The Impact of Migration on Productivity and Native-born Workers' Training

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Abstract

We investigate the relationship between migration and productivity in the UK, using an instrumental variable along the lines suggested by Bianchi, Buonanno and Pinotti (2012). Our results suggest that immigration has a positive and significant impact (in both the statistical sense and more broadly) on productivity, as measured at a geographical level; this appears to be driven by higher-skilled workers. The results for training are less clear, but suggest that higher-skilled immigration may have a positive impact on the training of native workers. We discuss the implications for post-Brexit immigration policy.

Keywords: Immigration, Productivity, Training, Great Britain.

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1 Introduction and Motivation

There is now a considerable body of evidence on the direct labour market impacts of migration to the UK (see Wadsworth, 2017, for a summary). There is a clear consensus that, in aggregate, migration has little or no impact on employment or wages, but that it may have some, relatively small, impact on the distribution of wages (depressing wages for some, generally low-paid, sectors, while increasing it for others).

This broad consensus has been extremely helpful in establishing that the lump of labour fallacy (or indeed the broader fallacy that immigration increases only labour supply, not labour demand, and hence must as a matter of theory not empirics depress wages) is not only false in the long run but appears to have little or no predictive power even in the short term. The UK's flexible labour market appears to adjust surprisingly quickly to labour supply shocks.

However, beyond the direct labour market impacts, relatively little is known about the broader impacts of immigration on the UK economy. In this paper, we focus on two of these potential impacts: productivity and the training of non-immigrants (that is, UK-born workers). These topics are clearly of great importance. The UK's low level of labour productivity, compared to many other advanced economies, has long been recognised as a key weakness; and this has been greatly exacerbated by its extremely poor productivity performance since the 2008-09 financial crisis (see, for example, Office of Budget Responsibility, 2018). Moreover, to the extent that it is the impact of immigration on "prosperity", or GDP per capita, that is of most interest to policymakers (as opposed to the overall, undeniably positive, impact of immigration on GDP), productivity is likely to be key. The impact of immigration, and in particular of changes to immigration and immigration policy, on productivity is therefore of immense policy relevance. Similarly, for training, the quantity of employer provided training has fallen over recent decades, and there is significant policy concern that the availability of relatively cheap, flexible immigrant labour reduces the incentive for employers to provide training to existing resident workers.

However, the theoretical impact of immigration on productivity is ambiguous, because there are a number of conceptually different mechanisms that are potentially work. These include:

- The simple "batting average" effect. If individual immigrants are more or less productive on average than natives, they will directly raise or lower productivity for the whole economy, even if they don't affect the productivity of natives;
- Within-firm complementarities, where immigrants increase the productivity of natives in the same firm (or, conceivably, reduce it, if for example there are increased frictions within the firm, perhaps because of language differences);
- Within-sector spillovers, because of economies of scale, clustering effects, and/or increased competition;
- Local or geographical effects, again because of complementarities – for example the availability of low-skilled immigrant workers could increase the productivity or labour supply of high skilled native workers (Barone and Mocetti, 2011);
- Incentive effects: immigration could increase or decrease the incentive for native workers to acquire human capital, either general or sector-specific, depending on the type of immigration and how it impacted wages and labour demand;
- Impacts on investment. If immigration reduced the incentive to invest in productivity-enhancing capital – perhaps the availability of low-skilled labour makes it uneconomic to invest in automation – then it could reduce productivity. On the other hand, some investment might be complementary to the skills of immigrants.

It is worth listing and distinguishing these possible mechanisms, since they have somewhat different implications for our empirical analysis below. For example, if the impact of immigration on productivity operates primarily at a sectoral or firm level, then the definition of the appropriate labour market in which to estimate the impacts will be different than if it operates at a geographical level.

Similar issues arise for training. Immigration may reduce the incentive for firms to train native workers, if immigrants with the required skills are already available; but it may also increase the incentive for native workers to "upskill", or for firms to train natives for complementary roles. And such effects may manifest themselves within firms, within sectors, or at a geographical level.

2 Literature Review

In contrast to the labour market impacts on jobs and wages, relatively little evidence exists for the UK (or indeed internationally) on the impact of migration on productivity and training. There is therefore no clear consensus in the literature on either the sign or the magnitude of the possible impacts. At a cross-country level, Ortega and Peri (2014 examine the impact of both immigration and trade; they find that while openness to trade and migration both boost (per capita) income, migration has considerably larger impacts than trade. However, their dataset is dominated by developing countries. Boubtane et al. (2016) find that migration in general boosts productivity in advanced economies, but by varying amounts; for the UK, the estimated impact is that a 1 percentage point in the migrant share of the working age population leads to a 0.4 - 0.5% increase in productivity. This is higher than in most other advanced economies and reflects the relatively high skill levels of migrants to the UK, who are assumed to be complementary to other factors of production. Their data set, however, only runs up to 2006.

Jaumotte et al. (2016) find that a 1% increase in the migrant share of the adult population results in an increase in GDP per capita and productivity of approximately 2 percent: this is a very large impact and would have considerable macroeconomic significance. This result is consistent across a variety of empirical specifications. Perhaps surprisingly, the estimated aggregate impact of high and low skilled migration are not significantly different (although the distributional implications are). One possible, partial explanation is that low skilled migration appears to increase labour force participation among native women (a result also found in individual country studies, cf. Barone and Mocetti, 2011). As noted above, this is one example of the type of complementarity or spillover effect by which migrants might indirectly increase productivity and output at a geographical level.

Within countries, there exists a small body of research looking at this relationship. For the US, Peri (2012) looks at Total Factor Productivity in US, analysing state-level data, and find positive impacts. In the UK, Ottaviano, Peri and Wright (2015) look at the services sector in the UK, while Rolfe et al (2013) look at productivity by region and sector (as we do in this paper), although they do not attempt to establish causality. In Germany, Brunow, Trax and Sudekum

(2013), use firm-level data, and find a positive impact of diversity (or fractionalisation) by nationality on productivity, at both a firm and a regional level.

Overall, the message from these papers is that the impact of immigration on productivity is generally positive, but the size (and the implicit causal mechanisms assumed to be at work) vary and results are generally not conclusive.

The evidence is even sparser for training. The few empirical studies related to this topic concentrate on natives' school attendance (Hunt, 2017) and performance (McHenry, 2015) in US. These authors find that, given the potential downward pressure put by immigrants on low-skilled sectors' wages, natives have more incentives to invest in human capital. In the UK, Geay, McNally and Telhaj (2013) find neutral or slightly positive spillover effects from non-native English speakers on school performance among natives. However, as far as we know, no empirical research has investigated the relationship between immigration and training, both on- and off- the-job, which is another important form of human capital investment, and in which firms play a key role.

3 Policy Relevance

Evidence on the sign and magnitude of any impacts is essential to inform the current UK policy debate on immigration policy. Immigration to the UK rose sharply after 1997, as the then government liberalised policy towards work-related migration from outside the EEA, and rose further after the expansion of the EU in 2004 to ten new Member States. While the direct labour market impacts of immigration, as noted above, appear to have been largely benign, since the late 2000s policy has become more restrictive towards non-EU migration, particularly since the change of government in 2010, as the new government set a target of reducing net migration to the "tens of thousands".

