traded and other non-traded sectors.

Similarly most dots lie to the right of the zero change in immigrant workforce share, consistent with a rise in workforce share of skilled adult migrants across most of these sectors. While training rates of UK-born workers have risen in some sectors alongside rising sector workforce shares of skilled adult immigrants (Eg Elementary transport, Skilled manual Energy) they have fallen in others (Eg Health Professionals, IT Professionals) traded and non-traded. Similar associations can be seen when the EEA skilled adult migrant occupation workforce share is used instead of all immigrants, (Figure 16). Ultimately whether training rates vary across the traded and non-traded sectors is a matter for empirical verification, which is the subject of the next section.

Figure 15. Long Difference (2001-2017) Changes in UK-Born Training Rates and Workforce Immigrant Shares by Traded and Non-Traded Sectors

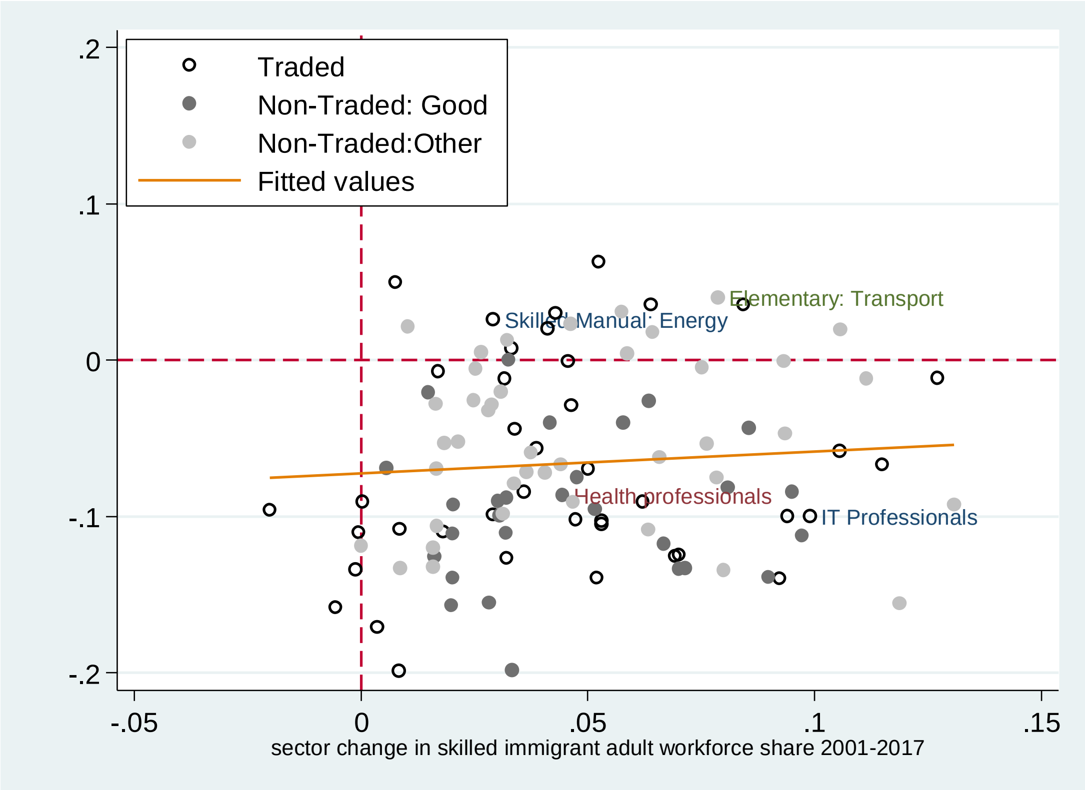
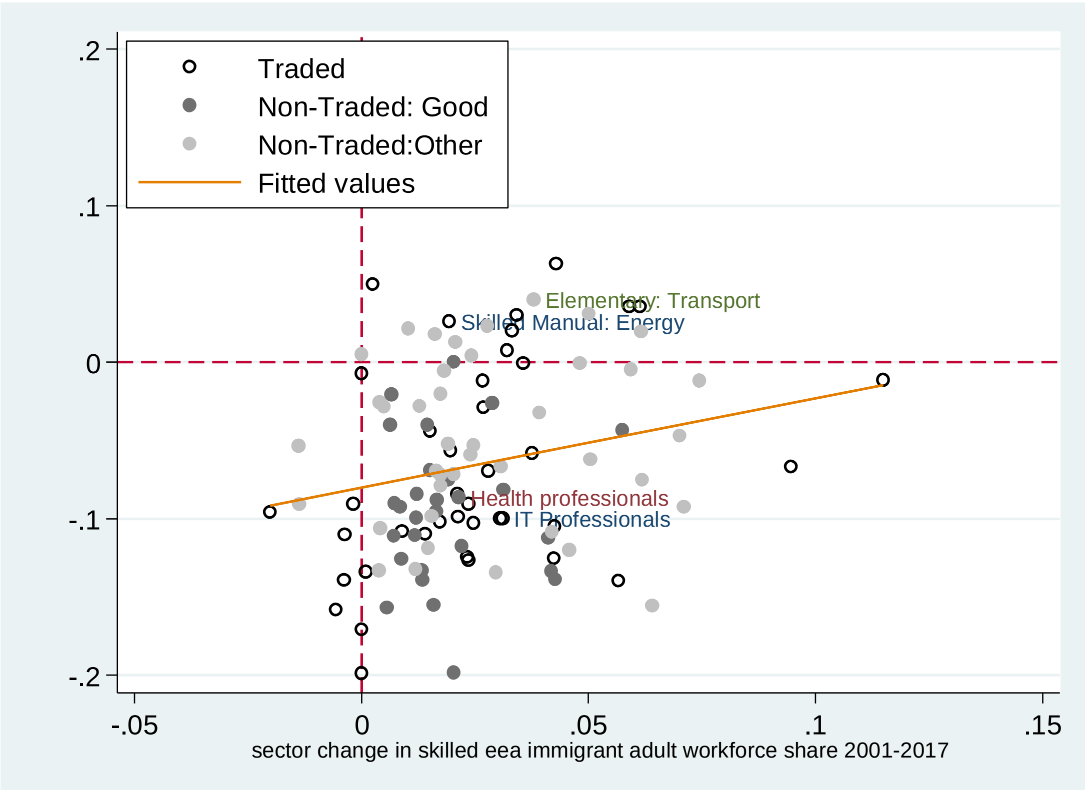


Figure 16. Long Difference (2001-2017) Changes in UK-Born Training Rates and EEA Skilled Adult Migrant Workforce Immigrant Shares



Regression Analysis

The results from the individual level regression analysis are given in Table 2 below. The sample is the set of employed UK-Born adults of working age. The dependent variable is a dummy variable coded 1 if the individual is in receipt of training and 0 otherwise. The explanatory variable of interest is the number of immigrants who arrived as skilled adults as a share of the sector workforce measured at time t-1. The data are pooled over the period 2001-2017. The level of industry/occupation disaggregation is 1 digit. Standard errors are clustered at the industry/occupation interaction.[21]

The first column gives the association between immigrant share in the sector and the likelihood of a UK-born individual receiving training. The overall correlation with training (column 1), is insignificantly different from zero , but panel B column 1 suggests a positive correlation between training and the Non-EEA immigrant share and a negative correlation with the EEA immigrant share. Panel C splits EEA migrants further into those from the EU13 and others. These estimates suggest that the negative EEA correlation with UK-born training is driven by EEA migrants from outside the EU13, who tend to work more in sectors that train UK-born workers less.

Since there may be many other factors that influence the likelihood of a native-born worker receiving training, the subsequent columns in the Table add demographic and job controls. Column 2 also includes sector fixed effects to control for any time invariant characteristics of a sector that may otherwise be correlated with training and immigrant share variables. This specification is close to the trends picked out in Figure 15 and in Figure 16. Some sectors may be inherently less likely to train given the nature of the job. If this is correlated with hiring of migrants we may wrongly attribute a sector training propensity to the migrant share. When we include fixed effects, the immigrant share

[21] We construct a single variable giving the share of immigrants in sector i and occupation j in year t. The industries are 1=Agriculture, 2=Energy, 3= Manufacturing, 4=Construction, 5=Retail, 6=Transport, 7=Food &Accommodation, 8=IT Services, 9=Finance, 10=Professional Services, 11=Protective Services, 12=Public Admin, 13=Education, 14=Health & Social Work, 15=Other Services. The occupations are 1=Managerial, 2=Professional, 3=Associate Professional, 4=Admin., 5=Skilled Manual, 6=Personal Services, 7=Sales, 8=Processing, 9=Elementary.

variables are now identified off cross-sector differences in the change in the share over time. The EEA/Non-EEA share estimates change noticeably when sector fixed effects are added. The overall immigrant share effect on training remains positive and significant (Panel A column 2), while the EEA migrant share estimate changes sign and becomes positive and statistically significant and the NON-EEA share is insignificantly different from zero, (Panel B column 2). The signs of the estimates on EU13 and other EEA worker shares also switch with the addition of sector fixed effects, (Panel C column 2). EU13 migrants work in sectors that offer more training, which accounts for the positive estimate seen in column 1.

