‘Good jobs’, training and skilled immigration

Article:

Mountford, Andrew and Wadsworth, Jonathan (2023) ‘Good jobs’, training and skilled immigration. Economica, 90 (359). pp. 851-881. ISSN 0013-0427

https://doi.org/10.1111/ecca.12472

DOI: 10.1111/ecca.12472

ORIGINAL ARTICLE

Economica LSE

‘Good jobs’, training and skilled immigration

Andrew Mountford[1] | **Jonathan Wadsworth**[2]

[1]Royal Holloway, University of London and CReAM

[2]Royal Holloway, University of London, CEP(LSE), CReAM and IZA

Correspondence
Andrew Mountford, Department of Economics, Royal Holloway, University of London, Surrey, Egham, TW20 OEX.
Email: A.Mountford@rhul.ac.uk

Abstract
Has skilled immigration into the UK led to a reduction in the training of native-born workers? To address this concern, this paper describes a theoretical model where immigration can affect the training of native-born workers both positively and negatively, and where its effects may differ according to the characteristics of the migrant and of the training firm's sector. It then investigates this issue empirically using UK Labour Force Survey data from 1995 to 2018. At the aggregate level, there is a small positive association between skilled immigration and native training rates. However, a more disaggregated analysis finds that the relationship between immigration and native training depends on the skill level of the immigrant, the skill level of trainees, and the sector into which immigration occurs. In particular, traded goods sectors show a positive association between training of UK-born workers and both unskilled and skilled immigration. In non-traded high-wage sectors, the association between skilled immigration and UK-born training is negative. These findings highlight the importance of allowing for heterogeneous effects from immigration when formulating policy or when modelling immigration's effects across the wider economy.

1 | INTRODUCTION

Recent studies on the economic effects of immigration have argued that skilled immigrants add to the human capital stock of an economy and thereby improve its productivity. Moreover, the empirical evidence for the UK suggests that rising immigration has had few detrimental effects on the average employment prospects of UK-born workers.[1] Yet these findings do not exclude the possibility that migrants with human capital may crowd out the human capital formation of some native-born workers, if firms hire ready-trained workers from abroad rather than undergoing the expense of hiring and training a local workforce. This paper investigates for the first time the theoretical and empirical relationship between skilled immigration and training at the sectoral level, highlighting, in particular, differences between traded and non-traded sectors.

The distinction between the effects of immigration in the traded and non-traded sectors is an important one that has been made before in other contexts. Hanson and Slaughter (2002) find that increased output in the traded sector is the most important factor in US states' adjustment to labour supply shocks, with little role for changes in factor prices. More recently, the Dustmann and Glitz (2015) study of local labour markets in Germany finds larger (negative) relative wage effects from changes to skill-specific labour supply in the non-traded sectors than in the traded sectors. When looking specifically at responses of native-born workers to immigration changes across sectors, Burstein *et al.* (2020) find that immigrants in the USA crowd out the employment of native-born workers in more immigrant-intensive non-tradable jobs, but not in tradable occupations.[2] Intuitively, the demand, supply and prices of traded goods will be determined at a higher level (national or global) than those of non-traded goods. Thus the prices of traded goods may have less freedom to change, while the quantities of traded goods may have more ability to adjust than those of non-traded goods. In this paper, we investigate whether the differential effect of immigration between traded and non-traded sectors carries over to training provision.

Why is training important? Training is important because it is a plausible mechanism by which agents and firms can mitigate the effects of labour market imperfections in skill accumulation over and above that provided by compulsory public education. There is a long tradition in economic theory highlighting potential causes of sub-optimal equilibria both in general and in the labour market specifically.[3] Recently, there has been renewed interest in the relationship between sub-optimality in the labour market and training or firm-specific skill accumulation. In particular, Doepke and Gaetani (2020) highlight the potential importance of firm-specific relationships. They calculate that during the period 1981–2013, over 45% of less-educated German workers aged between 45 and 54 years old had a job tenure of over 20 years. They then show that in a labour market with durable tenures, firms may create more jobs that allow for skill accumulation, that is, 'good jobs', when there are stronger employment protection laws. Relatedly, Dustmann and Schönburg (2012) show how the regulation of apprenticeship training in Germany may act as a commitment device that allows a welfare-improving equilibrium with higher training, productivity and wages—that is, with 'good jobs'—to exist. Mion *et al.* (2020) show that 'good jobs', in this case defined as those with better career development, are associated with 'internationally active' firms. They show, using Portuguese data, how geographical frictions in the labour market may cause regional inequality in the distribution of 'good jobs' and wages. Our paper contributes to this literature by analysing the implications of immigration for training both empirically and theoretically in a labour market with 'good jobs'.

Our theoretical model describes a labour market where there may exist a limited number of jobs with training which, in equilibrium, are preferred by unskilled workers to other jobs. These are the 'good jobs' in the model. The equilibrium wage of 'good jobs' is not competed down due to the inability to make *ex ante* commitments about the post-training wage, following Christiano *et al.* (2016). We then analyse the implications of immigration in this context, distinguishing between skilled and unskilled immigration. Intuitively, the effects of immigration, good or bad, will be stronger in a labour market where the marginal agent discretely prefers some jobs to others than in one where the marginal agent is indifferent across alternatives.[4]

The purpose of the theoretical model is not to provide a structural model for estimation, but to demonstrate how the provision of 'good jobs' can mitigate inefficiencies in the skill accumulation market, and thereby to show how even small static effects of immigration, like those suggested by the empirical analysis, may potentially be amplified by the dynamic process of income and skill accumulation. The model also demonstrates the potential differences in the effects of skilled immigration on traded and non-traded sectors, as well as the potential for immigration to cause static gains (which may accrue mostly to firm owners) but dynamic losses (to native workers if their access to 'good jobs' is diminished). Finally, the model also provides an example where the wage prospects of domestic workers may be adversely affected by the possibility of immigration, even if does not actually occur, which is a useful caveat to the existing empirical literature.

It is important to emphasize that the model gives rise to both positive and negative potential effects of immigration on training. Increased profitability caused by skilled immigration may induce firm entry and increase training provision. Equally, access to increased supply of trained labour may reduce the need to train as much. Both positive and negative effects may be operating at the same time and differently across sectors. Ultimately, therefore, the effect of immigration on the training of native workers is an empirical matter, and this motivates our empirical analysis.

Faced with rising immigration, native-born workers may change their educational decisions (Hunt 2017), occupation (Llull 2018), or task specialization focus (Foged and Peri 2016). Similarly, firms can modify their choices of technology (Lewis 2011; Danzer *et al.* 2020). However, there is little in the existing literature studying the link between immigration and the training of the native-born workforce, which is the subject of this paper. As we show, training in the UK has been declining for some time on aggregate, a trend that contrasts with the trend in educational attainment in the UK. Although it may be that formal education has substituted for skills acquired on the job, this would sit oddly with the regular reports of skill shortages from UK employers. On-the-job training allows employers to provide both firm-specific skills and general skills perceived to be lacking. The UK Government acts in the UK training market both directly, paying for training to internalize the externalities associated with the decision to offer general training, and indirectly, through its provision of a visa route for skilled immigration to address skill shortages. Workers, too, have the option of paying for training, though as we show below, unlike with higher education, very few workers pay for their own training, nor do they appear to move much in search of training opportunities. The relationship between immigration and training, net of changes in educational attainment, is the focus of this paper.

Empirically, the paper investigates the effects of immigration on on-the-job training using sector-level data from the UK Labour Force Survey 1995–2018. The results suggest that the type of immigration and the type of sector that receives immigrants matter for the relationship with the provision of native workers training. Overall, there is a small statistically significant positive association of immigration on native-born training rates, although this also varies somewhat with the measure of immigration concentration used in the analysis. At the sectoral level, however, there is substantial heterogeneity in the impact of immigration on training, both by type of sector and by type of immigration. In the traded sector, native-born training rates are positively associated with skilled immigration, while in non-traded high-wage sectors, the association is negative. Workers in this latter sector, as we show below, have higher than average levels of training and wages, and these correspond to our definition of 'good jobs'. Both the positive and negative associations of immigration on training across sectors appear to be larger for skilled, longer-tenured UK-born workers, and are robust to the type of immigration concentration variable used. We find no negative association for less-skilled immigration on training in any sector. Indeed, less-skilled immigration appears complementary to the training of UK-born workers.

This paper employs the usual techniques for dealing with confounding variables by including time-varying sectoral variables (e.g. education levels) and by using sector-specific time trends. We also report results that address other remaining sources of endogeneity using shift–share instruments and immigration lags. However, the instrumentation does not always work well in this dataset, and generally produces imprecise estimates, although the signs of the relationships are robust to instrumentation. In our view, a causal explanation for the results—that is, that the availability of skilled immigrants is reducing employers' incentives to train native workers in some sectors and raising it in others—is simple, intuitive and consistent with the theoretical model. However, whatever the ultimate cause of the contrasting relationship between skilled immigration and native training across the traded and high-wage non-traded sectors, the importance of training provision for productivity, income inequality and social mobility should mean that this proximate relationship is of interest to policymakers, researchers and students of the UK economy.

The paper is organized as follows. Section 2 motivates the analysis and outlines some of the broad stylized facts about recent immigration, hiring and training trends in the UK economy. Section 3 describes a theoretical general equilibrium model of training, and discusses the effect of immigration on training and social mobility in this model. Section 4 describes the empirical analysis, and Section 5 concludes.

2 | RECENT TRENDS IN UK TRAINING AND IMMIGRATION

In this section, we describe recent trends in training and immigration in the UK economy, highlighting in particular the contrast in trends at the aggregate and sectoral level.

On-the-job training in the UK is not mandated, but comprises a myriad of initiatives from formal apprenticeships to *ad hoc* firm-based schemes. At the aggregate level, on-the-job training rates in the UK—defined here as having received training at work in the last 3 months—have been falling since 2001, though they had grown strongly in the five years prior to that. Figure 1 shows a large downward trend in the share of UK-born employees who say that they have received some training (at work or at college) while employed over the previous 3 months.[5] The UK immigration system over this period consisted of two separate work routes. There was free movement of any type of labour, skilled or unskilled, from anywhere in the European Union (EU). As the EU expanded, the labour supply from this route grew. At the same time, a work visa route was kept open to skilled workers from outside the EU. The skill requirement for non-EU workers varied over time, but always involved a requirement for some post-secondary education or training (Wadsworth 2018).

The general downward trend in the training rate after 2001 coincides with continued growth in both the total immigrant and skilled immigrant shares of the workforce—though Figure 1 makes it clear that immigration to the UK had begun to rise in the years before training began to decline.

These patterns vary somewhat if we disaggregate across sectors of the economy. Different sectors utilize training at different rates. Different sectors make more (or less) use of skilled immigrant labour. Figure 2 and Table 1 outline the levels of and changes in the rate of on-the-job training, skilled immigration and workforce shares of UK-born workers over time by aggregating sectors into three broad groups that feature in the model outlined in the next section: high-wage non-traded sectors, low-wage non-traded sectors, and traded sectors.[6]

Non-traded high-wage sectors train more and, over the full sample period, have a higher average share of skilled immigrants in the workforce than the other broad groups. The rise in

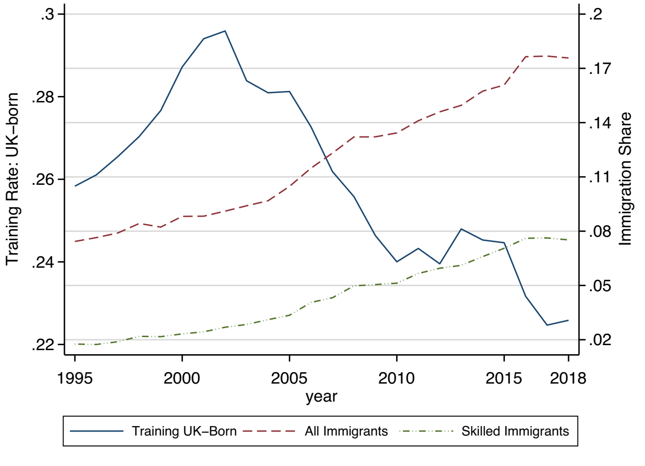
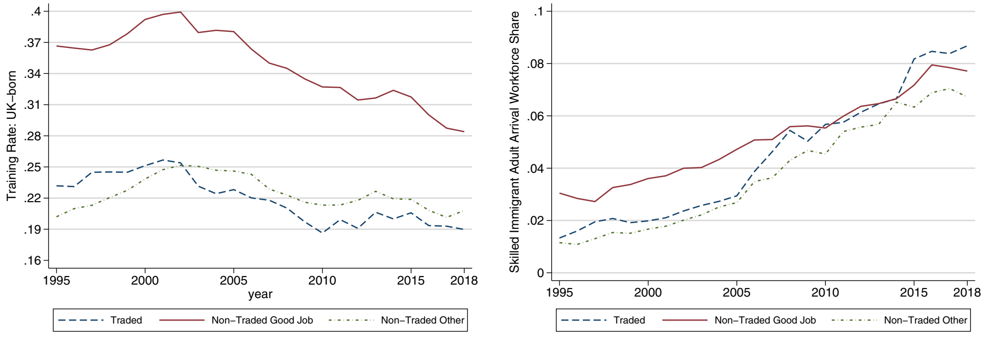


FIGURE 1 Aggregate on-the-job training of UK-born workers and immigration. Source: LFS, authors' calculations.