In an effort to meet this target, restrictive measures have been applied to work-related migration, with the imposition of a quota system on skilled ("Tier 2") migrants, and of income thresholds for family migration. However, the UK's membership of the EU means that it is almost entirely unable to control migration from elsewhere in the EEA. As a consequence, immigration continued to rise, with measured net migration peaking at approximately 330,000 in the year leading up to the Brexit referendum in June 2016. Since then, as a consequence of the fall in the exchange rate (which makes the wage differential between the UK and poorer countries less sharp), the weakening of the UK economy relative to the eurozone, and the psychological and political impact of the Brexit vote, migration from the EU to the UK has fallen sharply. This has in turn had some impact on the policy debate, with increasing concern among business about the availability of workers in both high and low-skilled occupations.

Of course, the UK continues to be a member of the EU, and the government has proposed that during the "transition period" from March 2019 until December 2020 free movement should continue as now. However, after the expiry of the transition period, the UK will be able to control immigration, in particular immigration for work purposes, from the EEA. Moreover, the likely reduction in EEA migration flows will in turn have indirect implications for migration from outside the EEA, and hence for policy. The UK will need to determine its approach on a number of dimensions:

- Should EU/EEA citizens continue to have preferential treatment with respect to those from outside the EEA?
- Should policy favour (as it now does for those from outside the EEA) those with particular skills or who are employed in particular occupations? And to the extent that it does (as almost all immigration systems do) what should the relative weight be on skills/qualifications, salary levels, and/or employment in specific occupations where there are few or no qualified domestic workers? What is the role of government, as opposed to employers and the labour market, in determining who should be allowed to come?
- Should there be specific migration schemes for individual sectors, and if so how should such sectors be chosen, or for regions that are particularly dependent on immigration either for economic or demographic regions?

It was in this context that the then Home Secretary commissioned the Migration Advisory Committee to advise on the economic and social impacts of the UK's exit from the European Union and also on how the UK's immigration system should be aligned with a modern industrial strategy (Home Office, 2017). Given the broader UK policy context after Brexit, in particular the need to boost productivity overall while at the same time addressing pervasive structural inequalities and imbalances (regional, demographic, and ethnic) the impact of immigration on productivity, and to a lesser extent training, particularly disaggregated by the "type" of immigrant (skill level and region of origin) is clearly of prime importance here. Specifically, the Home Secretary asked the MAC to address the following questions:

- What is the current impact of immigration, both EU, EEA and non-EEA, on the competitiveness of UK industry, including on productivity, innovation and labour market flexibility?
- What impact does immigration have on skills and training?
- Is there any evidence that the free availability of unskilled labour has contributed to the UK's relatively low rate of investment in some sectors?
- Are there advantages to focussing migrant labour on highly skilled jobs or across the entire skills spectrum? Does the shortage occupation list need to be amended to include skills shortages at lower skills levels than NQF6?

An example of the policy relevance of such analysis on the links between migration and productivity is provided by Forte and Portes (2017), who produce scenario analyses of potential reductions in net migration resulting from Brexit (which, so far, appear to have been reasonably accurate). They then apply the coefficients estimated by Boubtane et al and Jaumotte et al to estimate the potential impact on productivity and GDP per capita and find potentially macroeconomically significant – that is, large and negative - impacts. This illustrates that migration policy post-Brexit could potentially have substantial impacts on UK productivity (and hence overall prosperity); however, they caution that the applicability of quantitative estimates based on historical cross-country data to scenarios for the impact on the UK economy going forward is inevitably speculative. The objective of this paper is to provide more detailed and UK-specific evidence to inform the MAC's recommendations.

4 Empirical Strategy

The research design in this paper follows the standard methodology used in the literature to analyse the impact of migration; we examine the relationship between the variation in levels of migration and outcomes of interest across labour markets within Great Britain. In the literature, labour markets can be defined either by reference to geography, to sector or to skill group. The latter is not relevant here (since productivity is a firm-level concept) so we look at both geography and sectoral settsings, and a hybrid specification which interacts the geographical and sectoral dimensions. Specifically, we define our units of observation as:

- aggregates of Local Authorities (NUTS3);
- aggregates of 2 digit-SIC industries;
- agg. of 2-digit-SIC industries-by-agg. of Regions (NUTS2).

As noted above, it is important to look at both geographical and sectoral impacts, since different causal mechanisms might be expected to have different impacts, depending on the nature of the complementarities and spillovers between migrants and natives, which could operate at the firm, sectoral or geographic level.

The independent variable of interest is the number of migrant workers. We first focus on aggregate impacts, looking at all migrant workers, and then distinguish the role played by skilled and unskilled migration. We have two different measure of immigrants' skills; the first is based on education, where we distinguish between immigrants with at least tertiary education (college degree or equivalent) and those with high-school degree or less. The second is based on occupation, the 1 digit-SOC occupation codes (divisions 1, 2, 3 and 5 for high-skilled occupations; divisions 4, 6, 7, 8 and 9 for low-skilled occupations). We specify a linear model in differences where 1-year changes in either productivity or training are regressed on 1-year changes in migrants' share of employed population at labour market level. This is standard in the literature. However, while this may be a reasonable time-frame for examining the impact of migration on wages or employment, it is by no means obvious that impacts on productivity or training would materialize over a relatively short period; some impacts might be much slower, as firms adapted production techniques, ways of working or management techniques to take advantage of migrants' skills. We therefore also take as an outcome variable the cumulative impacts over the entire time period in our dataset.

A further set of estimates introduces an additional level of disaggregation by assessing the impact associated with workers from both European Union and non-European Union countries. Since workers from outside the EU are subject to a very different, and much stricter, migration control regime, their characteristics and impacts may differ significantly. Moreover, as explained above, the issue of whether, post-Brexit, the UK should continue to give some form of preferential treatment to EU migrants is high on the political and policy agenda.

We do not seek to control for other variables that might influence productivity growth – most obviously investment. This is because we are seeking here to identify the impact (direct and indirect) of immigration on productivity. Some of those effects might manifest themselves via investment: the availability of immigrant workers could be a substitute for investment, or a complement to it. So controlling for investment could bias our estimates in either direction. Clearly the interaction between immigration, investment and productivity is of interest, and further work, with a more sophisticated modelling structure, would be required to investigate this relationship.

The key issue in establishing the causal impact of migration using this methodology is the potentially non-random distribution of immigrants across labour markets. If immigrant flows are in part driven by productivity, then a simple regression of productivity (or productivity growth) or training on immigration (or immigration flows) may be biased. Note, however, that in contrast to employment or wage impacts, the direction of the bias is not obvious. That is, immigration flows might be higher to low productivity sectors, which need more workers to expand or maintain output; or they might be higher to high productivity sectors which are more likely to be growing.