To try to account for the different ways in which the migrant workforce share can change (numerator or denominator driven), column 3 adds the yearly percentage change in the total sector workforce as an additional control. Column 3 also includes the share of other immigrants in the workforce as a check that the effects we estimate are picking up changes in the skilled adult immigrant workforce rather that general trends in the sectoral profile of immigrants. The size of the skilled immigrant training effect is reduced somewhat by the additional controls (column 3), but the general patterns observed in column 2 still hold.

The statistical significance of these estimates also depends on how the standard errors are clustered. The first row of Table 2 reports two sets of standard errors, the first (in round brackets) clustered by sector and the second clustered by sector and year. In each case the estimated standard errors when clustered by sector and year are much smaller – though the difference falls noticeably with the addition of sector trends. Since clustering by sector and year ignores autocorrelation within sectors (as well as across sectors) and other forms of heteroscedasticity, we should be more wary of clustering this way. Clustering at the higher level also makes it harder to find statistically significant estimates which we see as a tougher hurdle for any applied researcher to surmount.[22] We report the sector only cluster standard errors in the rest of the Table.

Since the sample period is quite long (17 years) it might be argued that the fixed effects assumption is harder to hold to (ie it is unlikely that the characteristics of an industry or occupation are really constant over a period as long as 17 years). In the final two columns we add sector trends. These may then help control for unobserved industry/occupation level factors that are changing over time and may be otherwise picked up by the immigrant share. When sector trends are added to the model (columns 4 and 5), the signs and significance of the estimates change again. The overall skilled immigrant share effect on native training is now negative but insignificantly different from zero, (Panel A column 5).

When the immigrant adult data is split by EEA/Non-EEA entrants, EEA workforce share has a positive statistically significant effect on training while the estimated non-EEA effect in column 5 is negative but insignificantly different from zero. [23] The estimated EEA effect is not large. Since the skilled EEA adult immigrant share grew by 3 percentage points, in aggregate, over the sample period, column 5 suggests that training rates of UK born workers would have been 0.8 points *lower* had the EEA skilled adult sector share remained the same as in 2000.[24] When the EEA country of origin is split into EU13 and other (panel C) both effects are positive but insignificantly different from zero.

Overall however, on this basis the rise in the adult skilled immigrant workforce share explains very little of the fall in the training incidence of UK-Born workers.

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[22] Choosing the higher standard errors in this way reduce type I error – reduce the chance of rejecting a false null hypothesis (at the expense of raising type II error).

[23] The EEA and Non-EEA shares estimates in column 8 are not significantly different from each other.

[24] 0.253*0.03=0.00759 =0.8 of a percentage point

Table 2. Skilled Adult Arrival Immigrant Workforce Share and Individual On-the-Job Training Probability: UK-Born 2001-2017

Variable	(1)	(2)	(3)	(4)	(5)
Panel A					
Skilled Adult Immigrant Share	1.059**	0.489**	0.246**	0.004	-0.028
	(0.505)	(0.136)	(0.097)	(0.084)	(0.084)
		{0.076}	{0.070}	{0.082}	{0.080}
Other Immigrant Share			0.396**		-0.063
			(0.075)		(0.057)
log change workforce			0.001		-0.013
			(0.011)		(0.0009)
Panel B					
EEA Share	-3.317**	0.740**	0.628**		0.253**
	(0.674)	(0.148)	(0.143)		(0.107)
Non-EEA Share	3.133**	-0.043	-0.024		-0.129
	(0.677)	(0.175)	(0.142)		(0.107)
Panel C					
EU13 Share	0.526	-0.613**	-0.342		0.366
	(2.892)	(0.297)	(0.241)		(0.196)
Other EEA Share	-3.677**	1.027**	0.935**		0.179
	(0.808)	(0.179)	(0.167)		(0.132)
Non-EEA Share	2.685**	0.239	0.012		-0.128
	(0.889)	(0.167)	(0.133)		(0.108)
Controls					
Demographic	No	Yes	Yes	Yes	Yes
Job	No	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Sector	No	Yes	Yes	Yes	Yes
Sector Trends	No	No	No	Yes	Yes

Standard errors in brackets clustered by 1 digit industry and 1 digit occupation (110 clusters). ** notes significance at 5% level. Demographic controls include gender, 6 age, 4 education and 19 region dummy variables. Job controls include dummy variables for self-employment, part-time working, job tenure, firm size, temporary job and public sector. Sample size is 2,808,282 in all regressions. Mean of dependent variable = 0.27

Traded v Non-Traded Sectors

The theoretical framework to this paper suggest however that there may not be uniform effects from immigration, rather this may depend on the sector where a migrant is employed and on the type of skill a migrant brings. To try to address this, Table 3 splits the sample into traded and non-traded sectors and "good" and other jobs. [25] The Table gives the baseline immigrant sector share variable and interactions of the immigrant share and dummy variables for the traded and non-traded good job sector.[26] When fixed effects are included in the model, the coefficients on these terms become, respectively, the immigrant effect for the non-traded other sector, the additional immigrant effect for the traded sector and the additional immigration effect for the non-traded good job sectors.[27]

The estimates for fixed effects (columns 1 and 2) are consistent with the predictions of the model – that there may be differences in training rates between non-traded and traded sectors and the largest negative effects on training of UK-born workforce pressure among "good" jobs in the non-traded sector. The results in columns 1 and 2 suggest that UK-born workers in the non-traded other sector may receive more training, on average, as the immigrant workforce share rises. The immigrant effect in the skilled non-traded sector is negative and statistically significant. [28] Similar effects can be seen in Panel B when the immigrant workforce share is split into EEA and Non-EEA workers. There is however little to suggest that the effects may differ between the EEA and Non-EEA workforce shares (Panel B). The point estimates of the effects of the respective workforce shares are quite similar.

[25] Skilled non traded is defined as SOC 111 to SOC 399 and SIC 34 to SIC 97.
[26] A "good job" sector is defined here as any sector paying above the mean hourly wage across all sectors.
[27] The presence of sector fixed effects nets out the trade and non-traded dummies and means that the interaction terms are identified off the relative change in, respectively, the traded and non-traded "good" sector immigrant share relative to the non-traded "other" immigrant share.
[28] The immigrant share for the skilled non-traded sector is the sum of the two workforce share coefficients. So in column 5 the effect for the non-traded good job sector is 0.646-0.917 = -0.271

However once again the inclusion of sector trends leaves the immigrant share variables insignificantly different from both zero and from each other (though the sign of the estimates is the same as in the fixed effects estimates). As before this makes it hard to draw strong conclusions from these estimates.

Table 3. Immigrant Share and On-the-Job Training Probability: UK-Born 2001-2017 (1 digit occ/ind) Traded v Non-Traded Sector

Variable	(1)	(2)	(3)	(4)
Panel A				
Skilled Adult Immigrant Share t-1	0.758**	0.646**	0.084	0.091
	(0.148)	(0.144)	(0.158)	(0.155)
Traded Sector*Immigrant Share t-1	0.097	0.097	0.225	0.223
	(0.186)	(0.183)	(0.183)	(0.238)
Non-Traded Good *Immigrant Share t-1	-1.046**	-0.917**	-0.268	-0.271
	(0.212)	(0.212)	(0.192)	(0.191)
Panel B				
EEA Skilled Adult Immigrant Share t-1		0.856**		0.184
		(0.215)		(0.171)
Traded*EEA		0.303		0.251
		(0.242)		(0.258)
Non-Traded Good*EEA Share t-1		-1.203**		-0.056
		(0.278)		(0.254)
Non-EEA Skilled Adult Share t-1		0.650**		0.026
		(0.220)		(0.361)
Traded*Non-EEA		-0.747**		0.070
		(0.364)		(0.361)
Non-Traded Good*Non-EEA Share t-1		-0.897**		-0.310
		(0.286)		(0.255)

Standard errors in brackets clustered by industry, occupation. ** notes significance at 5% level. Columns include same controls as in Table 2. Columns 1 to 2 include sector fixed effects alongside controls. Columns 2 and 4 add log sector change in total workforce and change in other immigrants as additional controls Columns 3 and 4 include sector trends and sector fixed effects

Robustness Checks

Of course it can always be argued that any estimated effects are not robust to changes in model specification. In what follows we attempt to address some of these concerns.

Table 4 attempts to test the robustness of the findings by using different levels of measuring the immigrant workforce share variables. The first four columns uses estimates of the change in the sector skilled immigrant workforce share, $\Delta\{M_{st}/(M_{st} + N_{st})\}$. This may be useful if training reacts to the flow of immigrants rather than the stock. The second four columns use a measure of the immigrant to UK-born workforce ratio benchmarked to the year 2000, M_{st}/N_{st}^{2000} The idea here is to try to reduce one cause of the simultaneity element of endogeneity in the workforce share by using an arguably exogenous (out of sample) measure of UK-born workers in the denominator.