(a) Training rates (b) Skilled immigration

FIGURE 2 On-the-job training and immigration: traded and non-traded sectors. Source: LFS, authors' calculations.

TABLE 1 Broad Sector Trends in Training, Hiring and Immigration 1995–2018

Broad sector	On-the-job training % of UK-born employees in sector	Skilled adult immigrant % in sector	Sector % of all UK-born workers
Average level 1995–2000			
Traded	23	1.3	25
Non-traded low-wage	20	1.1	49
Non-traded high-wage	37	3.0	26
1995–2000 % point change			
Traded	+1.9	+0.6	−2.0
Non-traded low-wage	+3.6	+0.5	+0.0
Non-traded high-wage	+2.6	+0.6	+2.0
Average level 2001–18			
Traded	21	5.2	20
Non-traded low-wage	23	4.5	48
Non-traded high-wage	34	5.7	32
2001–18 % point change			
Traded	−6.7	+6.6	−7.0
Non-traded low-wage	−3.9	+4.9	−3.0
Non-traded high-wage	−11.3	+4.0	+10.0

Notes: Traded sector comprises 15% of all sectors and 20% of all employment over the sample period. Non-traded high-wage comprises 38% of sectors and 33% of employment. Non-traded low-wage comprises 47% of sectors and 46% of employment.
Source: LFS and authors' calculations.

on-the-job training in the 1990s is driven by growth in low-wage non-traded sectors. Traded sectors show much less growth at this time. Thereafter, there is a clear downward trend in the share of UK-born employee on-the-job training across all three broad groups. While native-born training levels remain highest in high-wage non-traded sectors, the absolute trend decline is notably steepest here. Training in these sectors fell from about 39% to 28% between 2001 and 2018, compared to traded sectors, which fell from about 25% to 19%. Skilled immigration, however, rose strongly across all three broad groups in this period. Traded sectors experienced the largest rise in the skilled immigrant workforce share. At the same time, the traded sector's share of all UK-born workers fell, while high-wage non-traded sectors increased their share of all UK-born workers.

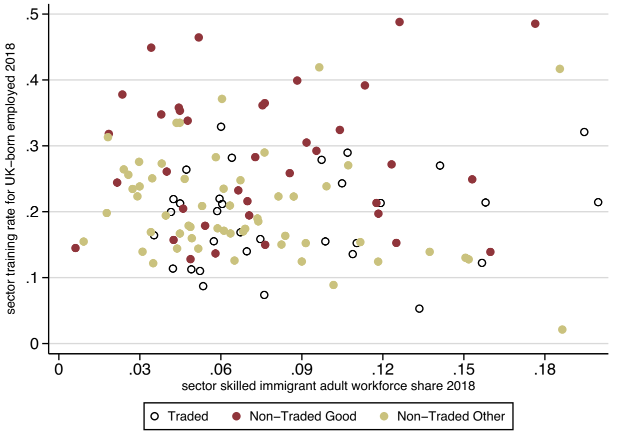


FIGURE 3 On-the-job training of UK-born workers and skilled immigration by disaggregated sector, 2018. Source: LFS, authors' calculations.

However it is also worth noting that there is considerable heterogeneity within these broad groups regarding training and utilization of skilled immigrant workers. Figure 3 plots the variation in these two variables for each of the 125 disaggregated sectors used in our study for the last year in our sample, 2018. While the broad group averages outlined in Table 1 can be seen to emerge from the graph, the within-group variation in both training and utilization of skilled immigrants is notable, particularly in non-traded sectors. The model of the next section shows why the impacts of skilled immigration may differ across sectors, while the empirical section that follows examines whether skilled immigration is significantly associated with any changes in within-group variation of on-the-job-training over time.[7]

3 | TRAINING: LABOUR MARKET SUB-OPTIMALITY AND SOCIAL MOBILITY

In this section, we describe a theoretical model designed to demonstrate how training may mitigate sub-optimal equilibria in the labour market and how this may be affected by immigration. As is well known from the previous literature (e.g. Galor and Zeira 1993), agents with insufficient resources are unable to borrow to accumulate human capital due to informational asymmetries. Lenders cannot observe the effort that agents put into their studies. On-the-job training may be able to circumvent this problem, as training occurs while the worker is employed, so employers may be able to monitor the effort that a worker puts into their training and ensure that it is mutually beneficial. Thus training may allow some agents who are unable to borrow to accumulate human capital to nevertheless achieve greater productivity and higher wages.

The model also shows how the potential effects of immigration may differ between traded and non-traded sectors. Sectors may differ for many reasons, of course, but in this paper, we focus on a fundamental asymmetry between the traded and non-traded sectors. In the traded sector, as demonstrated by Moretti (2010), increased immigration and employment will also boost demand and increase employment in the non-traded sector. In contrast, increased immigration into the non-traded sector will have only a negligible effect on demand in the traded sector (which is determined at the global level) and will, all else equal, reduce the need for native workers in the non-traded sector.[8]

The contribution of this model is its focus on the effects of immigration on training. Its approach is to illustrate these effects in the simplest model possible. The constituent parts of the model by themselves are well known. We take the modelling of informational asymmetries that prevent optimal borrowing for human capital accumulation from Galor and Zeira (1993). We take the idea that monitoring can mitigate credit constraints caused by informational asymmetries from Holmstrom and Tirole (1997), and the modelling of wage bargaining in the labour market from Christiano *et al.* (2016). Given this, our explanation of the model can be brief. The reader is referred to these original texts for further explanation.

A model of training

We consider a model, following Galor and Zeira (1993), where all agents would like to accumulate transferable skills via the market and become highly skilled labour, denoted L^H, but where not all agents are able to do so due to informational frictions in the credit market and differing levels of wealth. In the absence of alternative options, these agents must remain as unskilled labour, denoted L^U. We then add a possible alternative option, on-the-job training, to this framework. We assume that some employers are able to provide firm-based training to unskilled workers at a cost C to the firm. This is consistent with the empirical evidence that firms bear most of the costs of training. See note 20 for a discussion of the UK Labour Force Survey (LFS) evidence on this, and Acemoglu and Pischke (1998, 1999) for other countries. We assume that these employers are rare, so that, as we describe below, in equilibrium there are more workers who would like to be trained than there are employers able to train them. This is what makes these jobs ‘good jobs’.

We assume a small open economy, Diamond overlapping generations model with perfect international capital mobility, where the fixed world rate of interest is denoted by R. We assume that there are two sectors, a traded goods sector and a non-traded goods sector. In both sectors, we will assume that there are a limited number of firms able to provide on-the-job training to unskilled workers.

Training In our model, training concerns otherwise unskilled labour, L^U. We assume that in both sectors, there is a ‘backstop’ technology for unskilled labour with a constant marginal product that firms can use with zero entry costs. We assume that jobs using the backstop technology are always available to workers with no other labour market option, and that there are always workers employed using the backstop technology in both sectors. The backstop technology parameters determine the unskilled wage and relative price of non-traded goods, as we detail below. However, we also assume that in each sector, there is a finite population of firms with the potential to provide training at a cost to the firm of C. Training allows a previously unskilled worker to use a more productive technology. Potential training firms incur fixed setup costs. We assume, in the spirit of Acemoglu and Pischke (2003), that in each sector j, there is a distribution of setup costs across potential training firms, denoted by $J_j(\Phi_j)$, with support $[\underline{\Phi_j}, \overline{\Phi_j}]$. Setup costs $J_j(\Phi_j)$ may differ across sectors, so there may be more potential entrants in some sectors than in others. However, we assume that potential training firms are otherwise identical. These setup costs limit the number of firms offering training in equilibrium.

Wages and profits in firms providing training are determined by wage bargaining. We follow the bargaining setup of Christiano *et al.* (2016) for these firms, and assume that the payment of the setup cost allows a potential training firm to meet with one worker with probability 1. The firm and worker then bargain with each other over the wage. In Online Appendix B, we show that this process leads to the surplus from the match being split between the worker and the firm. The precise split between firm and worker is determined by the parameters of the bargaining process, and a wide range is possible. In our analysis below, we assume that parameters are such that the wage of a firm-trained worker is substantially above the unskilled wage.

The labour market for jobs with training has a ‘hold-up’ problem. The wage of these ‘good jobs’ is not competed down in equilibrium due to the lack of an ability to make *ex ante* commitments to post-training wages. There is only one match per period per worker and training firm. The model does not give the firm the option of refusing a match in the hope of agreeing lower wages in another match. Once the match is made, the bargaining process will play out and will result in a training wage above the unskilled wage. Thus jobs with training are ‘good jobs’ in the sense that they are jobs that all unskilled workers would want but not all unskilled workers can get.

The important assumption for the model is that jobs with training are ‘rare’ in each sector, so that unskilled and untrained labour are always working in both the traded and non-traded sectors.[9] We describe the equilibrium below.

Production We denote the productivity of unskilled labour in the backstop technology by a^j, where $j = T$ for the traded sector, and $j = NT$ for the non-traded sector. Similarly, the productivity of on-the-job trained labour is denoted by $a^{*,j}$, where again $j = T, NT$, and where $a^{*,j} > a^j$.

In period t, output in the traded sector is given by

$$Y_t^T = a^T L_t^{U,T} + a^{*,T} L_t^{*,T} + F^H\left(L_t^H, K_t^T\right),$$

where $L_t^{U,T}$, $L_t^{*,T}$ and L_t^H are the amounts of unskilled, on-the-job trained and highly skilled labour working in the traded sector, respectively, and where K_t^T is the level of capital employed in the traded sector.

In period t, output in the non-traded sector is given by

$$Y_t^{NT} = a^{NT} L_t^{U,NT} + a^{*,NT} L_t^{*,NT},$$

where $L_t^{U,NT}$ and $L_t^{*,NT}$ are the amounts of unskilled and on-the-job trained labour working in the non-traded sector, respectively.

We assume for simplicity that highly skilled labour, L^H, does not work in the non-traded sector. Thus the price of non-traded goods, p^{NT}, is determined by the free mobility of unskilled labour across sectors, which will ensure that $p^{NT} = a^T/a^{NT}$, which is a constant.[10]

Wages The model describes an economy where wage rates are fixed. The wage for unskilled workers, w^U, is fixed by the backstop technology, so that $w^U = a^T = p^{NT}a^{NT}$. The skilled wage, w_t^H, is fixed by world interest rate R and perfect international capital mobility, which implies a unique marginal product of skilled labour, as in Galor and Zeira (1993). The wage for on-the-job trained workers in sector j, $w^{*,j}$, is fixed as fraction of the surplus from a match by the bargaining process. We assume for simplicity that this is the same in both sectors, but it could be allowed to differ.[11] In equilibrium, training matches will be accepted as long as the wage for on-the-job trained workers is above w^U. It does not depend by how much.

Individuals We assume, following Galor and Zeira (1993), an overlapping generations economy with constant population. We consider the effects of immigration in the next subsection. Agents live for two periods: young and old. Each individual has one parent and one child. When young, agents receive a bequest from their parent and have a choice of whether or not to invest in human capital. When old, agents choose optimally between consuming and bequeathing to their child. We assume that agents are subject to a subsistence constraint in the tradeable good, that is, consumption cannot fall below level $\widetilde{c}$.

Preferences of each individual agent i born in period t are defined over their second period choices for consumption of the traded good c_{t+1}^T, their consumption of the non-traded good c_{t+1}^{NT}, and their bequest b_{t+1}, and are represented by the utility function

$$u_t = \left(c_{t+1}^T - \widetilde{c}\right)^\alpha \left(c_{t+1}^{NT}\right)^\beta b_{t+1}^{1-\alpha-\beta},$$

where $0 < \alpha, \beta < 1$ and $0 < \alpha + \beta < 1$.

Each agent has a budget constraint

$$c_{t+1}^T + p_{t+1}^{NT} c_{t+1}^{NT} + b_{t+1} = I_{t+1}^i,$$

where I_{t+1}^i is the income of agent i at time period $t+1$. This I_{t+1}^i will depend on the wage w^i that agent i receives in period $t+1$, plus the net savings from their bequests, as we describe below.