Empirically, we will attempt to tackle the endogeneity related to the non-random distribution of immigrants across areas/sectors by employing a shift-share instrumental variable approach based on that developed in Card (2001), which has been largely adopted by the migration literature, and is generally regarded as best practice. The rationale of this type of instrument is to isolate an exogenous component in the migration flows by country of origin, driven by supply-push factors, such as economic and political crisis or natural calamities, and therefore not related to regional/sectoral specific pull-demand factors. These migration flows are then allocated across labour markets on the base of the historical concentration of immigrants by area of origin, exploiting the enclave effect, i.e. the fact that new immigrants are more likely to settle in regions/sectors where same-origin immigrant presence is higher, and benefit from the resulting network effects in the labour market. This process creates counterfactual inflows that should be correlated with the real-world inflow, but credibly uncorrelated with local economic or labour market developments (including sector or region-specific trends in productivity or training) that also, on the demand side, may influence actual immigration flows. If this is the case, the requirements for a valid instrument will be satisfied and unbiased estimates of the causal impact of immigration on the dependent variables of interest can be calculated.

We adopt a specification of the Card instrument similar to Bianchi, Buonanno and Pinotti (2012), in which the shift-share instrumental variable considers as the common shift to UK from country/area of origin a, which is then allocated across subnational labour markets on the base of the historical concentration (i.e. the share), not the national inflows from a[1](e.g. the inflow of immigrants from China to UK), but the aggregate inflow from a to all countries except UK. The national inflows from a set of countries/areas of origin, as in the classical specification of Card's instrument, may indeed be affected by endogeneity issues if even few of the labour market cells have a high relative size which may influence the national figures, e.g. labour-demand shocks in London may significantly affect the national migration inflows and spill over other geographical areas, therefore compromising instrument's validity. The shift-component of the instrument in this paper, conversely, considers migration inflows, from each area of origin, which are allegedly exogenous, assuming that UK is unable to affect migration to other countries, and indipendent from pull-demand labour markets-specific characteristics.

The instrumental variable for migration inflows in labour market c is:

$$IV\text{-}\Delta Imm._{c,t} = \sum_{a=1}^{25} \Delta\widehat{M_{a,c,t}} = \sum_{a=1}^{25} S_{a,c,1991} \times \Delta M_{a,t}^{OECD} \tag{1}$$

[1]In many specifications the shift is the national inflow from country/area a minus the inflow to the labour market cell c, in order to net out the component of aggregate inflow from a which may be endogenous to shocks taking place in c.

The predicted migration inflow from area of origin a to labour market c, $\Delta\widehat{M_{a,c,t}}$, is the product of:

- $\Delta M_{a,t}^{OECD}$: inflow of immigrants from area a to OECD countries except UK;
- $S_{a,c,1991} = \frac{M_{a,c,1991}}{M_{a,GB,1991}}$, which allocates the OECD migration inflow on the basis of the 1991 Great Britain's Census (2 % sample) share of immigrants from a in c over the Great Britain's total.

The $\Delta M_{a,t}^{OECD}$ component is derived from the OECD International Migration Flows Database[2], collecting information on yearly inflows for each origin-OECD destination pair, spanning from 2000-2015. We match the OECD data with the set of 25 areas of origin identifiable from the 1991 Census[3], and take into account a set of 15 OECD destinations[4], representing a group of developed countries comparable to UK, with an experience of substantial migration inflows for the last two decades, which are reasonably indipendent from migration patterns concerning UK.

The final instrument $IV\text{-}\Delta M_{c,t}$ is the sum of predicted inflows from all 25 areas of origin. Most of the specifications in the migration literature use to standardize the instrument with the lagged variable of population in the labour market, which may induce, according to Clemens and Hunt (2017), spurious correlation since the endogenous migration variable and the instrument share the same denominator. They suggest to rather control for labour market population growth in the first stage estimates. We follow this suggestion by including a control for employed population growth (BRES estimates) as in the specification in equations 1, 2, 3 and 5.

5 Data

Our key independent variable is the number of migrants in employment in each labour market. This is constructed from the Annual Population Survey (APS), Secure Access 2004-2016, which comprises 3-400,000 individual observations from 5 quarters of the Longitudinal Labour Force Survey. The survey includes the following individual characteristics:

- Country of birth;

[2]Available on OECD site: https://stats.oecd.org/Index.aspx?DataSetCode=MIG.

[3]Australia, Bangladesh, Canada, Cyprus, France, Germany, Hong Kong, India, Ireland, Italy, Jamaica, Kenya, Malaysia, Middle East, New Zealand, Nigeria, Other Caribbean Commonwealth, Pakistan, Poland, Singapore, South Africa, Spain, Sri Lanka, U.S.A., Uganda.

[4]These are the destination countries in OECD database having no breaks in the time series of inflows from the countries/areas of origin identifiable from 1991 GB Census: Australia, Austria, Canada, Denmark, Finland, France, Germany, Italy, South Korea, Luxembourg, Netherlands, New Zealand, Norway, Spain, United States.

- Industry (2 digits-SIC92) of employment[5];
- Local Authority and Region of residence and employment;
- Human capital (highest educational degree);
- Occupation (SOC).

We define migrant workers as those born outside UK (that is, we use country of birth, as is standard in the literature, rather than country of nationality). We associate workers with their local authority or region of employment rather than residence, so that we avoid measurement error resulting from cross-border commuting. The immigrants' concentration variables are computed as share of employed population (estimated from APS using population weights) in the labour market, and disaggregated according to the type of migration considered (i.e. all; tertiary- vs below-tertiary-educated; EU vs non-EU origin).

As a robustness check, we construct an alternative measure of migration flows, using National Insurance Number (NINo) registrations. Natives, and immigrants who have been resident in the UK as children, automatically receive an NINo at 16; however, immigrants arriving as adults have to register if they wish to work. The Department of Work and Pensions publishes data on the number of registrations by local authority and by country of nationality. This allows us to construct a variable measuring migration flows by local authority of residence and country of origin; however, there is no information on sector, occupation or skill level.

For productivity, our dependent variable is gross value added (GVA) per head. Data on GVA (mln £, current prices) are taken from the December 2017 ONS release by ONS (Trenton, 2017)[6]. The dataset provides yearly estimates by Local Authority and by 2 digits-SIC07 Industry-by-Region cells, covering 1998 to 2016, and is based upon 7 components from the Business Register Employment Survey (BRES) and the Annual Business Survey (ABS). GVA figures are matched with estimates of employed population from BRES[7] (1998-2015, with the same level of disaggregation as GVA data) to compute GVA per head. We define tertiary education-immigrants as those whose highest educational attainment is college degree or equivalent, and below-tertiary education-immigrants those with high-school degree or less. Alternatively, we define immigrants in high-skill occupations as those with SOC

[5] APS waves from 2008 onward classify industries according to SIC07, but include a look-up variable for 2 digits-SIC92, which allows comparability with previous waves.

[6] Available on ONS site: https://www.ons.gov.uk/economy/grossvalueaddedgva/datasets.