The results when using the change in immigrant share, (columns 1 and 2), suggest no significant effect on training. The results using the benchmarked ratio, (columns 3 and 4), are similar to those in Table 2. There again seems to be a small positive training effect for the EEA immigrant ratio (Panel B) and again suggestions of negative training effects in the non-traded good job sector, (Panel C), which disappears when sector trends are added. The results are broadly in line with the earlier findings. After the inclusion of sector trends, training incidence is insignificantly affected by the immigrant sector share (columns 2 and 4).[29]

[29] If anything the training effect is weakly positive, for the EEA migrant sector share.

Table 4. Different Measures of Immigrant Supply: Skilled Adult Arrival Immigrant Workforce Share and Individual On-the-Job Training Probability: UK-Born 2001-2017

	Change in Immigrant Share		Mst/Ns,$_{2000}$	
	(1)	(2)	(3)	(4)
Panel A				
Skilled Immigrant Share t-1	0.031	0.028	-0.013	0.015
	(0.073)	(0.073)	(0.034)	(0.023)
Panel B				
EEA Share t-1	-0.033	-0.083	0.130**	0.106**
	(0.106)	(0.099)	(0.044)	(0.049)
Non-EEA Share t-1	0.078	0.097	-0.081	-0.004
	(0.082)	(0.085)	(0.047)	(0.028)
Panel C				
Skilled Immigrant Share t-1	0.031	0.015	0.285**	-0.113
	(0.073)	(0.130)	(0.142)	(0.098)
Traded*Skilled Immigrant Share t-1	-0.136	-0.281	-0.211	0.150
	(0.204)	(0.186)	(0.143)	(0.099)
Non-Traded Good* Skilled Immigrant Share t-1	0.081	0.178	-0.429**	0.096
	(0.170)	(0.174)	(0.148)	(0.102)
Controls	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Sector Trends	No	Yes	No	Yes

Note: See Table 2.

Endogeneity of Immigrant Share

As discussed above if immigrants (or UK-born workers) sort into a sector by choice or there are missing unobserved determinants of the delivery of training correlated with migrant share or training opportunities influence the number of immigrants attracted into the sector or the immigrant share numbers are measured with error or some combination of the above, then the estimates in Tables 2 to 4 will be affected by endogeneity bias. In order to try to address endogeneity issues we instrument the lagged migration share variables by the shift-share instrument beloved of many applied studies (see discussion in Data section above). The results are given in Table 5, using two different explanatory variables – the immigrant workforce share $M_{st}/(M_{st}+N_{st})$ –Table 5a - and the immigrant workforce ratio benchmarked to the year 2000, M_{st}/N_{st}^{2000} –Table 5b.

As discussed above the latter measure of immigrant concentration removes one potential source of endogeneity, selection into sector from UK-born workers. Instrumenting the first measure means making predictions of both the numerator and the denominator. We present results with fixed effects (IV Estimation 1) and also with fixed effects together with sector trends (IV Estimation 2). We present estimated standard errors i) clustered by sector and year and ii) sector only.

We instrument a single measure of concentration (panel A) and the skilled adult immigrant share split by EEA and non-EEA (panel B). When we estimate the latter there are two endogenous variables (EEA share and Non-EEA share) which means that there are two first stage regressions requiring two instruments.[30] In practice each endogenous variable is regressed separately on both the instruments together with controls.

[30] We estimate the EEA and non-EEA share in the same way as the single endogenous variable as $\sum_{i=1}^{N} s_{i0} M_{it} \Big/ \sum_{i=1}^{N} b_{i0} P_{it}$ but using country of origin sector shares for the set of EEA and non-EEA countries respectively.

In Table 5a the first stage estimates are generally insignificant while in Table 5b, the first stage estimates for the relevance of the instruments are generally significant. It seems that having to instrument the denominator as well as the numerator weakens the effectiveness of the instrument particularly in the presence of sector fixed effects.[31] The level at which the clustering is estimated also makes a big difference to the significance of the estimates, both first and second stage. This suggests researchers should be very careful when reporting significance of IV estimates. Results clearly depend on the extent of clustering. Ignoring the possibility of autocorrelation in the residuals tends to make the standard errors much lower and the significance of the instrument higher than otherwise. The differences are more muted when sector trends are added to the model.

In general the second stage estimates using this instrument, in the presence of fixed effects and/or sector trends performs poorly so it is hard to take much from these estimates.[32]

[31] The instrument also performs a little better the more countries are used to construct the instrument. Overall researchers would probably be wise to assess the sensitivity of estimates when using this type of instrument.

[32] The 1st stage results in Panel B show that only one instrument (the Non-EEA proxy) is, at best, significant in either first stage. Note also that the associations of the EEA predicted share with the actual EEA workforce share in the first stages in Table 5A are negative. This probably reflects the fact that recent growth in EEA has been dominated by A8 migrants who were underrepresented in the base year, 2000, from which the instrument is constructed.

Table 5a. IV Estimates of Immigrant Share and Training Probability: UK-Born 2001-2017 (1 digit occ/ind)

	IV Estimation 1			IV Estimation 2		
	Train 1st Stage		Train 2nd Stage	Train 1st Stage		Train 2nd Stage
Panel A						
Immigrant Share t-1	-0.014 (0.036) {0.015}			0.059 {0.079} (0.049)		
Immigrant Share t-1			13.261 (33.397) {13.904}			1.271 (2.680) {2.381}
Panel B	EEA 1st stage	Non_EEA 1st stage		EEA 1st stage	Non_EEA 1st stage	
EEA Share t-1	-0.285** (0.062)	-9.041 (124.9)		-0.148 (0.271)	-0.375 (0.325)	
Non-EEA Share t-1	-0.002 (0.016)	0.065** (0.026)		-0.033 (0.090)	0.624** (0.161)	
EEA Share t-1			-9.041 (124.9)			11.671 (18.086)
Non-EEA Share t-1			45.792 (352.7)			0.703 (2.256)
Controls						
Demographic	Yes			Yes		
Job	Yes			Yes		
Year	Yes			Yes		
Sector	Yes			Yes		
Sector Trends	No			Yes		

Standard errors in { } brackets clustered by sector and year. Sector-only clustered standard errors in ( ) brackets. ** notes significance at 5% level based on sector=-only standard errors.

Table 5b. IV Estimates of Immigrant Share and Training Probability: UK-Born 2001-2017 (1 digit occ/ind)

	IV Estimation 1			IV Estimation 2		
	Train 1st Stage		Train 2nd Stage	Train 1st Stage		Train 2nd Stage
Panel A						
Immigrant Ratio t-1	0.071** (0.028) {0.016}			0.166** (0.056) {0.033}		
Immigrant Ratio t-1			-0.162 (0.324) {0.232}			0.072 (0.129) {0.156}
Panel B	EEA 1st stage	Non_EEA 1st stage		EEA 1st stage	Non_EEA 1st stage	
EEA Ratio t-1	-0.001 (0.016) {0.029}	0.002 (0.021) {0.043}		0.024 (0.070) {0.053}	-0.020 (0.090) (0.060}	
Non-EEA Ratio t-1	0.090** (0.020) {0.031}	0.335** (0.040) {0.092}		0.050 (0.032) {0.030}	0.573** (0.135) {0.085}	
EEA Ratio t-1			0.372 (3.798) {3.685}			-5.777 (16.287) {12.925}
Non-EEA Ratio t-1			0.074 (0.936) {0.960}			0.766 (1.235) {0.846}
Controls						
Demographic	Yes			Yes		
Job	Yes			Yes		
Year	Yes			Yes		
Industry	Yes			Yes		
Occupation	Yes			Yes		
Occ. Trends	No			Yes		
Ind. Trends	No			Yes		

Standard errors in brackets clustered by industry, occupation and year. ** notes significance at 5% level

Sector Level Analysis

Arguably looking at an individual's chances of being trained does not address the issue of shifts in the sectoral allocation of training across UK-Born workers closely enough. The model can also be interpreted as suggesting variation willingness to hire (and train) UK-born workers. One alternative to investigate is therefore to construct a measure of each sector's share of hiring for UK-born workers, H_{st}/H_t . If the sector share of training changes in response to changes in the workforce immigration share this may help address the issue.