Utility maximization implies the following optimal shares of expenditure:

$$c^T_{t+1} = \widetilde{c} + \alpha\left(I^i_{t+1} - \widetilde{c}\right),$$
$$p^{NT}_{t+1}\, c^{NT}_{t+1} = \beta\left(I^i_{t+1} - \widetilde{c}\right),$$
$$b^i_{t+1} = (1-\alpha-\beta)\left(I^i_{t+1} - \widetilde{c}\right).$$

Again, note that bequests and non-traded consumption are fixed shares of above-subsistence income.

Capital market imperfections and human capital We assume, in the spirit of Holmstrom and Tirole (1997), that becoming a skilled worker in period $t+1$, L^H_{t+1}, requires an indivisible investment of size e in period t, but where the success of this investment depends on the effort of the agent and is not guaranteed. Individuals have a choice between being diligent, which implies a success probability π^h, and being less diligent, which implies a success probability π^l, where $\pi^l < \pi^h$, but which also confers a private benefit B. The action of the individual and so the probability of success cannot be observed by the financial markets—only the outcome.

For the model to be of interest, it must be the case that in the absence of informational asymmetries and financial frictions, being a skilled worker is preferred to being an unskilled worker, and that being diligent is the best strategy for all agents. This implies that parameters are such that

$$\pi^h\left(w^H - w^U\right) > eR + \pi^{train}\left(w^* - w^U\right),$$
$$\pi^l\left(w^H - w^U\right) + B < eR + \pi^{train}\left(w^* - w^U\right),$$

where π^{train} is the probability of finding a job with training as an unskilled worker. Thus we are assuming that w^H is significantly high so that the prospect of obtaining a job with training does not make wealthy agents prefer to be unskilled. We think that this is a reasonable characterization of reality.

Financial intermediaries cannot force borrowers below the subsistence level of consumption, $\widetilde{c}$, in the event that training is not successful. To break even, they will have to charge an interest rate $R^\star$, higher than R, and this changes an individual’s incentive to be diligent. In equilibrium, financial intermediaries need to make the expected international rate of return R. This implies that only agents with wealth higher than $\widehat{b}$ will be able to borrow to invest, where

$$\widehat{b} = e - \frac{(w^U - \widetilde{c}) + \pi^h(w^H - w^U) - \widetilde{B}}{R},$$

where $\widetilde{B}$ is a constant.

The model thus describes a labour market with a Holmstrom and Tirole (1997) style equilibrium, where agents with higher wealth will use their wealth to accumulate skills, while agents with low wealth, in contrast, are unable to borrow from financial markets to invest in human capital accumulation. In the absence of government intervention or training, there would be no upward income mobility for low-wealth agents.

Income distribution dynamics The agents’ optimal human capital decisions together with their demand functions imply that the intergenerational dynamics of the economy are described by equation (IDD) below. This equation has three sections. Those with wealth (bequests) above e will find it optimal to invest in skills and will become skilled workers with probability π^h. For those with wealth (bequests) below a critical level $\widehat{b}$, those who can obtain on-the-job training will receive the trained wage, while the rest become unskilled workers. Those with wealth (bequests) greater then $\widehat{b}$ but less than e will use their bequest and borrow the remainder to become skilled

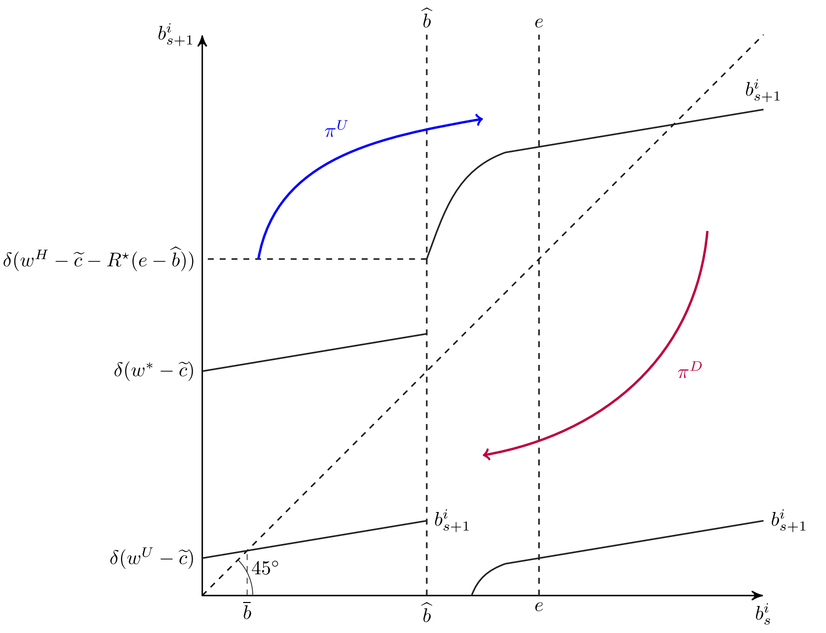


FIGURE 4 Income distribution dynamics.

with probability π^h. Writing HCA for human capital accumulation, and OJT for on-the-job training, we have

$$\begin{cases} \text{for } b^i_t > e, & b^i_{t+1} = \begin{cases} \delta\left[w^H_{t+1} - \widetilde{c} + R(b^i_t - e)\right] & \text{if HCA successful,} \\ \delta\left[w^U_{t+1} - \widetilde{c} + R(b^i_t - e)\right] & \text{if HCA unsuccessful,} \end{cases} \\ \text{for } \widehat{b} < b^i_t < e, & b^i_{t+1} = \begin{cases} \delta\left[w^H_{t+1} - \widetilde{c} - R^\star(e - b^i_t)\right] & \text{if HCA successful,} \\ \max\left\{0, \delta\left[w^U_{t+1} - \widetilde{c} - R^\star(e - b^i_t)\right]\right\} & \text{if HCA unsuccessful,} \end{cases} \\ \text{for } b^i_t < \widehat{b}, & b^i_{t+1} = \begin{cases} \delta\left[w^*_{t+1} - \widetilde{c} + Rb^i_t\right] & \text{if OJT successful,} \\ \delta\left[w^U_{t+1} - \widetilde{c} + Rb^i_t\right] & \text{if unskilled,} \end{cases} \end{cases} \tag{IDD}$$

where $\delta = (1 - \alpha - \beta)$, and the expressions in brackets represent I^i_{t+1} for agent i minus the subsistence constraint.

The dynamics described by equation (IDD) are depicted in Figure 4. The income distributional dynamics have forces for upward mobility as well as downward mobility. Downward mobility, depicted by the arrow labelled π^D in Figure 4, is when a wealthy agent does not succeed in becoming skilled and so earns only an unskilled wage and suffers a reduction in wealth e.[12] Upward mobility, depicted by the arrow labelled π^U in Figure 4, is when low wealth agents succeed in accumulating enough wealth for their offspring to purchase education in the following period. Clearly, this potential depends on workers trained via on-the -job training obtaining significantly higher wages than unskilled workers. As stated above, the bargaining parameters allow for a large range of possible wages w^*. Figure 4 depicts the case where w^* is high enough so that trained workers' bequests will be above $\widehat{b}$ and thus their offspring will have as great a chance as anyone of becoming skilled in the following period. This is the most optimistic case for upward social mobility. Clearly, a w^* value lower than this will imply a lower prospect for upward social mobility.

Equilibrium and the number of training firms The model that we have described above is one where all relative prices are pinned down by the market structure and fundamentals, so equilibrium is achieved by the allocation of labour between sectors. Given the agent's first-order conditions, the market clearing condition in period t is given by

$$\frac{\beta}{p_t^{NT}}\left[\int_{i\in L^U}(I_t^U-\widetilde{c})\,\mathrm{d}i+\int_{i\in L^*}(I_t^*-\widetilde{c})\,\mathrm{d}i+\int_{i\in L^H}(I_t^H-\widetilde{c})\,\mathrm{d}i\right]\quad\text{(Demand)}$$
$$=a^{NT}L_t^{U,NT}+\int_{i\in L_t^{*,NT}}a^{*,NT}\,\mathrm{d}i\qquad\text{(Supply)}.$$

We assume that $L^{U,T}$ and $L^{U,NT}$ are both positive in equilibrium, so p_t^{NT} is fixed. This is a restriction on the size and productivity of the trained and skilled sectors. If all workers were unskilled, then the economy would resemble the two-sector small open economy of Matsuyama (1992), so $L^{U,T}$ and $L^{U,NT}$ would both be positive if both β and $w^U-\widetilde{c}$ are positive. We also ignore demand from the profits of firm owners, which assumes implicitly that these are consumed abroad. Thus equilibrium is achieved by the allocation of unskilled workers between the traded and non-traded sectors, that is, by solving for $L_t^{U,NT}$.

The number of training firms in equilibrium will depend on the distribution of setup costs across potential training firms, denoted by $J_j(\Phi_j)$, in each sector. The bargaining process between a firm and worker leads to a split of the surplus of the match between the firm and the worker so that the surplus π^j of the firm in sector j from a match is given by

$$\pi^j=a^{*,j}-w^{*,j}-C\quad\text{for }j=T,NT.$$

For the marginal firm k in sector j, with setup costs $\Phi_{j,k}$, the value of the match in equilibrium must equal the fixed setup costs, thus $\Phi_{j,k}=\pi^j$. The number of firms in equilibrium will therefore be the integration of the distribution $J_j(\Phi_j)$ over the interval $[\underline{\Phi_j},\pi^j]$.

The effect of skilled immigration

We assume that skilled immigrants are distinguished from natives by having a back-up wage w^m, where $w^m<w^U$. Skilled immigrants will affect both the demand and supply of goods, as well as the profitability of firms offering training.[13] The wage bargaining process implies that immigrants will have a lower equilibrium wage in training firms, which implies greater profits for training firms and so the entry of more firms offering training.[14] We assume for simplicity that skilled migrants are as costly to train as unskilled native workers. However, clearly, if skilled migrants are cheaper to train, then this would increase the surplus further and so magnify this effect. We first describe in detail the implications of skilled immigration into the on-the-job training firms before going on to discuss the implications of skilled immigration more generally, and why skilled immigration has different implications to unskilled immigration. These effects follow straightforwardly from the structure of the model described in the previous subsection.

Skilled immigration and the training wage If potential training firms have a probability, π^m of being matched with a skilled migrant worker, then the bargaining process implies that their expected profit rises, so more firms will enter. In equilibrium, it must be the case that the marginal firm, k, makes zero expected profits. Whether the net effect of skilled immigrants on training places for native workers is positive or negative depends on the strength of this entry effect relative to the direct immigration effect. The number of entering firms is determined by the slope of the $J_j(\Phi_j)$ distribution function at the equilibrium point. The flatter the distribution, the more firms enter, so for a given migration probability, the number of training opportunities for native workers rises. There is no reason why $J_j(\Phi_j)$ will be the same across sectors, so sectors may react differently to the same immigration shock. Thus immigration may cause the number of training places for native workers to rise or fall with potentially differential effects across sectors. Ultimately, therefore, this is an empirical matter, which we address in Section 4.

Under the bargaining structure of the model described in the previous subsection, the wages of native workers matched with a training firm would not be affected by skilled immigration (although, of course, their chances of obtaining a match may be). However, if one modified the bargaining structure to give an additional increase in bargaining power to a training firm under the possibility of skilled immigration, then native trained wages may also fall even if a migrant is not hired by a firm in equilibrium. This is modelled most simply by assuming that each firm k paying the fixed cost Φ_k also has a probability of meeting another migrant worker in between subperiods 2 and 3 of the bargaining process. Intuitively, this has the effect of reducing the equilibrium share of the match's surplus given to trained workers.[15] This would imply a bigger increase in expected profits and so a larger entry effect of training firms in equilibrium. However, it may also lead to a detrimental effect on social mobility if trained wages fall significantly so that the w^* line in Figure 4 shifts down, thereby reducing the chances of the offspring of trained workers to become skilled workers in the future.

The different implications of skilled and unskilled immigration The focus in this paper is on the effects of skilled immigration and how this may affect the provision of training for native-born workers. As we have discussed above, skilled immigration will increase the profitability of the firms that provide training and so should cause entry by firms offering training. This may or may not cause a net increase in training provision for native workers, so may or may not increase social mobility and long-run productivity in the economy. Immigration into unskilled labour demanding firms, in contrast, will have no effect on the provision of training and will reduce average productivity in the economy. If training positions are scarce, as we assume, and the allocation of training positions is random, then unskilled migrants will also take some of these training places and so will reduce the prospects for upward social mobility for native workers. Of course, many skilled immigrants in the UK work in unskilled jobs (see Wadsworth 2018), so these workers will have the same effects, in this model, as unskilled immigrants.

Extensions of the model Our approach has been to use the simplest model that is able to demonstrate the potential for both positive and negative effects of skilled immigration on native training, and for differential effects of skilled immigration across sectors. This simple model does not have, for example, 'good jobs' for skilled workers. However, if the model were extended so that there were also potential firms that could train skilled workers to achieve even higher productivity levels, and where the wage was determined by the same bargaining procedure as above, then such jobs would be 'good jobs' for skilled workers.