[7] Available on NOMIS site: https://www.nomisweb.co.uk. Estimates from 1998 to 2007 are computed from Annual Business Inquiry, replaced, from 2009 onward, by BRES.

codes 1,2, 3 or 5. Our other dependent variable is training: the APS asks about any form of training (on- and off-the job) acquired by the worker in the last three months. We use the percentage of natives in each labour market who respond positively to this question.

To construct the variables described above, the empirical strategy requires combining several data sources which cover different time periods, and code the relevant information for the definition of labour markets (e.g. industry of employment) according to different standards. We therefore perform a mapping of both geographical and sectoral variables in order to get comparable labour markets units across the different datasets employed in this analysis. The geographical matching yields 214 aggregates of Local Authorities, resulting from the mapping between 278 aggregates of Local Authorities available in 1991 Great Britain's Census (individual 2% sample) and about 390 Local Authorities in APS and ONS GVA datasets, with London Boroughs merged into one labour market. 10 aggregates of Government Regions (NUTS2) are obtained from matching 12 aggregates of 1991 Census Regions with 19 Regions in the APS and ONS GVA datasets. The sectoral mapping provides 39 aggregates of 2 digits-SIC industries, resulting from the mapping between 1991 Census 2 digits-SIC80 industry aggregates, 2 digits-SIC92 in the APS and 2 digits SIC07 aggregates in the GVA dataset. The matching between 2 digits-SIC80 (1991 Census) and 2-digits-SIC92 (APS) is based on the proportional LFS SIC mapping by Jennifer Smith. The matching between 2 digits-SIC92 (APS) and 2 digits-SIC07 (GVA) is possible from APS data, providing a look-up variable for the two standards from 2008 onward. The configuration with Industry-by-Region cells therefore yields $10 \times 39 = 390$ units.

6 The model

For the short-term analysis on productivity we specify a linear model in 1-year first-differences per labour market c:

$$\frac{\Delta gva_{c,t}}{gva_{t-1}} = \alpha_0 + \alpha_1 \Delta \frac{imm_{c,t}}{emp_{c,t}} + \gamma \frac{\Delta emp_{c,t}}{emp_{t-1}} + \mu_t + \epsilon_{c,t} \tag{2}$$

The model in equation 1 is estimated over 11 1-year differences as we consider the period from 2004 to 2015. The outcome variable, $\frac{\Delta gva_{c,t}}{gva_{t-1}}$, is the yearly growth in GVA per head. The explanatory variable of interest is $\Delta \frac{imm_{c,t}}{emp_{c,t}}$, the change in the share of immigrants over employed population in c as estimated from APS data. The coefficient can thus be interpreted as the growth in GVA per head (in percentage points) associated with a one percentage point increase in the immigrant share in the employed population in the relevant labour market. We control for the growth in employed population (as estimated from BRES) and include year fixed effects. Standard errors are clustered at c level in order to account for correlation over time at the labour market level. We control for the growth in employed population (as estimated from BRES) and include year fixed effects. Standard errors are clustered at c level in order to account for correlation over time at the labour market level.

To examine the differential impact of high and low skilled migration (and EU and non-EU migration), we adopt a similar approach, but with two independent variables and two coefficients of interest, α_1 and α_2 as in equation 3 below:

$$\frac{\Delta gva_{c,t}}{gva_{t-1}} = \alpha_0 + \alpha_1 \Delta \frac{ter.\ ed.\text{-}imm_{c,t}}{emp_{c,t}} + \alpha_2 \Delta \frac{below\text{-}ter.\ ed.\text{-}imm_{c,t}}{emp_{c,t}} + \gamma \frac{\Delta emp_{c,t}}{emp_{t-1}} + \mu_t + \epsilon_{c,t} \tag{3}$$

The long-term estimates are performed over 11-years first differences (2004-2015) with a specification, as in equation 5, which does not include time fixed effects as we rely on one observation per labour market and with White robust standard errors to account for heteroskedasticity:

$$\frac{\Delta gva_{c,t}}{gva_{t-11}} = \alpha_0 + \alpha_1 \Delta \frac{imm_{c,t}}{emp_{c,t}} + \gamma \frac{\Delta emp_{c,t}}{emp_{t-11}} + \epsilon_{c,t} \tag{4}$$

The specification adopted for the training analysis follow an identical approach throughout, with a different dependent variable:

$$\frac{\Delta trained\ nat._{c,t}}{emp.\ nat._{t-1}} = \alpha_0 + \alpha_1 \Delta \frac{imm_{c,t}}{emp_{c,t}} + \gamma \frac{\Delta emp_{c,t}}{emp_{t-1}} + \mu_t + \epsilon_{c,t} \tag{5}$$

$\frac{\Delta trained\ nat._{c,t}}{emp.\ nat._{t-1}}$ is the yearly flow of newly trained natives over native employed population in $t-1$. Same, as for productivity study, model specifications are employed for the analysis disaggregating by immigrants' human capital and the long-term estimates.

7 Results: productivity

7.1 OLS estimates

Table 1 shows OLS estimates of GVA per head on migration with 3 different definitions of local labour markets: by local authorities in Panel 1, by 2 digit SIC code in panel B, and by 2 digit SIC code by region in Panel C. [8].

Columns 1 and 2 of each panel show short term estimates (1-year differences), while Columns 3 and 4 show the long-term estimates (over the entire 11 year period). The coefficients represent the change in GVA per head associated with a change in the share of immigrants from 0 to 1. That is, a coefficient equal to 1 implies that a 1 p.p. increase in migration is associated with a 1 p.p. increase in GVA per head.

The short-term analysis does not reveal any significant relationship between GVA per head and immigration for any configuration of labour markets. A 1 p.p. increase in immigration at 2 digits-SIC industry, for example, is associated with a negligible and insignificant drop in GVA per head, amounting to around 0.017 p.p (Panel B, Column 1). A similar pattern is observed when we focus on labour markets definitions with either by Local Authority or industry-by-Region breakdown as in Panels A and C. In Column 2 we distinguish between immigrants with tertiary education and those without. The point estimates are again close to zero and no significant correlation is found between GVA per head growth and either type of migration inflows.

The results in Columns 3 and 4 also show no clear evidence of a significant correlation between GVA and migration even over the longer time interval. At the local authority level, there is a significant association between immigrants with tertiary education and GVA, with a positive coefficient equal to 0.654 (Panel A, Column 4). However, this does not hold in the sectoral analyses, suggesting that any impact reflects geographical clustering of productive enclaves, that vanishes when considering sectoral aggregates. In any case, even to the extent that this provides some tentative evidence that skilled migration is associated with higher productivity at geographical level, the direction of causality is unclear, since it is possible that local demand or supply shocks, increasing productivity, may have attracted at the same time relatively more skilled migration.

Although the OLS results do not give strong evidence of any impact, positive or negative, of migration on productivity, unobserved and time-varying labour market-specific characteristics may still simultaneously affect both migration and productivity, leading to a bias in the estimated effect; and, as noted above, the direction of this bias is ambiguous. Any claim about causality therefore needs to rely on a quasi-experimental empirical strategy which is able to single out plausibly exogenous variations in immigration. In what follows we attempt to address these endogeneity issues by employing an

[8] The 2 digits-SIC industries-by-Region configuration is supposed to yield 390 labour markets cells (i.e. 39 industries aggregates $\times$ 10 Regions aggregates), but some of these are empty because no employed worker has been identified by APS in that year.

instrumental variable for migration inflows approach as in Card (2001).