We first look to see if the training results obtained in Table 2 are similar when the analysis is repeated at sector level. Since the level of variation in the key explanatory variable of interest – the immigrant workforce share – only varies by sector and time, it can be argues that the analysis should be done at sector level. Table 6 gives the results for the sector level regressions. We use the same sectors as in Table 2 ie defined over a combination of 1-digit occupations and 2-digit industries that allow us to disaggregate into traded and non-traded sectors. We use two dependent variables i) the sector training rate of UK-born workers ii) the share of UK-Born workers who are receiving training in each occupation at time t. We present estimates using three different levels of adjustment to the standard errors: clustering a by sector and year, clustering by sector only and HAC standard errors allowing for autocorrelation up to order 2. Since clustering by sector only gives the largest standard errors this method makes it harder to produce t-statistics that are statistically significant from zero and so makes it a stronger test of finding any significant immigration effects.[33]

The sector level results for training are broadly similar to those found using individual data. There is now a small negative baseline effect of immigration on the training rate when sector trends effects

[33] Technically this reduces the chances of Type I error – finding a false significant result – at the expense of raising Type 2 error – failing to reject a false null. Note from Table 6 that the differences in the standard error estimates are large in the models with sector fixed effects but converge in the models with sector trends

are included. Again the magnitude of the estimated effect is not large.[34] Panel B splits the skilled adult immigrant sector workforce into EEA and Non-EEA country of birth. There is a suggestion that any negative training effect of immigration may be driven by changes in the Non-EEA skilled adult workforce, since the coefficient for this group is negative and significant in Panel B column 1. The coefficient for the EEA workforce is insignificantly different from zero (column 1). However the significant Non-EEA effect does not last in the presence of sector trends (panel B column 2). Panel C splits the sample into traded , non-traded good and non-traded other. The second and third variables reported in Panel C are for traded and non-traded good dummies interacted with the sector skilled adult immigrant share. These coefficients give any additional difference between the baseline effect for the non-traded other sector reported in the first row of Panel B. There is a suggestion that the negative effect may be stronger in the traded good jobs sector but the evidence for differences in the non-traded sector is not strong, (Panel C, columns 2 and 4).[35]

[34] A 5 percentage point rise in the skilled adult immigrant workforce share reduces training rates of UK-born workers in a sector by 0.5 percentage points

[35] The sum of the baseline coefficient and the traded interaction term are negative which means a negative overall effect for the traded sector.

Table 6. Training Rates of UK Born and Workforce Skilled Adult Immigrant Share (Sector: 1 Digit Occupation & Industry) 2001-2017

	Panel A: UK-Born Sector Training rate $T_{N,s,t}/N_{s,t}$		***Panel B: Sector Share of All UK-Born Training $T_{N,s,t}/T_{N,t}$***	
Panel A				
Skilled Adult Immigrant Share t-1	-0.034 (0.051) [0.072] {0.048}	-0.113 (0.054) [0.060] {0.055}	0.0077 (0.0031) [0.0051] {0.0023}	0.0014 (0.0012) [0.0014] {0.0012}
Panel B				
EEA Skilled Adult Immigrant Share t-1	0.112 (0.070) [0.096] {0.066}	-0.078 (0.082) [0.060] {0.055}	-0.0040 (0.0042) [0.0076] {0.0033}	0.0001 (0.0016) [0.0016] {0.0015}
Non-EEA Skilled Adult Immigrant Share t-1	-0.156** (0.071) [0.076] {0.065}	-0.114 (0.073) [0.060] {0.055}	0.0180 (0.0048) [0.0070] {0.0037}	0.0022 (0.0016) [0.0019] {0.0014}
Panel C				
Skilled Adult Immigrant Share t-1	-0.006 (0.056) [0.080] {0.052}	-0.086 (0.058) [0.066] {0.060}	0.0129 (0.0011) [0.0057] {0.0025}	0.0023 (0.0012) [0.0014] {0.0011}
Traded *Immig. Share t-1	-0.021 (0.038) [0.057] {0.035}	-0.115** (0.061) [0.053] {0.066}	-0.0144 (0.0026) [0.0048] {0.0035}	-0.0020 (0.0013) [0.0014] {0.0012}
Non-Traded "Good "*Immig. Share t-1	-0.131 (0.074) [0.091] {0.067}	0.009 (0.089) [0.105] {0.082}	0.0091 (0.0049) [0.0084] {0.0037}	-0.0015 (0.0016) [0.0016] {0.0017}
Controls				
Demographic	Yes	Yes	Yes	Yes
Job	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes

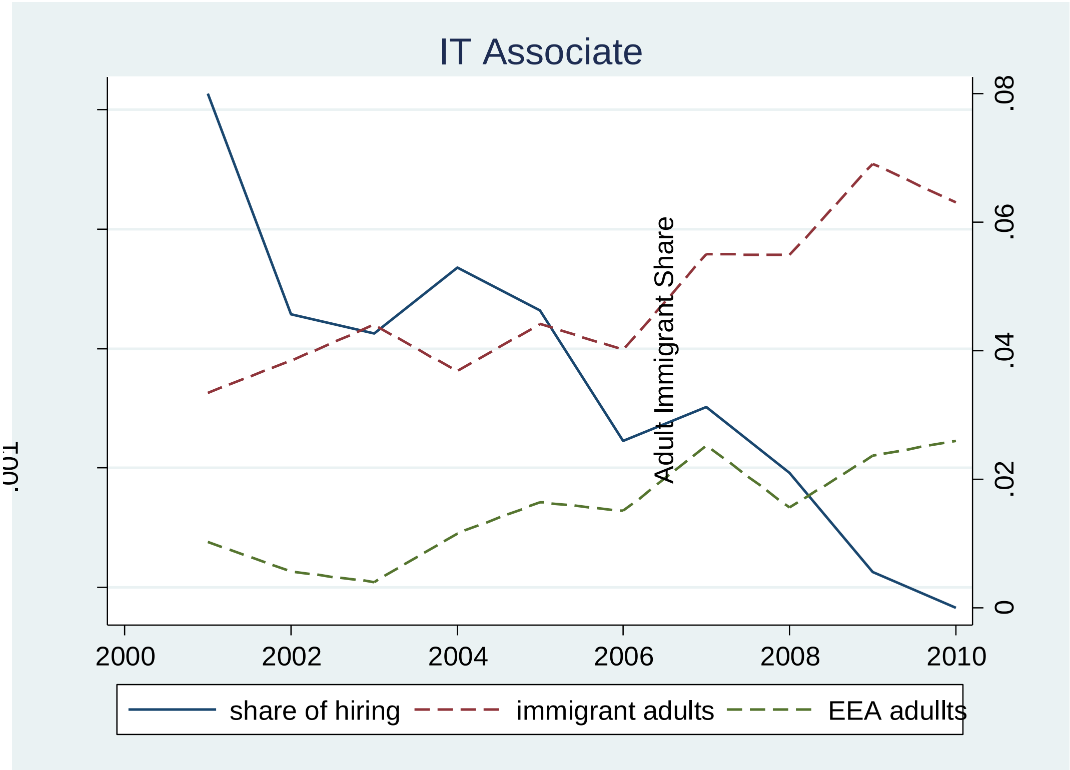
Sector Trends	No	Yes	No	Yes

Mean of training share=0.012. Sector time varying controls: age, sector shares of workers who are female, part-time, temporary, self-employed, public sector, graduates, firm>50, mean job tenure, real hourly wage and change in log sector size. 62 sectors. HAC cluster robust standard errors in 1st bracket. Cluster robust (sector) in 2nd bracket. Cluster robust (sector, year) in 3rd bracket. ** denotes significantly different from zero at 5% level using standard errors clustered by sector only.

7. Findings: Hiring

The theoretical framework underlying this analysis suggests there may be effects on hiring rates as well as on training rates of UK-born workers. Figure 17 illustrates the central concern, that rising workforce shares of skilled immigrants could affect hiring rates for the two sectors, IT and Nursing, highlighted earlier. The Figure plots the sector share of UK-born workers hired in each year alongside the sector workforce share of immigrants who arrived in the UK as adults with some level of tertiary education. The EEA immigrant workforce share is also graphed alongside. There is clearly a negative correlation between sector hiring share of UK-born workers and immigrant workforce share over this period (2001-2010). However this does not mean this trend holds for other sectors or in other periods. In order to establish this we need to undertake further regression analysis (below).