The simple model above also assumes that firms offering training supply only a fraction of the total non-traded goods market. However if all firms in the non-traded sector provide training, then the level of training in the economy would be affected by the level of demand for non-traded goods. In this case, for example, skilled immigrants in the traded sector would increase the demand for non-traded goods, as in Moretti (2010), and so would increase the level of training for unskilled workers in the non-traded sector. The same argument holds for wealthy immigrants. This case complicates the model somewhat as the relative price of non-traded goods will be determined by the entry of new firms into the non-traded sector, but the model is otherwise the same; see Mountford and Wadsworth (2019) for a longer discussion of this case.

4 | EMPIRICAL EVIDENCE

The model suggests that we might expect to see different effects of immigration on on-the-job training of native workers depending on both the sector under investigation and the skill level of immigrants in that sector. In this section, we investigate this issue empirically. We first describe the data used, and then the statistical model. The results are presented in the third subsection, and their robustness to a variety of changes in model specification and variable definitions is discussed in the final subsection.

Data

In order to test the implications of the model, we need data on the incidence of training, the age, education and country of origin of those trained, and the concentration of skilled immigrants working in a sector. All these pieces of information are contained in the UK LFS. The LFS is a quarterly random sample of around 40,000 households and the individuals therein. Since 1995, there have been questions on whether an employed individual has received any job-related training in the past 3 months or in the past 4 weeks. The training information can be split into whether it is college- or work-based, and into discrete duration of training categories.[16] This variable is used in Dearden *et al.* (2006) and shown to be positively associated with higher productivity. Abramovsky *et al.* (2011) also use this variable as part of their evaluation of the training response among less skilled workers to a UK government intervention.

Immigration variables The LFS also contains details of the country of birth of every individual in the sample. This allows us to split the workforce into UK-born and immigrants (anyone born outside the UK). The LFS also contains information on year of arrival and age leaving full-time education. From this, we define a skilled adult immigrant as someone born outside the UK who left full-time education after age 18 (i.e. with some level of tertiary education) and who arrived in the UK after age 22 (i.e. with some degree of work experience abroad). Other immigrants used in this study comprise the total number of immigrants less the skilled immigrant total.

Sector definition Since specific industries contain many occupations and a given occupation can be found across different industries, the definition of a sector in our analysis combines individual occupation and industry affiliation. A sector is built as a combination of 1-digit occupation and 2-digit industry. For example, sector 385 is an associate professional (1-digit SOC code 3) working in the health industry (2-digit SIC code 85). The occupational classifications change significantly in 2001, which makes matching before this period difficult for anything more disaggregated than 1-digit SOC.[17] We pool across all quarters in each year. This ensures that there is a minimum of 100 observations in each of 125 sectors in each year, with median sample cell size 2226.

Non-traded and high-wage sector definitions We measure training intensity as the share of UK-born workers in each sector who are in receipt of (various types of) on-the-job training. We define the traded sector as all occupations in industries Agricultural Production (SIC 01) to Miscellaneous Manufacturing (SIC 39), Finance (SIC 65, 66) and IT/Communications (SIC 72).[18] The 1992 SIC codes first appear in the 1994 LFS. It is very difficult to obtain an accurate 2-digit-level mapping to the SIC that preceded this. A high-wage job sector is defined as a sector with a mean wage higher than the aggregate mean sector hourly wage in the period 1994–7, i.e. just before the estimation period, to reduce concerns over the endogeneity of wages to immigration.[19] As we show in Table 1, in the non-traded sector, these high-wage jobs come with more on-the-job training, on average.

Training variables On-the-job training in the UK is not a homogeneous event. Some training is done at the workplace, some externally in colleges or training centres. Some training is financed by employers, some by individuals. Some training lasts for one day (though may be repeated at different points in the year), some runs for more than six months. The LFS asks whether training has been received in both a 13-week window and a 4-week window to try to capture this. Figure A1 in the Online Appendix shows the trends in these features over the sample window. Most on-the job training sessions last less than one week, and the share of short training spells has risen over time, more so in the non-traded low-wage sector.[20] However, training is provided increasingly at the workplace. While training away from work has fallen over time (see Figure

A1), training at work has risen over the same period. Around 50% of all training is now at the workplace, up from around 30% in 2000. We examine immigration's effects on all these different aspects of training in what follows.

The empirical model

The immigration, training and hiring data of individuals described above are averaged to sectoral level, and the following statistical model is estimated using a sample that starts in 1998 and ends in 2018:[21]

$$OJT_{it} = \beta_0 + \beta_1\ Skilled\_immigration_{it-1} + \beta_2\ Other\_immigration_{it-1} \\ + \gamma\ Z_{it-1} + \tau_t + s_i + t_i + \varepsilon_{it}, \quad (1)$$

where OJT_{it} is the share of all *UK-born* workers working in sector i at time t, who are in receipt of (different aspects of) on the job training, OJT^N_{it}/N_{it}.

The main explanatory variable of interest, $Skilled\_immigration_{it-1}$, is a measure of the intensity of skilled adult immigrants working in sector i at time $t-1$. We first measure this by the sector share of immigrants, $M_{it}/(M_{it}+N_{it})$, but use different measures of concentration when we test robustness of the results. The theoretical model above suggests that there may be heterogeneous 'treatment' effects from skilled immigration across sectors. In addition, the model suggests that there may be different effects of less-skilled immigration in the same sector. As such, we also include a measure of less-skilled immigration in the sector. Variables s_i and t_i are sector fixed effects and sector trends. These net out unobserved time-fixed and time-varying sector-specific factors affecting both immigrant presence and training intensity in a specific sector that would otherwise compromise the estimate of the immigration effect. The τ_t are year dummies.

The Z are a set of controls, known correlates with training incidence (see OECD 2020; Abramovsky *et al.* 2011), namely the time-varying mean proportions of women, part-time working, self-employment, temporary working, large firms (>50 employees), and public sector establishments, along with sector means of worker age, years of job tenure, and log hourly wages of the *UK-born* workers in each sector. We control for the share of graduates and level-4 vocational native-born workers. This is to control for the possibility that increased educational attainment seen in the UK over this period could be a substitute for on-the-job training and provide an alternative rationale for the observed fall in on-the-job training. We also construct and include the yearly unemployment rate for each sector to try to account for sector-specific cyclical influences on the provision of training that might also be correlated with the immigration variable.[22] There is also a control for the percentage change in sector size to try to account for the differential effect of employment growth on training across sectors. Some of these controls are arguably endogenous to training, so we check the robustness of the estimated immigration effects to their omission in the results below.

The training variables in the dataset are backward-looking indicators as training decisions are likely taken on the basis of the existing workforce. The immigrant and workforce variables are therefore lagged to reduce contemporaneous endogeneity concerns. This does not, however, exclude the possibility of a violation of strict exogeneity that would also compromise the estimation. If strict exogeneity is violated, then the bias in fixed effects estimation of equation (1) is $O(1/T)$, and $T=21$ for most of our estimation, so the bias from this form of endogeneity will be less than 5%.[23] We therefore proceed under this caveat, although we do explore alternative estimation procedures in the robustness checks that follow. The variance of the error term may contain a group-specific (sector-specific) component, but could also be influenced by possible unobserved spillovers across groups, both spatially and over time. We therefore estimate the model with heteroscedasticity- and autocorrelation-consistent (HAC) robust standard errors, robust to heteroscedasticity and autocorrelation of unknown form (see Cameron and Miller 2015).[24]

The sector-level data set has a spatial element to it and so may be open to the spatial correlations concerns that arise when working with such data. It is conceivable, for example, that UK-born workers faced with an influx of skilled migrants may leave the sector to find training opportunities elsewhere. This would tend to disperse the effects of immigration on UK-born training across sectors. Conversely, UK-born workers could be attracted into a sector with skilled migrants who are able to train more workers. This could then augment any positive effects of skilled immigration on training.

To help to address these concerns, Table A2 of the Online Appendix presents sector correlations between UK-born employment growth and immigration growth rates over the 21-year period covered by the sample. The table gives regression coefficients and their standard errors from simple OLS regressions of the 21-year percentage change in the UK-born level of employment on the 21-year percentage change in the level of immigration in each of the 125 sectors in the sample. The sample size for each regression is therefore 2625.

Immigration and UK-born employment are clearly positively correlated (see column (1) in panel A of Table A2 of the Online Appendix). Employment of UK-born workers has grown more in sectors where immigration has grown more. Employment of UK-born workers is much more positively correlated with the growth in skilled immigration than with other immigration (column (2) in panel A)—and within broad sectors, skilled immigration is most positively correlated with immigration growth in the non-traded 'good jobs' sector (column (3) in panel A). Panel B of Table A2 confirms that these correlation patterns hold for skilled UK-born workers. Skilled employment of UK-born workers has grown more in sectors where skilled immigration has grown more.

These associations contrast somewhat with the findings of Burstein *et al.* (2020) for the USA, where the association between immigrant growth and US-born employment growth is negative in the non-traded sector. Instead, they suggest that UK-born workers are net entrants into sectors where skilled immigration is growing.

Table A3 of the Online Appendix shows that UK-born employment growth is negatively correlated with the growth in training rates of UK-born workers, particularly in the non-traded 'good jobs' sector. This suggests that UK-born workers do not move, in the aggregate, towards sectors offering higher training. Taken together, these correlations suggest that if UK-born employment is growing in sectors where training is falling, then this would tend to augment any negative association of immigration with training.

Without a credible natural experiment, however, there remains the concern about endogeneity not accounted for by the confounders or the fixed and time-varying sector trends. This is why we phrase our discussion in terms of associations rather than causal effects. In our view, training is an important variable, with implications for productivity, income inequality and social mobility. Thus any robust empirical relationship concerning training should be of interest. Below, we also account for this issue using shift–share instruments. Recent debate on this sort of instrumentation (e.g. Adao *et al.* 2019; Borusyak *et al.* 2022; Goldsmith-Pinkham *et al.* 2020; Jaeger *et al.* 2018) suggests that identification is obtained if either the 'shifters' or the 'shares' are exogenous.[25] We also experiment with lagged explanatory variables as instruments in differenced equations. We report these results in the 'Robustness checks' subsection below.

Results

Table 2 outlines the estimates from a set of sectoral-level regressions of the share of UK-born adults receiving training on the lagged employment share of immigrants who arrived as adults with education after high school and a separate indicator for the sector share of less-skilled immigrants.

TABLE 2 Immigration and On-the-job Training of UK-born Workers

	(1)	(2)	(3)	(4)	(5)
Panel A					
Skilled immigrant	0.467**	0.095*	0.074	0.129**	0.130**
	(0.124)	(0.045)	(0.050)	(0.046)	(0.042)
Other immigrant	−0.011	0.233**	0.048	0.244**	0.207**
	(0.070)	(0.031)	(0.035)	(0.031)	(0.031)
Panel B					
Non-traded (high-wage) × Skilled immigrant	0.504**	−0.206**	0.116	−0.206**	−0.154*
	(0.190)	(0.073)	(0.088)	(0.072)	(0.069)
Non-traded (low-wage) × Skilled immigrant	0.773**	0.263**	0.072	0.246**	0.235**
	(0.189)	(0.063)	(0.080)	(0.068)	(0.063)
Traded × Skilled immigrant	0.328**	0.025	0.036	0.153*	0.136*
	(0.116)	(0.065)	(0.083)	(0.062)	(0.058)
Non-traded (high-wage) × Other immigrant	0.334*	0.045	0.101	0.021	0.049
	(0.153)	(0.068)	(0.062)	(0.066)	(0.066)
Non-traded (low-wage) × Other immigrant	−0.177	0.222**	0.028	0.269**	0.224**
	(0.091)	(0.045)	(0.050)	(0.045)	(0.043)
Traded × Other immigrant	−0.007	0.214**	0.040	0.214**	0.174**
	(0.078)	(0.053)	(0.067)	(0.057)	(0.055)
Controls					
Year	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	No	Yes
Sector	No	Yes	Yes	Yes	Yes
Sector trends	No	No	Linear	Reciprocal	Reciprocal

Notes: Sample size 2625. HAC robust standard errors in parentheses.
*, ** indicate $p < 0.05$, $p < 0.01$, respectively.

Panel A of Table 2 looks at average immigration across all sectors. The first column is an OLS regression without sector fixed effects. Skilled immigration is positively correlated with training of UK-born workers. Sectors with a higher share of skilled immigrants train relatively more native workers. This association persists when we include sector fixed effects in column (2). So sectors that have employed more skilled immigrants over time have relatively higher training rate growth for their UK-born workers. Or rather, given the outcomes in our sample window, training has fallen less in these sectors.