Table 1. Immigration and GVA per head. OLS estimates. 2004-2015				
Dep. Var.: Growth in GVA per head				
	(1)	(2)	(3)	(4)
	Short-term analysis: 1-year diff.		Long-term analysis: 11-years diff.	
EXP. VAR.	A) Unit of agg: Local Authorities [n=214]			
$\Delta(Imm./Emp.\ Pop.)$	-0.00386		0.250	
	(0.0283)		(0.207)	
$\Delta(Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$		0.00389		0.654***
		(0.0435)		(0.230)
$\Delta(Below\text{-}Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$		-0.00813		-0.150
		(0.0361)		(0.243)
Observations	2,354	2,354	214	214
R^2	0.466	0.466	0.220	0.251
	B) Unit of agg: SIC-2d industries [n=39]			
$\Delta(Imm./Emp.\ Pop.)$	-0.174		0.488	
	(0.462)		(1.414)	
$\Delta(Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$		-0.280		1.310
		(0.517)		(1.884)
$\Delta(Below\text{-}Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$		-0.0806		0.326
		(0.689)		(1.344)
Observations	429	429	39	39
R^2	0.300	0.300	0.453	0.456
	C) Unit of agg: SIC-2d industries-by-Region [n=388]			
$\Delta(Imm./Emp.\ Pop.)$	-0.161		-0.119	
	(0.232)		(1.089)	
$\Delta(Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$		-0.157		0.798
		(0.321)		(0.893)
$\Delta(Below\text{-}Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$		-0.164		-1.077
		(0.378)		(1.624)
Observations	4,282	4,282	388	388
R^2	0.049	0.049	0.030	0.039

[1] Robust standard errors in parentheses (clustered at labor market level in Columns 1 and 2, White robust s.e. in Columns 3 and 4). All regressions account for growth in employed population. Regressions in Columns 1 and 2 include year fixed effects.

7.2 Instrumental variable: first stage estimates

Table 2 presents first stage estimates of the endogenous migration variables using the shift-share instrument. In Columns 1 and 4 we perform the first stage regressions of the model with one endogenous variable, the share of all immigrants in the employed population by labour market, for, respectively, the short and long term analysis. In Columns 2, 3, 5 and 6 we estimate the first stage equations for the share of high and low education immigrants in the model with two endogenous immigration variables.

The point estimates for the Local Authorities specification, in Columns 1 and 4 of Panel A, exhibit strong and positive coefficients. The F-statistic of the excluded instrument, which tests the strength of the instrument in predicting the endogenous variable, is in both cases well above the threshold of 10, which Staiger and Stock (1997) suggest as a rule of thumb to identify a strong enough first stage. This suggests it is a strong and appropriate instrument for causal estimation.

The first stage results for the share of tertiary-education immigrants (Columns 2 and 5, Panel A) show insignificant coefficients, but the value of the F-statistics, for both short and long term analysis, is generally above 10, signalling that the combination of the two instruments provides a sufficiently strong first stage. However, Baum, Schaffer and Stillman (2007) argue that the standard F for excluded instruments is insufficient to assess the weakness of the first stage in the case of multiple endogenous variables. We thus rely on the test proposed by Angrist and Pischke (2009) for weak identification of individual endogenous regressors, which nets out linear projections of the remaining endogenous regressors.

This test returns a value of 5.87 in the short-term (Column 2), and 17.84 in the long-term analysis (Column 5). Angrist and Pischke did not release any tabulation for the critical values of the test, but, if we stick to Staiger and Stock's 10 threshold, we may encounter weak-identification issues in the short-term case (A-P F=5.87), while having a sufficiently strong first stage in the long-term analysis (A-P F=17.84). The results for the share of below-tertiary education immigrants (Columns 3 and 6, Panel A) show significant point estimates for both instruments. However, although the F-statistics are above 10, the values of Angrist and Pischke weak identification test are slightly below that threshold and the second stage estimates may therefore not be entirely reliable.

The specification with industries aggregates in Panel B[9] does not yield strong first stages. Although

[9] 38 industries aggregates, rather than 39 as in OLS, are considered in 2SLS estimates for this specification. One of the industries aggregates identified has not indeed any match in 1991 GB Census data we employed

the estimates disaggregated by immigrants' human capital show significant point estimates (Columns 2, 3, 5 and 6, Panel B), F-Statistics and values of Angrist and Pischke weak identification test never pass the 10 threshold.

The instrumental variables are significantly correlated with the endogenous migration variables in the industry-by-Region level across all specifications in Panel C. However, the F-statistics from the model with one endogenous variable for the short-term analysis, in Column 1, is 5.48 and is hence a weak predictor of migration. The instruments performs better in the long-term case, with a F-statistic equal to 10.87, which is just above the Staiger and Stock's threshold and provides only weak evidence of a second stage robust identification, especially if compared to the Local Authorities specification The model with two endogenous variables returns a strong first stage for the long-term inflows of highly educated immigrants (Column 4, Panel C), but in the remaining specifications the instrument only weakly identifies migration, and exhibits values of Angrist and Pischke weak identification test lower than the specification with Local Authorities.

First stage estimates clearly show that there is a stronger evidence for the enclave effect, which is the source of correlation between the instrument and the actual migration flows, when we rely on immigrants' geographical clustering. A possible explanation is that migrants are characterized by higher sectoral than geographical mobility, and then historical concentration of same-origin immigrants at industry level may fail to strongly predict actual migration flows. If immigrants tend to settle in certain regions, on the other hand, the geographical ties will be more persistent. Overall, we conclude that our instrumental variable performs considerably better for the specification using Local Authorities. In what follows, we therefore present results using this specification. Results using the alternative specifications are available on request.

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for the construction of the instrumental variable for migration. For the setting with industries-by-Region cells, in Panel C, 380 industry-by-Region cells(38 industries agg. $\times$ 10 Region agg.), rather than 390 as in OLS estimates.