Figure 17: Sector Hiring Share of All UK-Born Workers and Immigration



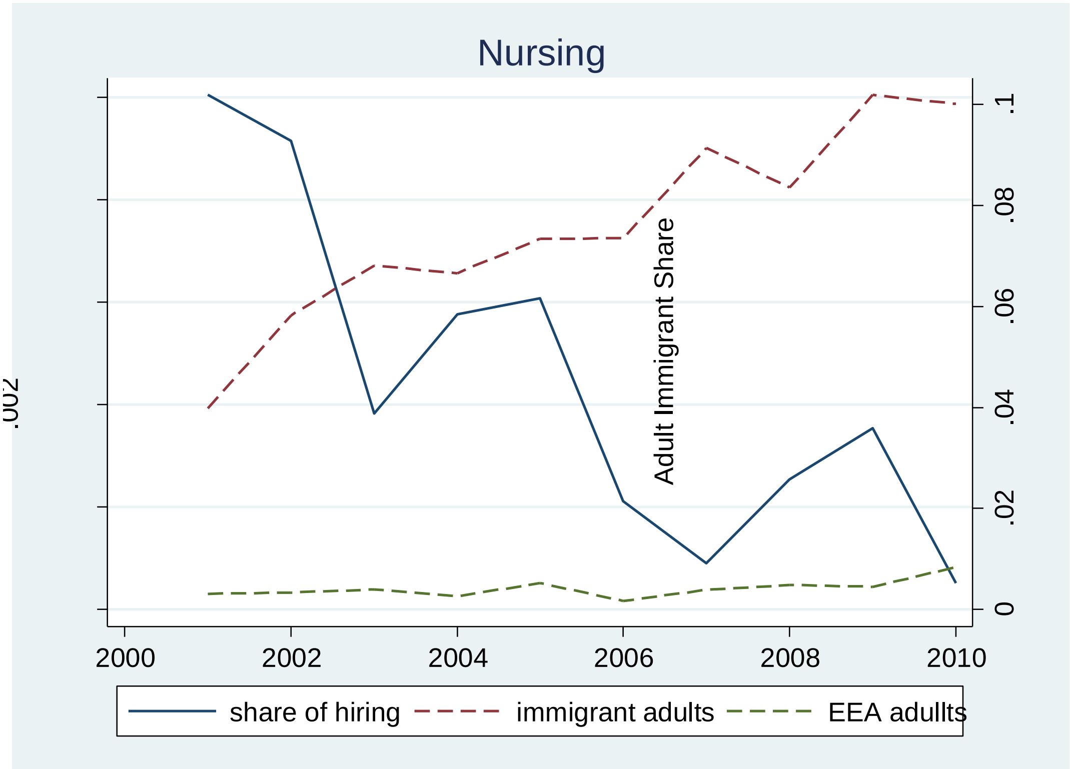
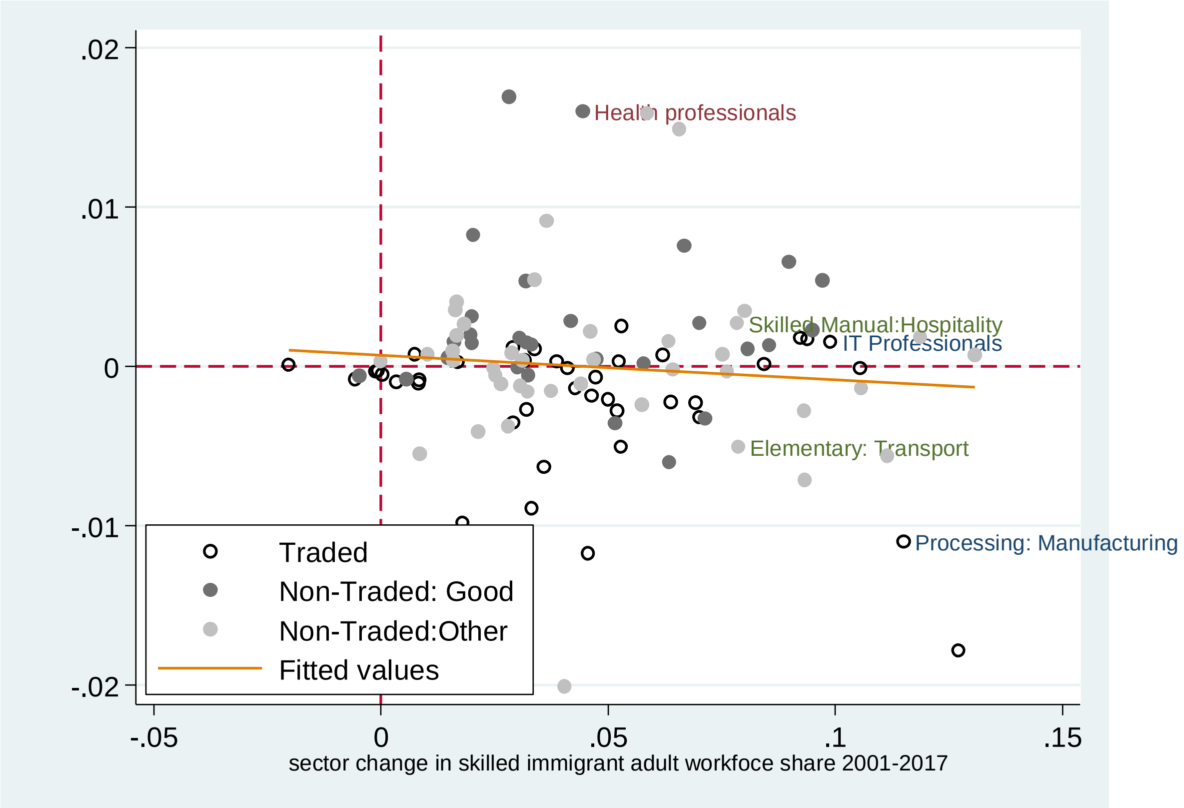


Figure 18 plots the long-term change in the sector hiring share of UK-born workers, H_s^N/H^N , against the long-term change in the skilled adult immigrant workforce share. Each dot represents a sector, which is again split into traded and non-traded sectors. The Figure suggests a weak negative relationship between sector immigrant workforce shares and the sector hiring share of UK-born workers. If anything this relationship is more negative when using the EEA skilled adult workforce share (second panel) and among the traded sector.

To see how robust this relationship is , Table 7 gives the sector level estimation results when i) the hiring rate ii) the sector share of hiring is used as dependent variable. The Table is, like in Table 6, split into Panel A - which gives the overall skilled adult immigrant workforce share effect – Panel B gives the separate estimates for EEA and Non-EEA skilled adults and panel C which gives the separate estimates for the traded and non-traded sectors. There is a suggestion of a negative effect of immigration workforce share on the occupation's hiring share for UK-born workers in column 3, which disappears when sector specific trends are added to the set of covariates. Panel B suggest that any hiring effect may be driven by changes in the EEA workforce share, but this effect is not robust to the presence of sector trends. The sample split reported in panel C again hints that there may be (small) negative effects of skilled adult immigration on the sector share of UK-born hiring in both the traded and non-traded good jobs sectors.

Figure 18: Changes in Sector Hiring Shares and Immigration, 2001-2017



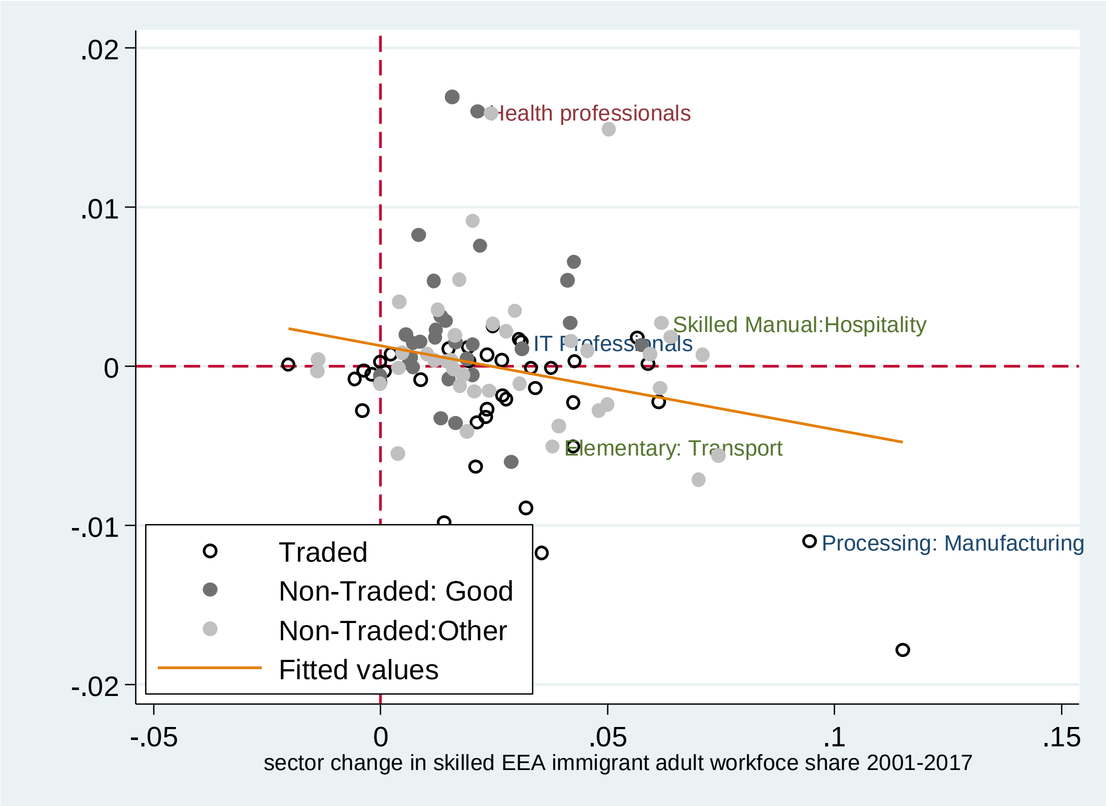


Table 7: Hiring Shares of UK Born and Workforce Skilled Adult Immigrant Share (1 Digit Sector) 2001-2017

	Sector Share of All UK-Born Hiring $H_{N,s,t}/H_{s,t}$	
Panel A		
Skilled Adult Immigrant Share t-1	-0.0002 (0.0038) [0.0070] {0.0029}	0.0011 (0.0014) [0.0017] { 0.0014}
Panel B		
EEA Skilled Adult Immigrant Share t-1	-0.0160** (0.0068) [0.0127] {0.0049}	0.0001 (0.0024) [0.0028] {0.0024}
Non-EEA Skilled Adult Immigrant Share t-1	0.0130 (0.0043) [0.0073] {0.0035}	0.0015 (0.0018) [0.0021] {0.0017}
Panel C		
Skilled Adult Immigrant Share t-1	0.0092 (0.0039) [0.0069] {0.0030}	0.0038** (0.0016) [0.0018] {0.0016}
Traded *Immig. Share t-1	-0.0242** (0.0041) [0.0077] {0.0029}	-0.0059** (0.0019) [0.0021] {0.0018}
Non-Traded “Good”*Immig. Share t-1	0.0107 (0.0046) [0.0083] {0.0035}	-0.0053** (0.0019) [0.0022] {0.0019}
Controls		
Demographic	Yes	Yes
Job	Yes	Yes
Year	Yes	Yes
Sector	Yes	Yes
Sector Trends	No	Yes

Mean of hiring share=0.012. Sector time varying controls: age, sector shares of workers who are female, part-time, temporary, self-employed, public sector, graduates, firm>50, mean job tenure, real hourly wage, change in log other immigrant size and change in log sector size. 110 sectors. HAC cluster robust standard errors in 1st bracket. Cluster robust (sector) in 2nd bracket. Cluster robust (sector, year) in 3rd bracket. ** denotes significantly different from zero at 5% level using standard errors clustered by sector only.