Since our 21-year sample window is arguably long enough that the sector fixed effects are no longer fixed, columns (3)–(5) of Table 2 additionally include time-varying sector trends. Column (3) includes a linear trend. Columns (4) and (5) replace this with a non-linear trend, specifically a reciprocal time trend. A linear time trend implies that training will continue declining (or rising) forever, at different rates across sectors. A reciprocal sector trend implies that training in a given sector will asymptote towards some minimum (or maximum) level over time. The linear sector trend is also highly collinear with the immigration variable and some other covariates, which have grown near continuously over the sample window. The combination of near continuous decline in training and a near continuous rise in immigration over the sample window makes it harder to identify any immigration effect (or other covariate effects) in the linear sector trend estimation. As can be seen, when linear sector trends are included, the immigration estimates in column (3) of panel A are insignificantly different from zero. When a non-linear sector trend is used, in columns (4) and (5), the immigration association becomes positive and significant once again. Column (4) removes the (potentially endogenous) explanatory confounders from the regression. Column (5) restores them to the model. This makes little difference to the estimated relationships (compare columns (4) and (5)).

The model presented above, however, suggests that we might expect to see different patterns according to whether the sector is traded or non-traded, and whether it is a high-wage or low-wage sector. Panel B of Table 2 therefore allows the immigration effects to vary across the three broad sectors suggested by the model: traded, non-traded (high-wage) and non-traded (low-wage) sectors.

Allowing for heterogeneous relationships across broad sectors suggests that there are indeed differences across traded and non-traded sectors and by immigration skill type. There is still a positive association in levels between skilled immigration and training (column (1) in panel B of Table 2). Within each sector, those with a higher-skilled immigrant workforce share train more UK-born workers. The association between the level of less-skilled immigration and level of training is much weaker. The inclusion of sector fixed effects now changes the signs and significance of the immigration variable (column (2) in panel B). The skilled immigration association with training in the non-traded ‘good job’ sector is negative and statistically significant, while the association is positive and statistically significant in other sectors. Within the non-traded ‘good jobs’ sector, groups where skilled immigration has grown more have reduced training of UK-born workers more. In contrast, recruiting more skilled immigrants in the low-wage non-traded and traded sectors is associated with increased training rates of UK-born workers (or more likely reduced training less). These latter two sectors are the drivers of the positive immigration effect on training seen in panel A. The addition of linear sector trends (column (3)) again nullifies these effects, but the inclusion of non-linear sector trends (columns (4) and (5)) restores these patterns of association. The overall conclusion of the results from panel B is that the association of skilled immigration in the non-traded high wage sector seems to be much more negative than elsewhere.[26]

The magnitude of the estimated skilled immigration relationship with training is not, however, large. A 5 percentage point increase in the skilled immigrant sector share, the average increase in the sample over the period (see Table 1), reduces the sector share of native training by around 0.01 percentage points, or some 3%.[27] Panel B of Table 2 also shows that the less-skilled immigration into the non-traded high-wage sector has little association with training (see columns (2), (4) and (5)). Elsewhere, less-skilled immigration has a similar positive relationship with skilled immigration in both the traded and non-traded low-wage sectors.

Table A4 in the Online Appendix gives the estimates for the control variables also included in the regressions. The signs of these controls generally conform to the findings from the earlier training incidence literature. The sector unemployment rate is negatively associated with training, so that firms do appear to cut back training faced with a sector-specific negative shock, and the share of native-born workers educated to age 21 and over is negatively associated with on-the-job training of native-born workers.[28] It seems that formal education may indeed be a substitute for some on-the-job training over this period, but this does not seem to preclude immigration from influencing training.

Robustness checks

We list below the robustness of these findings to a set of changes to the estimation sample. We focus our discussion on the findings based on the model specification reported in column (5) of Table 2, that is, the model with time-varying, non-linear sector trends and time-varying sector-level confounders.

Traded sector definition In panel A of Table 3, we remove IT and Finance from the traded sector group, place them in the non-traded sector, and repeat the estimation. The patterns that

TABLE 3 Skilled Immigration and Training Robustness Checks

	(1)	(2)	(3)	(4)	(5)
Panel A: Narrow trade definition					
Non-traded (high-wage) × Skilled immigrant	0.242	−0.215**	0.122	−0.169**	−0.128*
	(0.168)	(0.062)	(0.079)	(0.063)	(0.059)
Non-traded (low-wage) × Skilled immigrant	0.670**	0.248**	0.053	0.235**	0.226**
	(0.186)	(0.061)	(0.077)	(0.065)	(0.060)
Traded × Skilled immigrant	0.609**	0.111	0.046	0.214**	0.180*
	(0.183)	(0.079)	(0.095)	(0.079)	(0.072)
Non-traded (high-wage) × Other immigrant	0.366*	0.034	0.086	0.002	0.030
	(0.152)	(0.066)	(0.060)	(0.063)	(0.063)
Non-traded (low-wage) × Other immigrant	−0.117	0.190**	−0.014	0.223**	0.184**
	(0.093)	(0.044)	(0.050)	(0.045)	(0.043)
Traded × Other immigrant	−0.134	0.244**	0.145*	0.291**	0.243**
	(0.092)	(0.054)	(0.070)	(0.061)	(0.059)
Panel B: Training in last 4 weeks					
Non-traded (high-wage) × Skilled immigrant	0.431**	−0.159**	0.005	−0.136**	−0.112*
	(0.142)	(0.050)	(0.065)	(0.053)	(0.051)
Non-traded (low-wage) × Skilled immigrant	0.428**	0.106*	−0.024	0.078	0.076
	(0.107)	(0.047)	(0.066)	(0.050)	(0.049)
Traded × Skilled immigrant	0.244**	0.043	0.063	0.118**	0.108**
	(0.066)	(0.044)	(0.055)	(0.041)	(0.039)
Non-traded (high-wage) × Other immigrant	0.143	0.007	0.035	−0.002	0.007
	(0.102)	(0.048)	(0.046)	(0.043)	(0.044)
Non-traded (low-wage) × Other immigrant	−0.111*	0.096**	−0.008	0.119**	0.094**
	(0.052)	(0.029)	(0.035)	(0.030)	(0.029)
Traded × Other immigrant	0.016	0.096**	−0.003	0.093**	0.069*
	(0.041)	(0.032)	(0.043)	(0.033)	(0.034)
Panel C: Skilled UK-born workers					
Non-traded (high-wage) × Skilled immigrant	0.577**	−0.199*	0.064	−0.246*	−0.214*
	(0.218)	(0.098)	(0.113)	(0.098)	(0.096)
Non-traded (low-wage) × Skilled immigrant	0.509*	0.003	−0.218	0.047	0.016
	(0.225)	(0.129)	(0.195)	(0.144)	(0.145)
Traded × Skilled immigrant	0.086	−0.126	−0.231	−0.149	−0.196
	(0.140)	(0.114)	(0.176)	(0.115)	(0.114)
Non-traded (high-wage) × Other immigrant	0.089	0.073	0.167	0.032	0.043
	(0.171)	(0.102)	(0.098)	(0.099)	(0.100)
Non-traded (low-wage) × Other immigrant	−0.133	0.335**	0.110	0.307*	0.288*
	(0.126)	(0.108)	(0.156)	(0.120)	(0.119)
Traded × Other immigrant	−0.047	−0.005	0.116	0.156	0.116
	(0.118)	(0.126)	(0.143)	(0.114)	(0.111)
Panel D: Less-skilled UK-born workers					
Non-traded (high-wage) × Skilled immigrant	0.360*	−0.051	0.303*	−0.018	0.039
	(0.158)	(0.092)	(0.130)	(0.099)	(0.096)

(Continues)

TABLE 3 Continued

	(1)	(2)	(3)	(4)	(5)
Non-traded (low-wage) × Skilled immigrant	0.779**	0.266**	0.090	0.244**	0.237**
	(0.189)	(0.066)	(0.081)	(0.072)	(0.067)
Traded × Skilled immigrant	0.459**	0.082	0.046	0.219**	0.219**
	(0.118)	(0.073)	(0.092)	(0.068)	(0.065)
Non-traded (high-wage) × Other immigrant	0.423**	0.051	0.116	0.031	0.072
	(0.141)	(0.084)	(0.083)	(0.084)	(0.082)
Non-traded (low-wage) × Other immigrant	−0.222*	0.178**	−0.004	0.234**	0.185**
	(0.089)	(0.046)	(0.053)	(0.046)	(0.045)
Traded × Other immigrant	−0.067	0.215**	0.014	0.195**	0.169*
	(0.074)	(0.062)	(0.084)	(0.065)	(0.066)
Controls					
Year	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	No	Yes
Sector	No	Yes	Yes	Yes	Yes
Sector trends	No	No	Linear	Reciprocal	Reciprocal

Notes: HAC robust standard errors in parentheses.
*, ** indicate $p < 0.05$, $p < 0.01$, respectively.

we observe in Table 2, namely differential associations of skilled immigration across sectors, are changed little by this.

Training window The EU uses evidence of on-the-job training in the last 4 weeks to form its benchmark training targets. In panel B of Table 3, we replace the training in a 3-month window with the 4-week window. The findings again appear to hold across this narrower window of activity.

Effects on UK-born workers by skill Since the model indicates that skilled and less-skilled immigration may have different effects on skilled workers than on unskilled workers, panels C and D of Table 3 split the UK-born workforce into skilled (using the same definition of skilled as for immigrants) and less-skilled. The results show that the negative association of training with skilled immigration holds for skilled UK-born workers in the non-traded good jobs sector (panel C), but not for less-skilled UK-born workers in the same sector (panel D). This suggests that there may be substitution away from training skilled workers. There is no effect of less-skilled immigration on training of skilled workers in the not 'good jobs' traded sector. In the non-traded low-wage jobs sector, less-skilled immigration appears complementary to training of both skilled and less-skilled UK-born workers. These results seem to indicate that (a) the type of immigration matters, (b) the sector in which immigration changes matters, and (c) the skill level of the potential trainees matters.[29]

Job tenure It could be argued that the nature of training evolves with the length of job tenure. A new hire may receive induction training that is less likely to be associated with skill accumulation than training received later in a career. To examine this, we estimate the effect of immigration on training rates of newly hired UK-born workers (panel A of Table 4) and UK-born workers with greater than one year of job tenure (panel B). We define a new hire as anyone in a job for less than 12 months. It seems that the significant association of training with skilled immigration applies only to experienced UK-born workers. This is consistent with the idea that there is some substitution away from skills accumulation when ready-trained workers are hired in the non-traded high-wage sector. Once again, there is a positive association of skilled immigration with training elsewhere. Here, skilled immigration and training appear to be complementary.

TABLE 4 Skilled Immigration on Training Further Robustness Checks

	(1)	(2)	(3)	(4)	(5)
Panel A: Newly hired UK-born workers					
Non-traded (high-wage) × Skilled immigrant	0.137**	−0.002	−0.026	0.006	0.004
	(0.040)	(0.026)	(0.032)	(0.029)	(0.028)
Non-traded (low-wage) × Skilled immigrant	0.147*	0.031	−0.049	−0.013	0.001
	(0.065)	(0.036)	(0.044)	(0.035)	(0.033)
Traded × Skilled immigrant	0.048	−0.000	−0.057	0.030	0.035
	(0.029)	(0.034)	(0.046)	(0.028)	(0.028)
Non-traded (high-wage) × Other immigrant	−0.065*	0.003	−0.001	−0.004	−0.000
	(0.032)	(0.033)	(0.032)	(0.029)	(0.031)
Non-traded (low-wage) × Other immigrant	−0.087**	0.021	−0.011	0.021	0.012
	(0.033)	(0.022)	(0.027)	(0.023)	(0.021)
Traded × Other immigrant	−0.026	0.036	−0.091**	0.005	0.003
	(0.024)	(0.027)	(0.029)	(0.025)	(0.025)
Panel B: UK-born workers: tenure > 1 year					
Non-traded (high-wage) × Skilled immigrant	0.369*	−0.203**	0.142	−0.211**	−0.155*
	(0.158)	(0.069)	(0.085)	(0.074)	(0.069)
Non-traded (low-wage) × Skilled immigrant	0.627**	0.236**	0.122*	0.258**	0.238**
	(0.138)	(0.058)	(0.061)	(0.062)	(0.057)
Traded × Skilled immigrant	0.281**	0.030	0.092	0.123*	0.104*
	(0.098)	(0.052)	(0.072)	(0.052)	(0.050)
Non-traded (high-wage) × Other immigrant	0.399**	0.045	0.103	0.025	0.052
	(0.130)	(0.064)	(0.064)	(0.067)	(0.065)
Non-traded (low-wage) × Other immigrant	−0.089	0.208**	0.040	0.248**	0.217**
	(0.066)	(0.041)	(0.046)	(0.043)	(0.040)
Traded × Other immigrant	0.020	0.189**	0.132*	0.209**	0.180**
	(0.062)	(0.039)	(0.059)	(0.046)	(0.045)
Panel C: Regional immigration					
Non-traded (high-wage) × Skilled immigrant	0.084	−0.175**	−0.041	−0.144**	−0.131**
	(0.122)	(0.049)	(0.047)	(0.046)	(0.048)
Non-traded (low-wage) × Skilled immigrant	0.260**	0.089*	0.001	0.024	0.048
	(0.092)	(0.044)	(0.043)	(0.042)	(0.042)
Traded × Skilled immigrant	−0.048	−0.106*	−0.065	−0.044	−0.052
	(0.065)	(0.052)	(0.045)	(0.047)	(0.047)
Non-traded (high-wage) × Other immigrant	0.181	0.022	−0.015	−0.014	0.028
	(0.098)	(0.044)	(0.044)	(0.045)	(0.041)
Non-traded (low-wage) × Other immigrant	−0.121**	0.006	0.006	0.011	0.019
	(0.044)	(0.024)	(0.021)	(0.022)	(0.022)
Traded × Other immigrant	−0.091	0.093*	0.033	0.044	0.068
	(0.049)	(0.037)	(0.036)	(0.038)	(0.037)
Controls					
Year	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	No
Sector	No	Yes	Yes	Yes	Yes
Sector trends	No	No	Linear	Reciprocal	Reciprocal

Notes: HAC robust standard errors in parentheses.
*, ** indicate $p < 0.05$, $p < 0.01$, respectively.