Table 2. First Stage Regressions. 2004-2015						
	(1)	(2)	(3)	(4)	(5)	(6)
	Short-term analysis: 1-year diff.			Long-term analysis: 11-years diff.		
DEP. VAR.:	Δ(*Imm./ Emp. Pop.*)	Δ(*Ter. Ed. Imm./ Emp. Pop.*)	Δ(*Below-Ter. Ed. Imm./ Emp. Pop.*)	Δ(*Imm./ Emp. Pop.*)	Δ(*Ter. Ed. Imm./ Emp. Pop.*)	Δ(*Below-Ter. Ed. Imm./ Emp. Pop.*)
EXP. VAR.	A) Unit of agg: Local Authorities [n=214]					
IV-Δ(*Imm./Emp. Pop.*)	1.23e-08***			1.16e-08***		
	(2.00e-09)			(2.51e-09)		
IV-Δ(*Ter. Ed. Imm./ Emp. Pop.*)		1.14e-07	-1.90e-07***		-1.01e-08	-1.51e-07**
		(7.82e-08)	(5.98e-08)		(6.15e-08)	(5.85e-08)
IV-Δ(*Below-Ter. Ed. Imm./ Emp. Pop.*)		-1.22e-07	2.31e-07***		3.66e-08	1.82e-07**
		(1.02e-07)	(7.71e-08)		(7.93e-08)	(7.56e-08)
Observations	2,354	2,354	2,354	214	214	214
First stage F-Statistic	37.53	45.5	22.68	21.19	34.19	24.3
Angrist-Pischke multivar. weak instr. test		5.87	4.51		17.84	7.17
	B) Unit of agg: SIC-2d industries [n=38]					
IV-Δ(*Imm./Emp. Pop.*)	7.60e-09			6.90e-09		
	(1.68e-08)			(1.59e-08)		
IV-Δ(*Ter. Ed. Imm./ Emp. Pop.*)		1.29e-08**	-3.55e-08***		1.61e-08**	-3.80e-08***
		(4.92e-09)	(9.25e-09)		(6.41e-09)	(9.62e-09)
IV-Δ(*Below-Ter. Ed. Imm./ Emp. Pop.*)		-3.01e-08	8.76e-08**		-3.55e-08	9.12e-08**
		(2.02e-08)	(3.32e-08)		(2.72e-08)	(3.51e-08)
Observations	418	418	418	38	38	38
First stage F-Statistic	.2	3.58	7.37	.19	3.18	7.86
Angrist-Pischke multivar. weak instr. test		.01	.04		.02	.09
	C) Unit of agg: SIC-2d industries-by-Region [n=378]					
IV-Δ(*Imm./Emp. Pop.*)	1.76e-07**			2.13e-07***		
	(7.47e-08)			(6.45e-08)		
IV-Δ(*Ter. Ed. Imm./ Emp. Pop.*)		1.09e-07***	-1.60e-07***		1.17e-07***	-1.75e-07***
		(3.57e-08)	(4.41e-08)		(3.62e-08)	(4.95e-08)
IV-Δ(*Below-Ter. Ed. Imm./ Emp. Pop.*)		2.42e-07**	8.08e-08		2.94e-07**	8.76e-08
		(1.09e-07)	(1.24e-07)		(1.14e-07)	(1.49e-07)
Observations	4,175	4,175	4,175	378	378	378
First stage F-Statistic	5.48	18.08	10.73	10.87	22.55	11.94
Angrist-Pischke multivar. weak instr. test		8.94	4.43		11.48	4.17

[1] Robust standard errors in parentheses (clustered at labor market level in Columns 1 to 3, White robust s.e. in Columns 4 to 6). All regressions account for growth in employed population. Regressions in Columns 1 to 3 include year fixed effects.

7.3 Instrumental variable: second stage estimates

Table 3 presents second stage estimates for the Local Authority specification. A 1 p.p. increase in the share of immigrants over one year is significantly associated with a 1.89 p.p. increase in GVA per head (Column 1, Panel A). The magnitude of the point estimate is larger, even if not statistically different, in the short term analysis (Column 3, Panel A), with a 1 p.p. increase in immigration leading to a 2.3 p.p increase in GVA per head. Both estimates are strongly significant. These estimates are large enough to be of macroeconomic significance; they are of similar orders of magnitude to that found by Jaumotte (2016).

Disaggregating between immigrants with different educational levels suggest that this is driven by immigrants with at least tertiary education. Column 2 shows that a 1.p.p increase in skilled migrants' share is associated with a 1.13 p.p. increase in GVA per head, while no significant correlation is found with lower skilled migrants' share of employed population (Column 2, Panel A). The same pattern is observed for the long-term analysis. Note, however, that the instrument performs best for the long-term analysis and for higher skilled migration.

In Panel B we perform a series of second stage estimates with a disaggregation by immigrants' country of origin as well, distinguishing between the share of immigrants from European Union and non-European Union countries[10]. Table A4, in Appendix section, shows first stage estimates with this disaggregation level, which only exhibits a strong enough first stage for the short-term analysis. No significant correlation is found between one year changes in productivity and either EU or non-EU immigrants' share (Column 1, Panel B). When immigrants are segmented into four groups (both EU vs non-EU and tertiary education versus others), as in Column 2, a 1 p.p. increase in the share of EU immigrants with tertiary education leads to a statistically significant 6.52 p.p. increase in GVA per head. The impact of migration over 11 years differences, on the other hand, cannot be estimated in a robust fashion as the first stage is only weakly identified (Columns 7 to 12, Panel A, Table A4).

In Table 4 we define skilled migration on the basis of the 1 digit-SOC occupation code[11]. Given that many migrants to the UK with tertiary education are in fact working in medium or low-skilled occupations, it is important to consider whether any productivity impacts are driven by immigrants' educational qualifications or their occupations. Point estimates are similar to the findings obtained

[10] Table A1, in Appendix section collects OLS estimates with this disaggregation level.

[11] Table A2 (All immigrants inflows) and A3 (analysis disaggregated by EU vs non-EU origin), in Appendix section, present OLS estimates with this skills definition, while Table A5 and A6 show first stage estimates.

when we used education to define migrants' skills set as in Table 3. A 1 p.p. increase in the share of immigrants in high-skilled occupations (1 digit-SOC categories 1, 2, 3 and 5) is associated with a 2.73 p.p., in the short-term, and a 3.25 p.p., in the long-term analysis, increase in GVA per head. The instrument did not perform well enough to enable us to disaggregate this further (by EU vs non-EU migration, see first stage results in Table A6).

As noted above, we have also constructed an alternative measure of migration flows, using National Insurance numbers, which provides a measure of flows by Local Authority. Adopting the same specification as above, we obtain similar results. Table A7, in the Appendix section, shows a positive and significant impact of overall migration flows on productivity. The magnitude of the estimate is smaller, although note that migration flows as measured by NI registrations are much higher than those shown by the APS. Disaggregating between EU and non-EU migrants (it is not possible to disaggregate by skills or occupation), we do not get a strong first stage[12], and second stage estimates are not reliable enough to show any causal inference.