8. Conclusions

Immigration can have either positive or negative effects on training and sectoral allocation of UK-Born workers depending on the characteristics of the migrants and the sectors in which they work. The results in this study suggest that while there may be examples of specific occupations where training and hiring if UK-born workers is negatively associated with a rising workforce share of (trained) immigrants it is hard to find evidence that this is the case, on average, throughout the UK economy over the period studied. Nor do there appear to be many significant different effects for the share of EEA or Non-EEA migrants in the workplace. If anything, more EEA workers are associated with more training of UK-born workers, but the effects are not large. There are suggestions that the sectoral allocation of workers may be affected differently in traded and non-traded sectors and between "good" and other jobs. The negative effects on training that we observe are in the non-traded good jobs sector, consistent with our theoretical framework. The evidence is not large and not very robust, though we think worthy of further investigation.

Appendix: Brief Description of the Theoretical Model

The theoretical model distils the issue of migration and training into its simplest possible form. It considers a stylized economy with two skill levels, where, due to (endogenously determined) differential wealth, high skill agents' children are more likely to become high skilled but where training may allow some low skilled workers' children to become high skilled. These intergenerational dynamics are illustrated in Figure A1.

Figure A1 plots family wealth along the x axis and the wealth of the next generation of the family on the y axis. It is assumed families need wealth (bequests, b_t^i) to finance training/human capital accumulation. Families with high wealth above the costs of education, e, can purchase education for their young who thereby gain skills. Most of these educated workers will obtain a high skilled job and so will be able to pass down a high level of wealth to their next generation; a level of wealth that will allow them in turn to purchase education for their young. This is depicted by the higher arm of $b^i_{t+1,}$ for b_t^i that is more than e. However not all of those with education are successful and some only earn a low wage next period and so only pass down a low level of wealth to the next generation, a level of wealth that will not allow them to purchase education for their young. This is depicted by the lower arm of $b^i_{t+1,}$ for b_t^i that is more than e. This represents downward social mobility.

Low wealth families, with wealth below b^ -which is less than the cost of education, e - cannot borrow to purchase education for their young. For these families there are two possibilities. If they are lucky they get trained on the job and earn a wage that allows them to pass down a higher level of wealth to the next generation than they received. This is depicted by the higher arm of b^i_{t+1}, for b_t^i that is less than b^. This represents upward social mobility which will be faster the higher is the on the job training wage. However not all of the next generation are able to get on the job training and so will only earn a low wage next period and so only pass down a low level of wealth to the next generation, a level of wealth that will not allow them to purchase education for their young. This is depicted by the lower arm of $b^i_{t+1,}$ for b_t^i that is less than b^.

For families with intermediate levels of wealth, above b^ but less than the costs of education, e, their wealth is high enough that they don't need to borrow a large amount from the financial sector to pay for education. The financial sector is able to cover itself for these borrowers by charging high interest rates on the loans which are paid by the trainees who earn a high wage. This is depicted by the higher arm of b^i_{t+1}, in this intermediate range of b_t^i. This also represents upward social mobility. However not all of those with education are successful and some only earn a low wage next period and have to use all their wealth paying off their education debts. Their next generation start at the bottom with no wealth, which is also downward social mobility.

The degree of upward social mobility in this model is mostly determined the number of jobs with on the job training. If we abstract away from the traded sector and assume that these job are located in the non-traded sector then the size of the non-traded sector will determine the level of on the job training and the degree of social mobility[36]. In this context, as explained above, immigrants working in a job with training in the non-traded sector will produce more of the non-traded good than he or she will demand and so will reduce the remaining demand for native workers in this sector below its pre migration level. Thus, in this case, immigration that takes training position will have reduced the social mobility for indigenous workers. However there are also paths whereby immigrants can

[36] Note that if one modelled training in the traded sector then one could obtain similar results which would reinforce the mechanisms derived for the non-traded sector. We abstract from modelling training in the traded sector for simplicity but also as modelling this sector would require taking a position on the effect of training on prices and world market share and would thus have implications for industrial policy, which is an area of contentious debate which might obscure the separate analysis of this paper. Taken literally one could argue that the skill set is different to the traded sector and so firms are willing to offer training here because the skill is assumed to be more sector specific (or one could argue that an industry primarily serving o the domestic economy's needs – e.g. Health - may be better able to support an institutional set up that commits employers and employees to long run wage and training arrangements (Dustmann and Schoenberg (2012), Acemoglu and Pischke (1998)).

increase the level of social mobility. Immigrants with high wealth, who therefore increase the demand for domestic non traded goods with training, and high skill, who can increase the availability of training, will have a positive effect on domestic training.