Regional effects Immigrants are concentrated in the south of the UK. Arguably, immigration may not be as close a potential substitute for native-born labour in other parts of the UK with fewer immigrants. Panel C of Table 4 presents estimates of the model where the data are split by year and sector, and additionally by two geographical areas.[30] While the estimates are somewhat attenuated by the reduction in sample cell sizes, the significant negative association of skilled immigration with training in the high-wage non-traded sector remains in this alternative data cut.

Source of immigration The UK immigration system over the sample period consisted of two separate work routes. There was free movement of any type of labour, skilled or unskilled, from anywhere in the EU. As the EU expanded, the labour supply from this route also grew. At the same time, a work visa route was kept open to skilled workers from outside the EU.[31] It may be argued, therefore, that non-EU worker share in a sector reflects sector skill shortages and labour demand concerns more than the sector share of EEA workers, which is arguably a combination of labour demand and supply decisions. If so, then it is possible that the immigration effects on workforce training of native-born workers may be different depending on the origin source country. Table A5 in the Online Appendix splits the skilled immigrant workforce share into those originating in the EU and those originating elsewhere. The negative associations of training are statistically more significant for non-EEA immigrants (though not significantly different from the EEA point estimates), and the positive associations of training in the other sectors are statistically more significant for EEA immigrants. In the main, it is hard to discern obvious differences between the sources of immigration, but the overall findings of differential immigrant effects across sectors and a negative effect in the high-wage non-traded sector do not change appreciably.

Since training is far from a homogeneous activity, we now look at whether these sectoral patterns hold across different aspects of on-the-job training.

Apprenticeships One workplace role that requires training is an apprenticeship, which typically offers the apprentice a mixture of off- and on-the-job training. Apprenticeships can be used to hire new workers and to add skills to the existing workforce.[32] According to the LFS, around 1% of the UK-born workforce was undergoing an apprenticeship in 2018, up from 0.5% in 1998. Panel A of Table 5 looks at the effect of skilled immigration on apprenticeships of UK-born workers across sectors. Again, there is evidence of a negative association between skilled immigration and apprenticeship training rates of native-born workers in the non-traded 'good job' sector that is not apparent in other sectors. In the traded sector, skilled immigration and UK apprenticeships appear to be complementary.

Training location On-the-job training may take place at work or away from work at a college or institute of further learning. Arguably, training away from work involves a larger investment by the firm in terms of both cost and working days lost. We therefore split responses according to the shares of away from work (panel B of Table 5) and at work (panel C) training in each sector. It is clear from Table 5 that the negative training association is driven by training away from the job. The varying skilled immigration associations across sectors seen in Table 2 can also be seen in panel B of Table 5. No such pattern can be seen in panel C.[33]

Length of training Panels D and E of Table 5 look at the effects of skilled immigration on training by duration. For a training spell that lasts for less than a week, the negative association of skilled immigration in the non-traded high-wage sector, and positive associations elsewhere, particularly in the non-traded low-wage sector, can be seen to hold. There is, however, a much weaker association between immigration and long-duration training (panel E). It may be that short-duration training is simpler to cut, or indeed augment, depending on the sector, when faced with an alternative supply of skilled labour.

Measurement of immigration The results above use the immigrant share as the measure of immigration intensity at the workplace. Since there is little consensus in the literature regarding the appropriate measure of immigrant concentration, Table 6 displays the results from

TABLE 5 Skilled Immigration and Different Aspects of UK-born Training

	(1)	(2)	(3)	(4)	(5)
Panel A: UK-born apprentice rates					
Non-traded (high-wage) × Skilled immigrant	0.054**	−0.044**	−0.008	−0.037**	−0.035**
	(0.019)	(0.011)	(0.011)	(0.011)	(0.011)
Non-traded (low-wage) × Skilled immigrant	−0.034*	0.006	0.003	−0.004	−0.003
	(0.015)	(0.011)	(0.014)	(0.011)	(0.011)
Traded × Skilled immigrant	0.008	0.031	0.017	0.033	0.031
	(0.022)	(0.020)	(0.027)	(0.022)	(0.022)
Non-traded (high-wage) × Other immigrant	−0.117**	−0.011	−0.003	−0.012	−0.009
	(0.017)	(0.008)	(0.007)	(0.007)	(0.007)
Non-traded (high-wage) × Other immigrant	−0.037**	−0.030**	−0.018	−0.025**	−0.026**
	(0.010)	(0.008)	(0.011)	(0.008)	(0.009)
Non-traded (high-wage) × Other immigrant	−0.032**	0.003	−0.022	0.001	0.001
	(0.012)	(0.012)	(0.016)	(0.013)	(0.014)
Panel B: Away from work training					
Non-traded (high-wage) × Skilled immigrant	−0.007	−0.169**	−0.011	−0.112*	−0.131**
	(0.064)	(0.041)	(0.046)	(0.044)	(0.046)
Non-traded (low-wage) × Skilled immigrant	0.156**	0.092**	−0.018	0.088**	0.091**
	(0.039)	(0.032)	(0.039)	(0.030)	(0.031)
Traded × Skilled immigrant	0.069*	0.010	0.004	0.045	0.070*
	(0.031)	(0.027)	(0.040)	(0.026)	(0.028)
Non-traded (high-wage) × Other immigrant	0.222**	0.012	0.013	0.010	0.010
	(0.049)	(0.038)	(0.035)	(0.037)	(0.038)
Non-traded (low-wage) × Other immigrant	0.009	0.099**	−0.042	0.073**	0.089**
	(0.026)	(0.023)	(0.024)	(0.023)	(0.023)
Traded × Other immigrant	0.061**	0.082**	0.005	0.070**	0.094**
	(0.021)	(0.021)	(0.025)	(0.022)	(0.023)
Panel C: At work training					
Non-traded (high-wage) × Skilled immigrant	0.178**	0.038	0.038	0.029	0.028
	(0.038)	(0.028)	(0.032)	(0.026)	(0.027)
Non-traded (low-wage) × Skilled immigrant	0.135*	−0.034	−0.042	−0.055*	−0.050
	(0.054)	(0.028)	(0.035)	(0.026)	(0.027)
Traded × Skilled immigrant	0.070*	0.014	0.034	0.020	0.001
	(0.032)	(0.029)	(0.037)	(0.028)	(0.026)
Non-traded (high-wage) × Other immigrant	−0.040	−0.002	0.020	0.011	−0.001
	(0.031)	(0.027)	(0.024)	(0.026)	(0.027)
Non-traded (low-wage) × Other immigrant	−0.078**	−0.009	0.025	0.002	0.010
	(0.026)	(0.020)	(0.024)	(0.020)	(0.020)
Traded × Other immigrant	−0.042*	−0.010	−0.027	−0.027	−0.027
	(0.021)	(0.022)	(0.027)	(0.022)	(0.020)
Panel D: Training < 1 week					
Non-traded (high-wage) × Skilled immigrant	0.081	−0.132**	−0.015	−0.112*	−0.129**
	(0.060)	(0.050)	(0.060)	(0.048)	(0.048)

(Continues)

TABLE 5 Continued

	(1)	(2)	(3)	(4)	(5)
Non-traded (low-wage) × Skilled immigrant	0.252**	0.160**	0.049	0.127**	0.138**
	(0.061)	(0.036)	(0.042)	(0.035)	(0.034)
Traded × Skilled immigrant	0.069	0.017	0.041	0.039	0.045
	(0.038)	(0.029)	(0.042)	(0.032)	(0.033)
Non-traded (high-wage) × Other immigrant	0.105*	0.044	0.042	0.069	0.057
	(0.046)	(0.062)	(0.069)	(0.067)	(0.067)
Non-traded (low-wage) × Other immigrant	−0.054	−0.006	−0.037	−0.001	0.008
	(0.029)	(0.026)	(0.036)	(0.028)	(0.028)
Traded × Other immigrant	0.003	0.015	−0.054	−0.009	0.004
	(0.023)	(0.027)	(0.045)	(0.032)	(0.031)
Panel E: Training ≥ 1 week					
Non-traded (high-wage) × Skilled immigrant	0.221**	−0.065	0.037	−0.030	−0.045
	(0.076)	(0.048)	(0.060)	(0.048)	(0.050)
Non-traded (low-wage) × Skilled immigrant	0.119**	0.009	−0.034	0.005	−0.011
	(0.041)	(0.041)	(0.053)	(0.043)	(0.044)
Traded × Skilled immigrant	0.140**	0.116**	0.116	0.136**	0.139**
	(0.032)	(0.041)	(0.062)	(0.043)	(0.041)
Non-traded (high-wage) × Other immigrant	0.028	0.052	0.099	0.072	0.064
	(0.054)	(0.055)	(0.060)	(0.054)	(0.054)
Non-traded (low-wage) × Other immigrant	−0.017	0.118**	0.076	0.105**	0.114**
	(0.027)	(0.027)	(0.039)	(0.029)	(0.029)
Traded × Other immigrant	0.016	−0.015	−0.086*	−0.036	−0.032
	(0.023)	(0.030)	(0.037)	(0.032)	(0.033)
Controls					
Year	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	No
Sector	No	Yes	Yes	Yes	Yes
Sector trends	No	No	Linear	Reciprocal	Reciprocal

Notes: HAC robust standard errors in parentheses.
*, ** indicate $p < 0.05$, $p < 0.01$, respectively.

estimates of the model using different concentration measures. Column (1) repeats the results from column (5) of Table 2 using the immigrant share. In column (2), we replace the share with the immigrant–native ratio M/N, used as a measure of immigrant concentration in many studies; see, for example, Dustmann *et al.* (2013). In column (3), we use the fixed ratio M/N_0, where N_0 is the sector count of native workers in the initial data period, the year 1995. This nets out one source of potential endogeneity in the immigration concentration variable caused by the presence of the native employment in the denominator (Card and Peri 2016), and ensures that any change in the concentration measure is caused by changes in immigration. This fixed ratio does mean that any immigration effects are now identified off the absolute change in immigration numbers rather than the relative change. To help to address this, columns (4) and (5) use the log immigration share and log of the fixed ratio, respectively, with all other control variables measured in logs. The immigration variables are now identified off relative changes in immigrant numbers within and across sectors, and the reported estimates are elasticities.