[12] The values of the Angrist-Pischke weak identification test are below the threshold of 10, Panel B of Table A7

Table 3. Immigration and GVA per head. 2SLS estimates. 2004-2015

Dep. Var.: Growth in GVA per head

	(1)	(2)	(3)	(4)
	Short-term analysis: 1-year diff.		Long-term analysis: 11-years diff.	
EXP. VAR.	A) All Immigrants. Unit of agg: Local Authorities [n=214]			
Δ(*Imm./Emp. Pop.*)	1.892***		2.305***	
	(0.211)		(0.379)	
Δ(*Ter. Ed. Imm./ Emp. Pop.*)		1.134***		1.664***
		(0.431)		(0.523)
Δ(*Below-Ter. Ed. Imm./ Emp. Pop.*)		0.261		1.005
		(0.779)		(0.931)
Observations	2,354	2,354	214	214
EXP. VAR.	B) EU vs non-EU Imm. Unit of agg: Local Authorities [n=214]			
Δ(*EU Imm./Emp. Pop.*)	8.141		0.213	
	(5.335)		(2.837)	
Δ(*non-EU Imm./Emp. Pop.*)	-1.504		3.175**	
	(2.743)		(1.442)	
Δ(*EU Ter. Ed. Imm./ Emp. Pop.*)		6.529**		-5.309
		(2.608)		(26.17)
Δ(*Below-Ter. Ed. EU Imm./ Emp. Pop.*)		0.371		-0.762
		(1.152)		(3.717)
Δ(*Ter. Ed.non-EU Imm./ Emp. Pop.*)		-0.604		4.894
		(0.713)		(8.840)
Δ(*Below-Ter. Ed. non-EU Imm./ Emp. Pop.*)		1.852		1.784
		(2.453)		(7.033)
Observations	2,354	2,354	214	214

[1] Robust standard errors in parentheses (clustered at labor market level in Columns 1 and 2, White robust s.e. in Columns 3 and 4). All regressions account for growth in employed population. Regressions in Columns 1 and 2 include year fixed effects.

Table 4. Immigration and GVA per head. 2SLS estimates. 2004-2015
Immigrants' skills definition by 1 digit-SOC occupation code

Dep. Var.: Growth in GVA per head

	(1)	(2)	(3)	(4)
	Short-term analysis: 1-year diff.		Long-term analysis: 11-years diff.	
EXP. VAR.	A) All Immigrants. Unit of agg: Local Authorities [n=214]			
Δ(*Imm./Emp. Pop.*)	1.892***		2.305***	
	(0.211)		(0.379)	
Δ(*High SK. Occ. Imm./ Emp. Pop.*)		2.731***		3.256***
		(0.731)		(0.922)
Δ(*Low SK. Occ. Imm./ Emp. Pop.*)		0.727		1.090
		(1.372)		(1.646)
Observations	2,354	2,354	214	214
EXP. VAR.	B) EU vs non-EU Imm. Unit of agg: Local Authorities [n=214]			
Δ(*EU Imm./Emp. Pop.*)	8.141		0.213	
	(5.335)		(2.837)	
Δ(*non-EU Imm./Emp. Pop.*)	-1.504		3.175**	
	(2.743)		(1.442)	
Δ(*EU High SK. Occ. Imm./ Emp. Pop.*)		-7.406		-3.874
		(30.96)		(17.49)
Δ(*Low SK. Occ. EU Imm./ Emp. Pop.*)		8.520		0.599
		(19.20)		(4.013)
Δ(*Ter. Ed.non-EU Imm./ Emp. Pop.*)		15.77		5.789
		(31.86)		(12.03)
Δ(*Low SK. Occ. non-EU Imm./ Emp. Pop.*)		5.502		6.538
		(18.70)		(11.90)
Observations	2,354	2,354	214	214

[1] Robust standard errors in parentheses (clustered at labor market level in Columns 1 and 2, White robust s.e. in Columns 3 and 4). All regressions account for growth in employed population. Regressions in Columns 1 and 2 include year fixed effects.

8 Results: training

8.1 OLS estimates

The OLS estimates in Table 5[13] show a overall negative correlation between immigration and native-born workers' training. For the short-term analysis in Column 1, we find a significant and negative correlation between total immigration and training across all labour market specifications, ranging from a point estimate of 0.207 for Local Authorities (Panel A) to 0.355 for 2 digits-SIC industries (Panel B). A 1 p.p. increase in the migrants' share is thus associated to a significant, but rather small, drop in natives' training.

The direction and significance of the coefficients do not change if we distinguish migrants by human capital as in Column 2. For each definition of labour market, both tertiary education and below-tertiary education migrants' share show a negative and significant, although small, association with natives' training, with slightly higher magnitude for the latter category. The only exception is found in Panel B, where tertiary education migrants' share has a significant and positive association with training.

The pattern emerging from the long-term analysis is different. The migrants' share of employed population again shows a negative, and very small, correlation with natives' training (Column 3). However, when we disaggregate by immigrants' education level, the pattern is clearer: there is a negative, and somewhat larger, association with low-education immigrants across all labour market definitions in Column 4. There is no significant correlation with more educated immigrants.

These results cannot be interpreted as a negative causal impact of immigration. It is true that migration by increasing labour supply may reduce employers' incentive to train native workers via the potential drop in cost of labour. Reverse causality, however, may provide an alternative explanation of these findings: labour markets with lower level of training and related skills may attract more migrants to compensate the skills gap, resulting in a negative observed correlation. Again, we proceed to construct instrumental variable estimates to establish causality.

[13] We define here migrants' skills on the basis of highest education level. OLS estimates whit skills definition by 1 digit-SOC occupation code are available in Table A7 in Appendix section.

Table 5. Immigration and Natives' Training. OLS estimates. 2004-2015				
Dep. Var.: $\Delta(Trained\ Natives)_{t,t-1}/Employed\ Native\ Pop._{t-1}$				
	(1)	(2)	(3)	(4)
	Short-term analysis: 1-year diff.		Long-term analysis: 11-years diff.	
EXP. VAR.	A) Unit of agg: Local Authorities [n=214]			
$\Delta(Imm./Emp.\ Pop.)$	-0.207***		-0.114	
	(0.0401)		(0.111)	
$\Delta(Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$		-0.254***		0.0729
		(0.0648)		(0.125)
$\Delta(Below\text{-}Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$		-0.181***		-0.299***
		(0.0436)		(0.138)
Observations	2,354	2,354	214	214
R^2	0.148	0.149	0.010	0.036
	B) Unit of agg: SIC-2d industries [n=39]			
$\Delta(Imm./Emp.\ Pop.)$	-0.335**		-0.940**	
	(0.151)		(0.422)	
$\Delta(Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$		0.547**		0.106
		(0.206)		(0.494)
$\Delta(Below\text{-}Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$		-1.107***		-1.145**
		(0.253)		(0.547)
Observations	429	429	39	39
R^2	0.038	0.072	0.141	0.249
	C) Unit of agg: SIC-2d industries-by-Region [n=388]			
$\Delta(Imm./Emp.\ Pop.)$	-0.244***		-0.358*	
	(0.0385)		(0.184)	
$\Delta(Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$		-0.175**		0.0659
		(0.0756)		(0.229)
$\Delta(Below\text{-}Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$		-0.290***		-0.801***
		(0.0527)		(0.130)
Observations	4,282	4,282	388	388
R^2	0.033	0.034	0.024	0.096

[1] Robust standard errors in parentheses (clustered at labor market level in Columns 1 and 2, White robust s.e. in Columns 3 and 4). All regressions account for growth in employed population. Regressions in Columns 1 and 2 include year fixed effects.

8.2 Instrumental variable: second stage estimates

As for the productivity analysis, in Table 6 we only present 2SLS estimates at Local Authority level, since for the other labour market definitions we do not get a strong enough first stage for our instrumental variable.