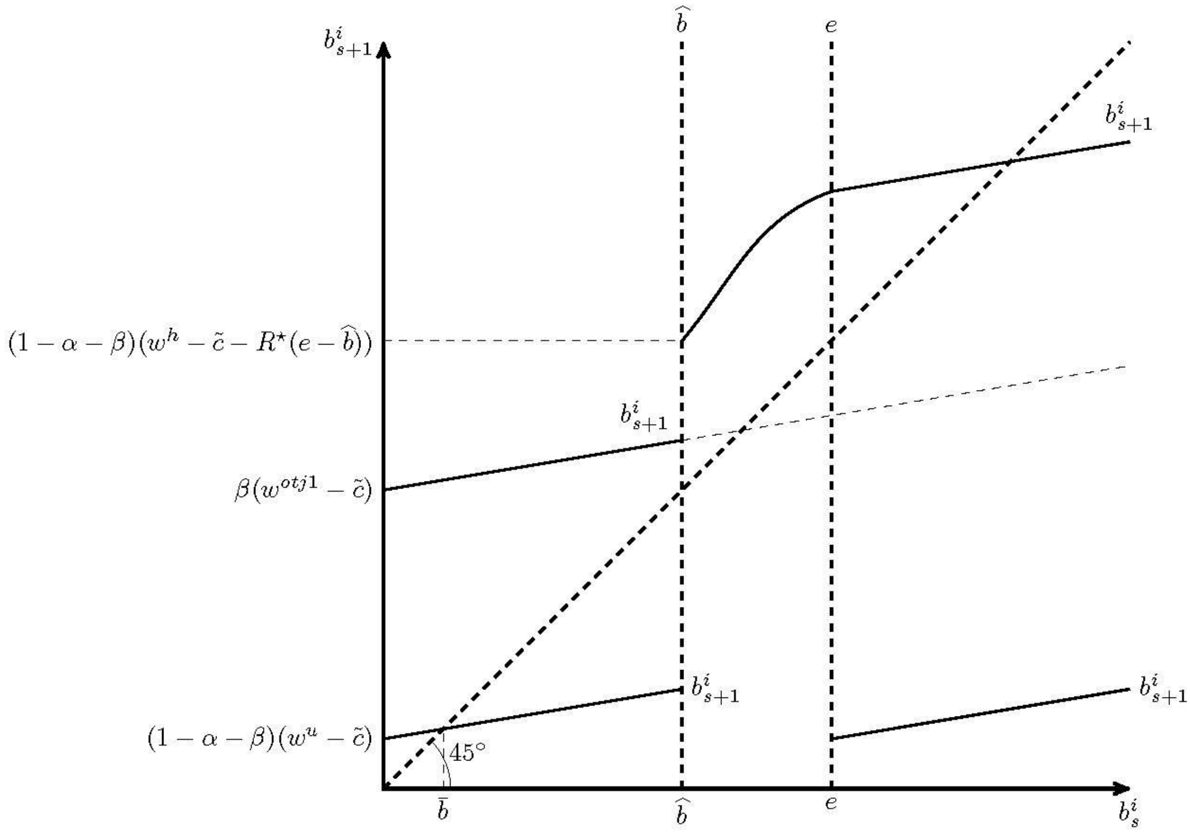


Figure A1

Appendix Tables

Table A1. Change in Employment by Occupation 2001-2010

Occupation (2000 SOC)	Change in Employment				Growing	Growing UK-Born	Growing Immigrant
	Total	UK-Born	Immigrant	Skilled Immigrant Adult			
421 secretarial and related occupations	-258583	-257293	-1290	-2925	No	No	No
813 assemblers and routine operatives	-212735	-207132	-5603	9829	No	No	No
521 metal forming, welding and related	-53973	-53345	-628	111	No	No	No
412 administrative occupations: finance	-156869	-162688	5819	15895	No	No	Yes
413 administrative occupations: records	-148726	-164093	15367	7967	No	No	Yes
522 metal machning, fitting, instr makng	-134045	-142620	8575	5386	No	No	Yes
811 process operatives	-117935	-171179	53244	22965	No	No	Yes
812 plant and machine operatives	-93294	-103283	9989	7333	No	No	Yes
549 skilled trades n.e.c	-84792	-85591	799	2398	No	No	Yes
921 elementary administration	-73090	-79689	6599	2957	No	No	Yes
913 elementary process plant	-62095	-120211	58116	21815	No	No	Yes
712 sales related occupations	-60873	-64341	3468	4005	No	No	Yes
311 science & engineering techinic.	-59056	-69549	10493	7590	No	No	Yes
711 sales assistants and retail cashiers	-57854	-119767	61913	28564	No	No	Yes
411 administrative: government& related	-55707	-57776	2069	1160	No	No	Yes
923 elementary cleaning	-44059	-141132	97073	37801	No	No	Yes
414 administrative: communications	-41292	-55318	14026	7238	No	No	Yes
914 elementary goods storage	-33665	-74393	40728	22008	No	No	Yes
523 vehicle trades	-30653	-32062	1409	1116	No	No	Yes
524 electrical trades	-24851	-30597	5746	4639	No	No	Yes
123 managers in other service sector	-23934	-33090	9156	2321	No	No	Yes

912 elementary construction	-23370	-29850	6480	3227	No	No	Yes
354 sales & related assoc professionals	-21001	-38857	17856	10420	No	No	Yes
814 construction operatives	-19956	-22348	2392	1643	No	No	Yes
621 leisure & travel service occupations	-19457	-21040	1583	3308	No	No	Yes
911 elementary agricultural	-18080	-24210	6130	3845	No	No	Yes
822 mobile machine drivers & operatives	-9402	-19617	10215	6580	No	No	Yes
313 it service delivery occupations	-7281	-18384	11103	5371	No	No	Yes
532 building trades	-7123	-15925	8802	1851	No	No	Yes
623 housekeeping occupations	-3016	-14018	11002	5935	No	No	Yes
111 corporate managers & senr off.	11599	12203	-604	25	Yes	Yes	No
118 health and social services managers	41281	42028	-747	1756	Yes	Yes	No
342 design associate professionals	16234	10723	5511	2192	Yes	Yes	Yes
629 personal services occupations n.e.c	19393	18701	692	649	Yes	Yes	Yes
114 customer care managers	21465	20647	818	4381	Yes	Yes	Yes
343 media associate professionals	26288	26250	38	-2410	Yes	Yes	Yes
243 architects, town planners, surveyors	29171	16950	12221	6335	Yes	Yes	Yes
115 financial instit and office managers	29916	24141	5775	3400	Yes	Yes	Yes
116 mngrs in distrib, storage and retail	29941	16732	13209	3883	Yes	Yes	Yes
925 elementary sales occupations	30987	19191	11796	3576	Yes	Yes	Yes
341 artistic and literary occupations	32351	24199	8152	2244	Yes	Yes	Yes
622 hairdressers and related occupations	35473	22879	12594	3748	Yes	Yes	Yes
211 science professionals	38483	24671	13812	14875	Yes	Yes	Yes
122 managers in hospitality & leisure	39037	21164	17873	11066	Yes	Yes	Yes

245 librarians and related professionals	44349	35696	8653	9171	Yes	Yes	Yes
322 therapists	48095	30768	17327	8662	Yes	Yes	Yes
511 agricultural trades	52573	47139	5434	1601	Yes	Yes	Yes
344 sports and fitness occupations	54521	50272	4249	997	Yes	Yes	Yes
241 legal professionals	55643	48059	7584	1447	Yes	Yes	Yes
331 protective service occupations	58695	53168	5527	88	Yes	Yes	Yes
721 customer service occupations	77980	40522	37458	16681	Yes	Yes	Yes
321 health associate professionals	88398	46734	41664	43721	Yes	Yes	Yes
323 social welfare assoc professionals	96635	82692	13943	3274	Yes	Yes	Yes
355 conservation associate profs	96994	75501	21493	11959	Yes	Yes	Yes
112 production managers	98718	73616	25102	14373	Yes	Yes	Yes
221 health professionals	99230	58127	41103	32113	Yes	Yes	Yes
242 business & statistical profs.	105519	74436	31083	25009	Yes	Yes	Yes
231 teaching professionals	270347	216879	53468	25063	Yes	Yes	Yes
612 childcare & reltd personal services	282274	249637	32637	19034	Yes	Yes	Yes
113 functional managers	287957	253798	34159	28045	Yes	Yes	Yes
821 transport drivers and operatives	801	-62849	63650	27588	Yes	No	Yes
924 elementary security occupations	18017	-19816	37833	14725	Yes	No	Yes
353 business & finance assoc profs	22000	-10000	32000	15743	Yes	No	Yes
531 construction trades	29202	-22501	51703	21841	Yes	No	Yes
922 elementary personal service	72593	-18949	91542	38775	Yes	No	Yes
611 healthcare & reltd personal	155897	48966	106931	53042	Yes	No	Yes
213 IT & communication	37559	4088	33471	32334	Yes	Yes	Yes
212 engineering professionals	72424	34564	37860	24287	Yes	Yes	Yes

Change in Employment by Occupation 2011-2017

Occupation (2000 SOC)	Change in Employment				Growing	Growing UK-Born	Growing Immigrant
	Total	UK-Born	Immigrant	Skilled Immigrant Adult			
411 Admin: Govt. & Related	-133347	-125540	-7807	136	No	No	No
421 Secretarial and Related	-71677	-81949	10272	4691	No	No	Yes
711 Sales Assistants and Retail Cashiers	-61930	-102778	40848	6450	No	No	Yes
331 Protective Service	-35019	-42766	7747	1841	No	No	Yes
521 Metal Forming, Welding and Related	-24287	-31210	6923	3110	No	No	Yes
544 Other Skilled Trades	-23439	-33837	10398	3050	No	No	Yes
412 Administrative Occupations: Finance	-23065	-52065	29000	5413	No	No	Yes
911 Elementary Agricultural	-19420	-19743	323	702	No	No	Yes
921 Elementary Administration	-15325	-16646	1321	4231	No	No	Yes
118 Health and Social Services Manager	-8326	-10518	2192	6092	No	No	Yes
523 Vehicle Trades	-8029	-10892	2863	2869	No	No	Yes
115 Financial Institution Managers and Directors	-6279	-10176	3897	4455	No	No	Yes
532 Building Finishing	-4619	-11762	7143	3629	No	No	Yes
812 Plant and Machine Operatives	-4229	-9960	5731	3	No	No	Yes
413 Administrative Occupations: Records	-2612	-11469	8857	12	No	No	Yes
524 Electrical and Electronic Trades	344	-20004	20348	13445	No	No	Yes
621 Leisure and Travel Services	12487	10115	2372	4059	Yes	Yes	Yes
814 Construction Operatives	14887	11810	3077	-239	Yes	Yes	Yes
416 Administrative: Office Mngrs	15111	11832	3279	-1311	Yes	Yes	Yes
823 Other Drivers and Transport Operatives	6193	3198	2995	1423	Yes	Yes	Yes
712 Sales Related	7024	3541	3483	227	Yes	Yes	Yes
912 Elementary Construction	16297	9123	7174	-2029	Yes	Yes	Yes
355 Conservation & Environmental Ass. Profs	19485	16037	3448	4148	Yes	Yes	Yes
243 Architects, Town Planners and Surveyors	20190	3749	16441	10658	Yes	Yes	Yes