TABLE 6 Different Immigration Concentration Measures

	Share $M/(N+M)$ (1)	Ratio M/N (2)	Fixed ratio M/N_0 (3)	Log share $\ln[M/(N+M)]$ (4)	Log fixed ratio $\ln(M/N_0)$ (5)
Panel A: OLS					
Skilled immigrant	0.130**	0.045	−0.043*	0.017*	0.016
	(0.042)	(0.029)	(0.018)	(0.009)	(0.009)
Other immigrant	0.207**	0.113**	0.026	0.049**	0.019
	(0.031)	(0.027)	(0.019)	(0.018)	(0.018)
Panel B: OLS					
Non-traded (high-wage) × Skilled immigrant	−0.154*	−0.167**	−0.092**	−0.024*	−0.025*
	(0.069)	(0.056)	(0.029)	(0.012)	(0.011)
Non-traded Other × Skilled immigrant	0.235**	0.098*	0.022*	0.022	0.020
	(0.063)	(0.047)	(0.038)	(0.013)	(0.013)
Traded × Skilled immigrant	0.136*	0.048	−0.020	0.025*	0.031*
	(0.058)	(0.045)	(0.030)	(0.012)	(0.013)
Non-traded (high-wage) × Other immigrant	0.049	0.040	−0.020	0.006	0.004
	(0.066)	(0.053)	(0.034)	(0.015)	(0.012)
Non-traded (high-wage) × Other immigrant	0.224**	0.100*	0.015	0.073*	0.047
	(0.043)	(0.039)	(0.028)	(0.033)	(0.034)
Traded × Other immigrant	0.174**	0.103**	0.009	0.026	−0.001
	(0.055)	(0.037)	(0.057)	(0.024)	(0.021)
Panel C: OLS					
Non-traded (high-wage) × Skilled immigrant	−0.186**	−0.167**	−0.102**	−0.027**	−0.026*
	(0.071)	(0.055)	(0.027)	(0.011)	(0.011)
Non-traded Other × Skilled immigrant	0.306**	0.159**	0.103**	0.031**	0.033**
	(0.065)	(0.052)	(0.033)	(0.011)	(0.010)
Traded × Skilled immigrant	0.179**	0.112**	−0.017	0.026*	0.029*
	(0.055)	(0.034)	(0.026)	(0.011)	(0.013)
Panel D: IV					
First-stage F-statistics					
Non-traded (high-wage) × Skilled immigrant	92.7**	38.6**	65.4**	47.4**	66.1**
Non-traded Other × Skilled immigrant	195.0**	49.8**	51.1**	64.6**	57.1**
Traded × Skilled immigrant	244.5**	47.1**	69.2**	59.7**	58.9**
Second stage					
Non-traded (high-wage) × Skilled immigrant	−0.624	−0.153	−0.067	−0.263**	−0.197**
	(0.655)	(0.340)	(0.080)	(0.122)	(0.098)
Non-traded Other × Skilled immigrant	0.315	0.273	0.556*	−0.055	−0.122
	(0.399)	(0.173)	(0.207)	(0.042)	(0.072)
Traded × Skilled immigrant	0.249	0.408*	0.178	−0.062	−0.122
	(0.301)	(0.185)	(0.089)	(0.043)	(0.077)
Year	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes
Sector trends (reciprocal)	Yes	Yes	Yes	Yes	Yes

Notes: IV estimates show GMM robust standard errors in parentheses. F-tests of first-stage instruments all have 3 and 2341 degrees of freedom.
*, ** indicate $p < 0.05$, $p < 0.01$, respectively.

Panel A of Table 6 suggests that the training results of panel A of Table 2 for the whole economy are somewhat sensitive to the choice of immigration measure used. The estimated immigration share association is generally more positive than the ratio measures. Indeed, the fixed ratio (column (3)) suggests an overall negative association of skilled immigration on training, though this disappears when measured in logs (column (5)). However, there is more consensus in the estimates when the sectors are disaggregated into traded and non-traded in panel B. All the different immigration intensity measures suggest that there is a negative association between skilled immigration and native training rates in the non-traded high-wage sector.[34] The discrepancies between the different immigration measures seen in panel A seem to stem from identifying different patterns of change in the traded and non-traded low-wage sectors.

Instrumenting immigration The inclusion of sector fixed effects and sector trends does not preclude the possibility that contemporary shocks to training could affect immigration into a sector. While our sample cell sizes for each sector are quite large, there is also still the possibility of some measurement error, and the 21-year sample window may still give rise to some violation of strict exogeneity, with the bias from the latter declining by $O(1/T)$. As such, we next attempt to explore the robustness of these estimates to instrumentation strategies. Since both immigration variables are potentially endogenous, an IV strategy that instruments both variables at the same time is challenging. We therefore focus on attempts to instrument the skilled immigration variable. As a precursor, panel C of Table 6 estimates the model again by OLS, dropping the less-skilled immigrant variable. The pattern of differential impacts of skilled immigration across sectors is largely unchanged by doing this.[35]

Panel D of Table 6 then presents IV estimates of this model using variations of the Bartik shift–share instrument in each column, where the base-year sector shares of each country of origin immigrant group are constructed using the 4 years of the LFS before the estimation sample window. We use the predicted immigrant sector levels benchmarked to the 1995 level of UK-born employment as the instruments interacted with the traded/non-traded dummy variables in columns (1)–(5). In most cases, despite the significance of the first stage, this instrument performs poorly.[36] The predicted immigrant populations over this sample window are generally similar, subject to a levels transformation. Moreover, their trends are also quite smooth and monotonic. The combination of sector fixed effects and linear sector trends removes much of the variation in this instrument. The point estimates for the high-wage non-traded sector, while not well-defined, are of the same signs as in panel C.

In Table A6 of the Online Appendix, we estimate the models using the immigrant share and the fixed immigrant ratio in first differences rather than within groups. While first differencing may reduce stationarity concerns in what is, by panel data standards, a relatively long time series, it is also likely to accentuate attenuation bias resulting from any measurement error. The estimates are indeed much less precise than for the fixed effects model, and it is hard to infer much from this. Since long differencing is known to reduce these concerns (Hahn *et al.* 2007), panel B of Table A6 estimates the model in 5th period differences. The estimated signs and significance seen in Table 2 duly begin to re-emerge from this specification, though they are still not determined precisely. One alternative approach to any remaining endogeneity is to instrument the 5th differenced immigrant variable with lagged level values of immigration concentration from $t-6$ and beyond. Panel C does this with lags from $t-7$ and $t-8$.[37] Again, the estimated signs on the skilled immigration variables are in line with what has been observed above, but the point estimates on the immigration share variables are again imprecisely estimated (columns (1)–(3)). The IV estimates using the fixed ratio as the measure of concentration are a little more precise. Instrumentation with lags makes the point estimate on the non-traded interaction term more negative compared to the panel estimates.[38] In short, the IV estimates—while far from precise, and subject to the concerns of all these different types of instrumentation—do not overturn the finding of a heterogeneous association of skilled immigration with training across sectors.

Corroborating evidence

The accumulated evidence so far suggests that some sectors of the economy will make use of the supply of (ready-trained) skilled workers from outside the UK rather than training the UK-born workforce more. To see how firms react to a change in the supply of trained overseas labour, we next examine the effect of the April 2011 imposition of an annual quota of 20,000 on the number of skilled immigrants from outside the EEA allowed into the UK.[39] The policy restricted the flow of migrants into sectors that were high users of skilled non-EEA labour relative to those that were not. The quota size was announced four months in advance, so it is unlikely that firms could have anticipated and changed behaviour much beforehand, thus the policy change is quasi-exogenous.

Faced with such a labour supply shock, any firm affected had the option to (a) increase the training of its existing workforce, (b) hire more native-born workers, and (c) hire skilled migrants from another source region, namely the EEA, where freedom of movement rules applied without any quotas. The model and results so far suggest that the response may differ by sector. Intuitively, different responses may occur due to differing usage by sectors of non-EEA skilled labour before the policy change, whether the sector was traded or non-traded, and whether the sector was high- or low-wage. We therefore compare the responses of high and low non-EEA usage sectors before and after the programme across these sectors.

Table 7 presents difference-in-differences (DiD) estimates of the effect of the change in UK immigration policy on the three possible outcomes listed. The DiD estimates are based on the standard model with multiple groups and multiple time periods, $Y_{st} = a_s + b_t + \delta X_{st} + \beta T_{st} + u_{st}$, where the a_s are sector fixed effects, the b_t are year dummies, and the X_{st} are sector–time-varying controls. The DiD effect β is the estimated coefficient on the dummy variable T_{st}, where T indicates whether the policy affects sector s at time t. The sample window is 2007–15 with a break after 2011. A high non-EEA user sector is defined as in the top 25th percentile of non-EEA workforce shares averaged over the period 2001–7 before the estimation begins. A low non-EEA sector (the control group) has an EEA sector share below the median. We therefore exclude the middle

TABLE 7 Difference-in-differences Estimation of Immigration Shock

	Non-traded (high-wage)	Non-traded (low-wage)	Traded
Panel A			
Training rate UK-born	−0.0015	0.0148	0.0057
	(0.0115)	(0.0152)	(0.0113)
Panel B			
Hiring rate UK-born	0.0002	0.0001	−0.0006
	(0.0005)	(0.0006)	(0.0007)
Panel C			
EEA skilled immigrant share	0.00113**	0.0052	0.0048
	(0.0033)	(0.0072)	(0.0079)
Sample size	168	294	161

Notes: HAC robust panel standard errors in parentheses. Controls same as in column (2) of Table 3, plus sector-specific time trends. *, ** indicate $p < 0.05$, $p < 0.01$, respectively.

25th percentile to reduce the possibility of spillovers, but the results are broadly unchanged if they are put in the control group.

The DiD estimates suggest that the short-run response to this constraint in non-traded high-wage sectors was to hire more skilled workers from the EEA rather than train more of its existing workforce or hire more UK-born workers. This effect is not observed in the traded goods sector or the non-traded low-wage sectors. It seems that the nature of the skill set in the non-traded 'good jobs' sector allows for the importation of ready-trained workers.[40]

5 | CONCLUSION

The first paragraph of this paper asked whether skilled immigration to the UK was causing a reduction in the training of the native workforce. This is an important question, as the UK has a long-standing problem with low productivity, but it is one that the literatures on both training and the effects of immigration on human capital accumulation have neglected. Theoretically, we have shown that a negative effect of skilled immigration on training is possible but not inevitable. Empirically, we have found that while on aggregate there is a small, positive association between skilled immigration and native training rates, at a more disaggregated level, there are very different patterns in this relationship across different sectors and across different types of immigration within the same sector. These findings show how, potentially, aggregate level analysis can be misleading, and highlights the importance of looking for heterogeneous effects in empirical investigations. We have emphasized the contrast between the traded sector, where skilled immigration appears to be complementary to the training of UK-born workers, and high-wage non-traded sectors where skilled immigration and native-born training appear to be net substitutes. These associations are stronger for skilled, more experienced UK workers, and for short spells of training away from work. In contrast, the relationship between less-skilled immigration and UK-born training appears to be much weaker.

ACKNOWLEDGMENTS

Many thanks to members of the UK Home Office's Migration Advisory Committee, participants at the CEPII/OECD workshop 'Immigration in OECD countries', and seminar attendees at CEP, Edinburgh, Surrey, Moscow Higher School, RES and UCD for helpful comments. Special thanks to Alan Manning and Alexander Danzer for very helpful advice on the earlier stages of this research and earlier versions of the paper, which were entitled 'Trainspotting: "good jobs", training and skilled immigration'.

NOTES

1. The literature is very large, but see, for example, Manacorda *et al.* (2012) and Wadsworth (2018).
2. See also Moretti (2010), who finds evidence of large positive spillovers from exogenous increases in employment in a tradable industry—e.g. from domestic or international inward migration—to increases in local employment in the non-tradable sector.
3. Again, the literature is very large, but see, for example, Acemoglu and Pischke (1998, 1999) and the references cited therein.
4. See also Michaillat and Saez (2015) for the related literature on macroeconomic implications of job rationing in the labour market.
5. This variable was used in Dearden *et al.* (2006) and shown to be positively associated with higher productivity.
6. We define high-wage as sectors paying above the mean sectoral hourly wage. 'Traded' is defined here as agriculture, energy and manufacturing, IT and finance. The results that follow are broadly robust to changes in this definition (see the subsection 'Robustness checks' in Section 4).
7. Table A1 in the Online Appendix gives sample mean training and immigration rates for the highest and lowest training sectors at the beginning and end of the sample by 3-digit-level sectors. The training rankings by sector are quite stable over time. In 2000 and in 2018, the sectors with the highest on-the-job training rates were associate professionals in health and social care, predominantly nurses. In both years, the sector with the lowest on-the-job training share is

manual domestic workers (cleaners). There is no clear association with immigrant share. Two of the best and worst sectors had greater than average shares of skilled migrants.

8 The increase in demand for non-traded goods from the immigrant must be less than his wage, which will be less than or equal to the extra non-traded output produced.

9 This is a restriction on primitives, i.e. that the mass of wealthy agents in the initial distribution of wealth, and the mass of firms with the potential to train, are sufficiently small.

10 See Costa *et al.* (2019) for an analysis of the effects of changes in the exchange rate on training in the UK.

11 Different trained wages in the traded sector, $w^{*,T}$, and in the non-traded sector, $w^{*,NT}$, would imply a separate line in Figure 4 and equation (IDD) below for each trained wage.

12 Downward earnings mobility is present in UK data but is less likely than upward earnings mobility; see Dearden *et al.* (1997).

13 The ability to emigrate will also affect human capital accumulation decisions in the sending economies; see Mountford (1997) and Mountford and Rapoport (2011). We do not consider these effects here.

14 See Kiguchi and Mountford (2019) for evidence of the positive effect of migration on non-residential investment at the macroeconomic level.

15 Online Appendix B discusses the bargaining solution.

16 The LFS question is: 'In the X 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?' This is asked only to those in employment under age 70, and not to working students. See Office for National Statistics (2016).