The estimates in Columns 1 and 3 of Panel A consider the share of all foreign-born workers for, respectively, short and long-term analysis. In both cases, immigration has a positive impact on natives' training: over the short term, a 1 p.p. increase in migrants' share leads to a large and significant increase in natives' training of about 6.49 p.p. (Column 1); the impact amounts to 1.33 p.p. when we consider 11 years changes (Column 3).

When we separately assess the role of migrants by human capital, the results suggest that, similarly to productivity, this positive contribution to training in the short-term mainly arise from skilled migration. A 1 p.p. increase in tertiary education-immigrants' share over one year is associated with a 3.89 p.p. increase in training of native workers (Column 2, Panel A). The impact of skilled migration, however, vanishes in the long term, as shown by the positive and insignificant coefficient in Column 4 of Panel A.

Panel B collects the estimates with disaggregation of migration by EU vs non-EU country of origin and shows there is not any significant association with training, except for the case of a positive and significant coefficient for non-EU migrants in the long-term analysis (Column 3). However, this relies on a weak first stage (see Table A4 in the Appendix) and is therefore too weakly identified to yield a reliable estimate.

In Table 7 we define immigrants' skills on the basis of 1-digit SOC occupation code and find a positive and significant association of skilled migration with natives' training, which in this case also holds in the estimates over 11 years differences (Column 3). The instrument did not perform well enough to enable us to disaggregate this further (by EU vs non-EU migration, see first stage results in Table A6).

Table 6. Immigration and Natives' Training. 2SLS estimates. 2004-2015				
Dep. Var.: $\Delta(Trained\ Natives)_{t,t-1}/Employed\ Native\ Pop._{t-1}$				
	(1)	(2)	(3)	(4)
	Short-term analysis: 1-year diff.		Long-term analysis: 11-years diff.	
EXP. VAR.	A) All Immigrants. Unit of agg: Local Authorities [n=214]			
Δ(*Imm./Emp. Pop.*)	6.488***		1.330***	
	(0.802)		(0.287)	
Δ(*Ter. Ed. Imm./ Emp. Pop.*)		3.892**		0.267
		(1.621)		(0.370)
Δ(*Below-Ter. Ed. Imm./ Emp. Pop.*)		0.773		-0.832
		(3.279)		(0.685)
Observations	2,354	2,354	214	214
EXP. VAR.	B) EU vs non-EU Imm. Unit of agg: Local Authorities [n=214]			
Δ(*EU Imm./Emp. Pop.*)	29.42		-4.494	
	(35.80)		(3.807)	
Δ(*non-EU Imm./Emp. Pop.*)	-6.547		3.751**	
	(2.743)		(1.442)	
Δ(*EU Ter. Ed. Imm./ Emp. Pop.*)		21.53		36.84
		(13.17)		(92.80)
Δ(*Below-Ter. Ed. EU Imm./ Emp. Pop.*)		-3.251		3.925
		(4.696)		(14.08)
Δ(*Ter. Ed.non-EU Imm./ Emp. Pop.*)		-0.433		-11.72
		(4.977)		(30.57)
Δ(*Below-Ter. Ed. non-EU Imm./ Emp. Pop.*)		10.69		7.947
		(8.654)		(23.83)
Observations	2,354	2,354	214	214

[1] Robust standard errors in parentheses (clustered at labor market level in Columns 1 and 2, White robust s.e. in Columns 3 and 4). All regressions account for growth in employed population. Regressions in Columns 1 and 2 include year fixed effects.

Table 7. Immigration and Natives' Training. 2SLS estimates. 2004-2015
Immigrants' skills definition by 1 digit-SOC occupation code

Dep. Var.: $\Delta(Trained\ Natives)_{t,t-1}/Employed\ Native\ Pop._{t-1}$

	(1)	(2)	(3)	(4)
	Short-term analysis: 1-year diff.		Long-term analysis: 11-years diff.	
EXP. VAR.	A) All Immigrants. Unit of agg: Local Authorities [n=214]			
$\Delta(Imm./Emp.\ Pop.)$	6.488***		1.330***	
	(0.802)		(0.287)	
$\Delta(High\ Sk.\ Occ.\ Imm./Emp.\ Pop.)$		10.73***		2.422***
		(3.571)		(0.573)
$\Delta(Low\ Sk.\ Occ.\ Imm./Emp.\ Pop.)$		0.00776		-0.770
		(5.766)		(1.028)
Observations	2,354	2,354	214	214

[1] Robust standard errors in parentheses (clustered at labor market level in Columns 1 and 2, White robust s.e. in Columns 3 and 4). All regressions account for growth in employed population. Regressions in Columns 1 and 2 include year fixed effects.

9 Conclusions and policy implications

Our results suggest that immigration has a positive and significant impact (in both the statistical sense and more broadly) on productivity, as measured at a geographical level. The results for training are less clear, but suggest that higher-skilled immigration may have a positive impact on the training of native workers. and natives' training, measured at a local level. So far we have been unable to construct reliable estimates of impacts at a sectoral level.

These results are not apparent in our initial OLS estimates, but emerge when we use an instrumental variable approach to identify causality. The implication here is that immigration is in fact concentrated in areas with slower productivity growth: or rather, areas that would have seen, absent immigration, slower growth, but that the influx of immigrants helps boost their productivity growth back to the overall average. Our results show consistently more positive results for immigrants with higher levels of education, or working in higher-skilled occupations: although, given data limitations, these disaggregations should be treated with some caution.

The broad policy implications of our results are the following, in decreasing order of confidence:

- Our results suggest that the overall impact of immigration on productivity is positive and significant, as measured at a geographical level. We find no evidence to substantiate concerns that immigration has any significant negative impact (either in the statistical sense or more broadly) on overall productivity. Fears that immigration is responsible, in whole or in part, for the UK's dismal productivity performance appear unfounded. The clear policy implication is that significant restrictions on immigration relative to the current position risk having a negative impact on productivity, and certainly are unlikely to improve it.
- This positive impact appears to be driven by immigrants with higher skill levels, as measured either by their level of education or by occupation. The policy implication is that any new system designed to control economic migration should favour those with skills. However, the empirical analysis in this paper does not give clear guidance on whether educational qualifications, occupation (or some combination) is a better indicator of which migrants are most beneficial, and does not shed light on any negative impact of low-skilled migrants on productivity.
- Similar considerations apply to training analysis. Although our OLS estimates show an association between t higher migration inflows and lower training among native-born workers, the instrumental variable approach finds no significant impacts of immigration overall. , In fact,

we find a positive impact from skilled migration on the training of native workers; there is no significant impact from lower-skilled immigration..

- Our results do not appear to show any differential impact between EU and non-EU migrants. At first glance, this would seem to imply that any new system should not have any specific form of "EU preference". However, note that the immigrants in our data have already been selected under different regimes (EU free movement as opposed to the current, much more restrictive) system for non-EU migration, so this implication is not necessarily clear-cut.

Given the limitations of the data, consisting mainly of survey datasets, which may fail to provide reliable statistics for smaller labour markets, , these results should be treated with some caution. Our estimates of the size of these impacts are large – large enough to have a significant macroeconomic impact - but not estimated with great precision.

10 References

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