111 Chief Executives and Senior Officials	21390	12804	8586	888	Yes	Yes	Yes
222 Therapy Profs.	22803	20804	1999	-1102	Yes	Yes	Yes
511 Agricultural and Related Trades	24819	13143	11676	1711	Yes	Yes	Yes
125 Managers in Other Services	25614	421	25193	14991	Yes	Yes	Yes
722 Customer Service Managers	25791	18128	7663	4695	Yes	Yes	Yes
522 Metal Machining, Fitting and Instrument Making Trades	26260	13485	12775	8865	Yes	Yes	Yes
813 Assemblers and Routine Operatives	27947	11466	16481	16243	Yes	Yes	Yes
321 Health Associate Professionals	28404	24951	3453	-312	Yes	Yes	Yes
241 Legal Professionals	29427	22014	7413	5603	Yes	Yes	Yes
245 Librarians and Related Professionals	33146	23338	9808	4924	Yes	Yes	Yes
212 Engineering Profs.	34292	17156	17136	14388	Yes	Yes	Yes
612 Childcare and Related Personal Services	35337	9275	26062	14663	Yes	Yes	Yes
721 Customer Service	36497	27475	9022	4736	Yes	Yes	Yes
629 Personal Service nec	37335	34411	2924	1356	Yes	Yes	Yes
247 Media Professionals	40488	31425	9063	3512	Yes	Yes	Yes
211 Natural and Social Science Professionals	48147	17342	30805	20148	Yes	Yes	Yes
246 Quality and Regulatory Professionals	49005	33896	15109	6617	Yes	Yes	Yes
344 Sports and Fitness	58146	44881	13265	1995	Yes	Yes	Yes
112 Production Managers	64181	46503	17678	7782	Yes	Yes	Yes
342 Design Occupations	66546	54721	11825	10282	Yes	Yes	Yes
311 Science, Engineering & Production Technicians	67298	50728	16570	11897	Yes	Yes	Yes
231 Teaching and Educational Professionals	71074	61144	9930	3506	Yes	Yes	Yes
354 Sales, Marketing and Related Associate	76606	39566	37040	20941	Yes	Yes	Yes
341 Artistic, Literary and Media Occupations	79216	44297	34919	25480	Yes	Yes	Yes
223 Nursing and Midwifery Professionals	82390	40729	41661	18778	Yes	Yes	Yes
221 Health Professionals	90086	67366	22720	11392	Yes	Yes	Yes
927 Other Elementary Services Occupations	99190	57744	41446	27113	Yes	Yes	Yes
543 'Food Preparation and Hospitality Trades'	102202	34636	67566	18579	Yes	Yes	Yes
353 'Business, Finance Associate Profs	108551	73622	34929	18921	Yes	Yes	Yes

614 'Caring Personal Services	143759	89094	54665	9425	Yes	Yes	Yes
213 IT & Telecomms Profs	159806	80664	79142	55870	Yes	Yes	Yes
414 Admin nec	185106	151419	33687	26562	Yes	Yes	Yes
113 Functional Managers and Directors	269600	188751	80849	50388	Yes	Yes	Yes
323 Welfare and Housing Associate Professionals	389	1906	-1517	-1738	Yes	Yes	No
313 Information Technology Technicians	14974	15745	-771	4891	Yes	Yes	No
122 Managers in Hsptlty and Leisure Services	18243	22704	-4461	2229	Yes	Yes	No
119 Managers and Directors in Retail	1251	-6973	8224	4228	Yes	No	Yes
124 Managers and Proprietors in Health	3021	-1919	4940	1717	Yes	No	Yes
923 Elementary Cleaning Occupations	4437	-52682	57119	25784	Yes	No	Yes
925 Elementary Sales Occupations	4708	-2276	6984	3145	Yes	No	Yes
811 Process Operatives	4946	-26795	31741	26471	Yes	No	Yes
713 Sales Supervisors	9143	-4734	13877	8359	Yes	No	Yes
623 Housekeeping and Related Services	10031	-12205	22236	3788	Yes	No	Yes
924 Elementary Security	12927	-20306	33233	8524	Yes	No	Yes
822 Mobile Machine Drivers and Operatives	13242	-5601	18843	2249	Yes	No	Yes
116 Managers and Directors in Transport	13860	-1058	14918	6460	Yes	No	Yes
913 Elementary Process Plant Occupations	15420	-1337	16757	521	Yes	No	Yes
622 Hairdressers and Related Services	20734	-4407	25141	12850	Yes	No	Yes
926 Elementary Storage	24082	-29311	53393	20776	Yes	No	Yes
531 Construction and Building Trades	33770	-4663	38433	8024	Yes	No	Yes
242 Business, Research and Administrative Profs	41693	-4874	46567	31801	Yes	No	Yes
821 Road Transport Drivers	84937	-3584	88521	27291	Yes	No	Yes

Table A3. Current Immigrant Share and On-the-Job Training Probability: UK-Born 2001-2017 (1 digit occ/ind) current level of share

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant Share	0.053			0.245**		
	(0.113)			(0.029)		
EEA Share		-2.513**	-1.480**		0.487**	0.002
		(0.199)	(0.116)		(0.045)	(0.041)
Non-EEA Share		2.310**	1.207**		-0.001	-0.090**
		(0.228)	(0.131)		(0.047)	(0.037)
	0.269**	0.225**	0.353**	0.249**	0.252**	-0.954
Constant	(0.009)	(0.008)	(0.008)	(0.014)	(0.014)	(5.956)
Controls						
Demographic	No	No	Yes	Yes	Yes	Yes
Job	No	No	Yes	Yes	Yes	Yes
Year	No	No	No	Yes	Yes	Yes
Industry	No	No	No	Yes	Yes	Yes
Occupation	No	No	No	Yes	Yes	Yes
Occ. Trends	No	No	No	No	No	Yes
Ind. Trends	No	No	No	No	No	Yes
Observations	2,808,282	2,808,282	2,808,282	2,808,282	2,808,282	2,808,282
R-squared	0.001	0.017	0.069	0.114	0.114	0.115

Standard errors in brackets clustered by industry, occupation and year. ** notes significance at 5% level. Demographic controls include gender, 6 age, 4 education and 20 region dummy variables. Job controls include dummy variables for self-employment, part-time working, temporary job and public sector. Mean of dependent variable = 0.27

Table A4. Mean Values of Explanatory Variables by Migrant Status

	UK-Born	EEA-Adult Migrant	Non-EEA Adult Migrant
Training Rate	0.272	0.230	0.294
Age 16-24	0.129	0.025	0.012
Age 25-34	0.205	0.448	0.293
Age 35-44	0.265	0.324	0.373
Age 45-54	0.259	0.151	0.232
Age 55-64	0.143	0.051	0.090
Female	0.472	0.480	0.436
Full-Time Education<=16	0.481	0.101	0.138
Full-Time Education 17-20	0.228	0.207	0.198
Student	0.032	0.005	0.009
Self-employed	0.127	0.144	0.139
Tyne & Wear	0.019	0.009	0.012
Rest of northern region	0.035	0.013	0.009
South Yorkshire	0.023	0.012	0.014
West Yorkshire	0.039	0.028	0.029
Rest of Yorks & Humberside	0.031	0.021	0.011
East Midlands	0.077	0.071	0.051
East Anglia	0.041	0.058	0.032
Inner London	0.024	0.143	0.162
Outer London	0.049	0.149	0.231
Rest of south east	0.201	0.191	0.207
South West	0.091	0.070	0.045
West Midlands (met county)	0.035	0.027	0.049
Rest of West Midlands	0.051	0.028	0.020
Greater Manchester	0.039	0.028	0.036
Merseyside	0.021	0.008	0.008
Rest of North West	0.042	0.024	0.016
Wales	0.049	0.024	0.019
Strathclyde	0.037	0.016	0.013
Rest of Scotland	0.055	0.047	0.025
Part-Time Job	0.252	0.170	0.229
Public Sector	0.295	0.164	0.280
Temporary Job	0.047	0.086	0.087
Job Tenure (years)	8.46	4.54	6.06
Firm Size<10	0.202	.166	.212
Firm Size 11-24	0.133	.119	.115
Firm Size 25-49	0.153	.146	.132

Table A5. Estimated Effects of other Explanatory Variables on Individual Probability of UK-Born Receiving Training

	Train	Train	Train
Immigrant Share t-1			
EEA Share t-1	-0.051 (0.089)	-0.051 (0.089)	-0.051 (0.089)
Non-EEA Share t-1	-0.088 (0.073)	-0.088 (0.073)	-0.088 (0.073)
Age 16-24	0.118** (0.006)	0.131** (0.013)	0.131** (0.013)
Age 25-34	0.046** (0.007)	0.045** (0.005)	0.045** (0.005)
Age 35-44	0.043** (0.005)	0.039** (0.004)	0.039** (0.004)
Age 45-54	0.039** (0.002)	0.036** (0.003)	0.036** (0.003)
Female	0.038** (0.010)	0.013** (0.006)	0.013** (0.006)
Left Education Age <=16	-0.075** (0.010)	-0.032** (0.004)	-0.032** (0.004)
Left Education Age 17-20	-0.023** (0.008)	-0.001 (0.003)	-0.002 (0.003)
Student	0.076** (0.011)	0.130* (0.011)	0.130* (0.011)
Self-Employed	-0.019 (0.028)	-0.046** (0.018)	-0.047** (0.018)
Part-Time	-0.073** (0.009)	-0.055** (0.008)	-0.054** (0.008)
Public Sector	0.159** (0.014)	0.056** (0.005)	0.055** (0.005)
Temporary Job	-0.008 (0.009)	-0.008 (0.011)	-0.008 (0.012)
Job Tenure	-0.001** (0.0001)	-0.001** (0.0001)	-0.001** (0.0002)
Firm Size<10	-0.049** (0.008)	-0.049** (0.006)	-0.049** (0.006)
Firm Size 11-24	-0.012 (0.009)	-0.019** (0.007)	-0.019** (0.007)
Firm Size 25-49	-0.003 (0.008)	-0.010 (0.008)	-0.010 (0.007)
Region Fixed effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Sector Fixed effects	No	Yes	Yes
Sector Trends	No	No	Yes

Note estimates based on regression with standard errors clustered at sector level.

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