17 The industry classifications also change in 2009, but we are able to correct for this using the mapping of Smith—see https://warwick.ac.uk/fac/soc/economics/staff/jcsmith/sicmapping (accessed 20 March 2023).

18 We investigate the sensitivity of our results to different definitions of the traded sector below.

19 The non-traded 'good job' sectors are managerial occupations (SOC 1) in Construction, Retail, Transport, Media, Real Estate, Legal Services, Engineering, Support Services, Protective Services, Public Administration, Education, Health and Residential Services; professional occupations (SOC 2) in Construction, Retail, Real Estate, Legal Services, Engineering, Scientific Support, Support Services, Protective Services, Public Administration, Education, Health, Social Services, Sport and Residential Services; assistant professionals (SOC 3) in Construction, Transport, Media, Legal Services, Scientific Services, Protective Services, Public Administration, Education, Residential Services, Social Services. The low-wage sector comprises the residual groupings across 1-digit SOC and 2-digit SIC.

20 The LFS has recorded who pays for training for around half the sample period, since 2010. Most training is employer- or government-funded. Only around 25% of LFS respondents in receipt of training are self-funded. This proportion has not changed much over a period when skilled immigration was rising. Around 60% of on-the-job training is paid for by employers.

21 This allows the first four years of data to be combined with immigration data to construct the familiar Bartik instrument using the period 1994–7 as the baseline for sector immigration shares (see the discussion in the subsection 'Robustness checks' in Section 4). The end date of the sample is when the country-specific data used to construct the instrument were removed from the LFS data. The LFS immigration estimates after 2019 are affected significantly by sampling issues over the course of the COVID-19 pandemic. The only individual longitudinal dataset in the UK that contains some training information—the BHPS/Understanding Society—has an inconsistent and incomplete definition of training over time and, perhaps because of this, shows no apparent training trend. Moreover, the BHPS contains a non-representative sample of UK-born and non-UK-born workers over time. For these reasons, and the fact that there is no variation in immigration shares other than at sectoral level, we focus on the sector-level regressions based on LFS data. Results of the model estimated using a consistent training definition and Understanding Society data from 2011–19 are, however, in line with our reported findings and available on request.

22 A sector-specific upswing, for example, may draw in more immigrants to the sector and increase demand for training of native-born workers at the same time.

23 See Wooldridge (2010, p. 310).

24 We also test the sensitivity of the estimated standard errors to different clustering assumptions; see below.

25 There are 100 countries/areas of origin in the 1990s LFS used to construct the base shares. The minimum number of countries in any sector is 39.

26 We also test the sensitivity of the standard error estimates to different assumptions about heteroscedasticity and/or autocorrelation. Changes to the bandwidths or kernels used to generate the HAC standard errors make little appreciable difference to the estimated standard errors. Simply clustering the standard errors at the level of the sector or the combination of sector and year, ignoring heteroscedasticity or serial correlation from any other source, does not change the overall conclusions regarding significance or otherwise of the various immigration effects.

27 The mean training rate in this period is 0.26, thus the effect is a reduction of $(0.15 \times 0.05)/0.26$, i.e. about 3%. This is approximately one-quarter of a standard deviation of the skilled training share in the high-wage non-traded sector.

28 Note that the inclusion of linear trends in column (3) of Table A4 also reduces the significance of many of the covariates, not just the immigration variables. The non-linear sector trends typically restore the significance of the controls.

29 The results are robust to the definition of skill used to define immigrant groups. If we use observed qualifications rather than age left education and a definition of graduate (or postgraduate) born outside the UK and who arrived

in the UK after age 22, the results are similar to those in Table 2. While there remains a degree of uncertainty in the LFS regarding the recording of qualifications obtained abroad, we do not report these in the main text, but they are available on request.

[30] The geographies are 'South'—London, South-East England and East Anglia—comprising 57% of all immigrants and 33% of the native-born working age population, and 'North'— the rest of the UK. Sample sizes preclude a more disaggregated geography.

[31] Free movement applied to citizens of the European Economic Area (EEA), i.e. the EU plus Norway, Liechtenstein and Iceland. Switzerland also joined in 1999.

[32] UK law currently requires an apprentice to receive a minimum of 20% training; see https://www.apprenticeships.gov.uk/employers/hiring-an-apprentice (accessed 21 March 2023).

[33] There is also a significant negative association of skilled immigration on training in the high-wage non-traded sector, with positive associations elsewhere if the dependent variable is training combining both off and on the job. Results are available on request.

[34] The training-immigrant elasticity in column (5) of Table 6 is −0.025 for the high-wage non-traded sector—statistically significant but rather small in magnitude.

[35] The effect of skilled immigration in the low-wage sector becomes larger across all specifications, but the change is not significantly different from the estimates in panel B of Table 6.

[36] The estimates using the instrumented immigrant share or ratios are even less precise (available on request). Predicting the denominator—UK-born workers are as potentially endogenous as migrants—weakens the instrument considerably.

[37] We use a finite set of lags since the literature finds that this type of IV estimator performs better in finite samples compared to the full set of possible lags. This approach assumes no serial correlation in the error levels in the original model or an MA(1) in the differenced residuals. Moreover, lagged values as instruments are unlikely to satisfy the strict exogeneity condition. See Wang and Bellemare (2019) for a discussion of this.

[38] We also added a lagged dependent variable to the empirical model in equation (1), and the patterns from Table 2 again hold broadly. Results are available on request.

[39] For more details, see UK Parliament (2015). The definition of skilled migrant was based on qualifications at ISCED level 3 and above, which broadly corresponds to the definition of 'skilled' used in our study.

[40] The omission of sector-specific trends from the model generates an estimate 0.0061 with standard error 0.0020 in the non-traded high-wage sector. If we estimate a placebo experiment entirely in the pre-treatment period 2004–10 with a split at 2008, then the equivalent estimate for the non-traded high-wage sector is 0.0045 (0.0113). A regression of the EEA skilled adult immigrant workforce share on a time trend and an interaction with the high non-EEA user sector in the period 2004–11 generates a statistically insignificant coefficient on the interaction term (and a statistically significant coefficient on the trend). Results are available on request.

REFERENCES

Abramovsky, L., Battistin, E., Fitzsimmons, E., Goodman, A. and Simpson, H. (2011). Providing employers with incentives to train low-skilled workers: evidence from the UK employer training pilots. *Journal of Labor Economics*, **29**(1), 153–93.

Acemoglu, D. and Pischke, J. (1998). Why do firms train? Theory and evidence. *Quarterly Journal of Economics*, **113**(1), 79–119.

——— and ——— (1999). The structure of wages and investment in general training. *Journal of Political Economy*, **107**(3), 539–72.

——— and ——— (2003). Minimum wages and on-the-job training. *Research in Labor Economics*, **22**, 159–202.

Adao, R., Kole, M. and Morales, E. (2019). Shift-share designs: theory and inference. *Quarterly Journal of Economics*, **134**(4), 1949–2010.

Borusyak, K., Hull, P. and Jaravel, X. (2022). Quasi-experimental shift–share research designs. *Review of Economic Studies*, **89**(1), 181–213.

Burstein, A., Hanson, G., Tian, L. and Vogel, J. (2020). Tradability and the labor-market impact of immigration: theory and evidence from the United States. *Econometrica*, **88**, 1071–112.

Cameron, C. and Miller, D. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources*, **50**(2), 317–72.

Card, D. and Peri, G. (2016). Immigration economics by George J. Borjas: a review essay. *Journal of Economic Literature*, **54**(4), 1333–49.

Christiano, L., Eichenbaum, M. and Trabandt, M. (2016). Unemployment and business cycles. *Econometrica*, **84**(4), 1523–69.

Costa, R., Dhingra, S. and Machin, S. (2019). Trade and worker deskilling. *CEP Discussion Paper* **no. 1622**.

Danzer, A., Feuerbaum, C. and Gaessler, F. (2020). Labour supply and automation innovation. *IZA Discussion paper* **no. 13429**.

Dearden, L., Machin, S. and Reed, H. (1997). Intergenerational mobility in Britain. *Economic Journal*, **107**, 47–66.

———, Reed, H. and Van Reenen, J. (2006). The impact of training on productivity and wages: evidence from British panel data. *Oxford Bulletin of Economics and Statistics*, **68**(4), 397–421.

Doepke, M. and Gaetani, R. (2020). Why didn't the college premium rise everywhere? Employment protection and on-the-job investment in skills. *NBER Working Paper* **no. 27331**.

Dustmann, C., Frattini, T. and Preston, I. (2013). The effect of immigration along the distribution of wages. *Review of Economic Studies*, **80**(1), 145–73.

———, and Glitz, A. (2015). How do industries and firms respond to changes in local labor supply? *Journal of Labor Economics*, **33**(3), 711–50.

———, and Schönberg, U. (2012). What makes firm-based vocational training schemes successful? The role of commitment. *American Economic Journal: Applied Economics*, **4**(2), 36–61.

Foged, M. and Peri, G. (2016). Immigrants' effect on native workers: new analysis on longitudinal data. *American Economic Journal: Applied Economics*, **8**(2), 1–34.

Galor, O. and Zeira, J. (1993). Income distribution and macroeconomics. *Review of Economic Studies*, **60**(1), 35–52.

Goldsmith-Pinkham, P., Sorkin, I. and Swift, H. (2020). Bartik instruments: what, when, why, and how. *American Economic Review*, **110**(8), 2586–624.

Hahn, J., Hausman, J. and Kuersteiner, G. (2007). Long difference instrumental variables estimation for dynamic panel models with fixed effects. *Journal of Econometrics*, **140**(2), 574–617.

Hanson, G. and Slaughter, M. (2002). Labor-market adjustment in open economies: evidence from US states. *Journal of International Economics*, **57**(1), 3–29.

Holmstrom, B. and Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. *Quarterly Journal of Economics*, **112**(3), 663–91.

Hunt, J. (2017). The impact of immigration on the educational attainment of natives. *Journal of Human Resources*, **52**(4), 1060–118.

Jaeger, D., Ruist, J. and Stuhler, J. (2018). Shift–share instruments and dynamic adjustments: the case of immigration. *NBER Working Paper* **no. 24285**.

Kiguchi, T. and Mountford, A. (2019). Immigration and unemployment: a macroeconomic approach. *Macroeconomic Dynamics*, **23**(4), 1313–39.

Lewis, E. (2011). Immigration, skill mix, and capital skill complementarity. *Quarterly Journal of Economics*, **126**(2), 1029–69.

Llull, J. (2018). Immigration, wages, and education: a labour market equilibrium structural model. *Review of Economic Studies*, **85**(3), 1852–96.

Manacorda, M., Manning, A. and Wadsworth, J. (2012). The impact of immigration on the structure of wages: theory and evidence from Britain. *Journal of the European Economic Association*, **10**(1), 120–51.

Matsuyama, K. (1992). Agricultural productivity, comparative advantage, and economic growth. *Journal of Economic Theory*, **58**(2), 317–34.

Michaillat, P. and Saez, E. (2015). Aggregate demand, idle time, and unemployment. *Quarterly Journal of Economics*, **130**(2), 507–69.

Mion, G., Opromolla, L. and Ottaviano, G. (2020). Dream jobs. *Cesifo Working Paper* **no. 8430**.

Moretti, E. (2010). Local multipliers. *American Economic Review*, **100**(2), 373–7.

Mountford, A. (1997). Can a brain drain be good for growth in the source economy? *Journal of Development Economics*, **53**(2), 287–303.

——— and Rapoport, H. (2011). The brain drain and the world distribution of income. *Journal of Development Economics*, **95**(1), 4–17.

——— and Wadsworth, J. (2019). Trainspotting: 'good jobs', training and skilled immigration. *CEP Discussion Paper* **no. 1618**.

OECD (2020). *Education at a Glance*. Paris: OECD.

Office for National Statistics (2016). Labour Force Survey User Guide Volume 2—LFS Questionnaire 2016; available online at http://doc.ukdataservice.ac.uk/doc/7985/mrdoc/pdf/lfs_user_guide_vol2_questionnaire2016.pdf (accessed 20 March 2023).

UK Parliament (2015). Immigration: skill shortages; available online at https://publications.parliament.uk/pa/cm201516/cmselect/cmhaff/429/429.pdf (accessed 6 April 2023).

Wadsworth, J. (2018). Off EU go? Brexit, the UK labour market and immigration. *Fiscal Studies*, **39**(4), 625–49.

Wang, Y. and Bellemare, M. (2019). *Lagged variables as instruments*. University of Minnesota Economics Department Working Paper, Miemo.
Wooldridge, J. (2010). *Econometric Analysis of Cross-section and Panel Data*. Cambridge, MA: MIT Press.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Mountford, A. and Wadsworth, J. (2023). 'Good jobs', training and skilled immigration. *Economica*, 1–31. https://doi.org/10.1111/ecca.12472