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 for 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 at 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; Peri, Romiti, and Rossi, 2015);
- 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, for which there exists now an extensive literature[4], the evidence for the UK (or indeed internationally) on the impact of migration on productivity and training has started to build up only recently. As a result, there is not as yet a clear consensus on either the sign or the magnitude of the possible impacts; nevertheless, it is worth reviewing the available empirical evidence on the topic.

At a cross-country level, Ortega and Peri (2014) examine the impact of both immigration and trade on income: they find that while openness to trade and migration both boost per capita income, migration has considerably larger impacts than trade; moreover, the impact of migration takes place chiefly via a positive effect on total factor productivity. However, their cross-sectional dataset is dominated by developing countries. Taking a different approach, Alesina, Harnoss, and Rapoport (2016) analyse the relationship between birthplace diversity – which they show is unrelated to traditional measures of diversity – and macroeconomic performance, showing that economic output is positively related with diversity caused by immigration, with immigrants from richer and culturally proximate countries being associated with higher productive effects.

In related research, Boubtane, Dumont, and Rault (2016) find that migration in general boosts productivity in advanced economies, but by varying amounts: for the UK, a short-term increase of 50% in net migration (as a proportion of the working age population) is associated

[4] For a recent meta-analysis, see Longhi, Nijkamp, and Poot (2010).

with a short-term increase in yearly GDP per worker of 0.32%, and a long-term increase of 2.23%. These estimates are higher than for 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. The dataset, however, only runs up to 2006 and includes a rather limited number of observations for a panel of 22 countries.

Similarly, Jaumotte, Koloskova, and Saxena (2016) apply a similar specification to that of Ortega and Peri to a panel of selected countries, finding 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. The findings are consistent across a variety of empirical specifications, although again the study analyses a limited dataset. Perhaps surprisingly, the estimated aggregate impact of high and low skilled migration are not significantly different. However, the distributional implications are: while both top and bottom earners seem to benefit from increases in immigration, the gain is larger for the highest decile. One possible, partial explanation for both skill levels benefiting domestic workers 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 and Peri, Romiti, and Rossi, 2015). 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 but growing body of research looking at the relationship between immigration and labour productivity. For the US, Ottaviano and Peri (2006) find evidence of diversity positively affecting the productivity of workers in major cities, going as far as stating that "data support the hypothesis of a positive productivity effect of diversity with *causation running from diversity to productivity of US workers*"[5]. Peri (2012) decomposes multiple components of output growth and estimates the impact of immigration on each, finding that immigration is consistently associated with increases in Total Factor Productivity in

[5] Italics in the original.

excess of 1% (which is found to be sufficient to counteract the lower associated growth of skill intensity and skill bias of production). The idea that migrant inflows lower the skill bias of production is also put forward by Quispe-Agnoli and Zavodny (2002), who find immigration to be associated with lower labour productivity in the manufacturing sector (although other sectors could experience countervailing effects that are not considered). In a more recent paper, Kemeny and Cooke (2018) use a large administrative longitudinal dataset and, proxying productivity with income, find "a robust positive relationship between earnings and both city- and workplace-specific manifestations of immigrant diversity" – although the effects tend to be significantly smaller than the estimates in Ottaviano and Peri (2006). Estimated spillovers are found to benefit higher-wage workers the most, with no negative effects on lower-wage quartiles; importantly, the authors find sizeable differences between city- and establishment-level spillovers, with the former unexpectedly larger than the latter.

In the UK, Ottaviano, Peri, and Wright (2018) analyse the services sector finding that a 1% increase in immigrant inflow in the firms' locality is associated with a (large) increase in labour productivity within the firm. It is however worth noting that, for lack of more granular data, their strategy relies on matching firm-level data with immigrant population estimated at TTWA level from the Labour Force Survey, which can present significant measurement error issues – especially in the determination of migration inflows (an issue that, as we will see below, is also relevant to this paper). Using the same data sources, Rolfe et al. (2013) look at productivity by region and sector and, although they do not attempt to establish causality, they find immigrant share to be positively associated with labour productivity; additionally, they provide significant qualitative evidence of the complementarity between domestic and foreign workers, as well as the existence of skill shortages that immigrants help overcome.

A smaller number of studies analyse other countries' experience. Exploiting the natural experiment associated with the large inflow of skilled Russian nationals to Israel in the 1990s, Paserman (2013) finds seemingly contrasting evidence: while at a macroeconomic level there seems to be a positive medium-term effect of immigration on productivity (consistent with

Ottaviano and Peri, 2006 and Peri, 2012), at a firm level the relationship between firm productivity and non-native employee share is negative (consistent with Quispe-Agnoli and Zavodny, 2002): the author suggests this could be a result of labour-force sorting among industries. For Germany, Trax, Brunow, and Suedekum (2015) use firm-level data on firm performance and nationality of employees to find a positive impact of employee diversity on productivity (at both a firm and a regional level), while interestingly they are unable to find a significant effect for the immigrant share *per se*.

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

The evidence is considerably sparser for education, skills and training. A few empirical studies related to this topic concentrate on natives' school attendance and performance: in the US, Hunt (2017) and McHenry (2015) find that, given the potential downward pressure put by immigrants on low-skilled sectors' wages, natives have more incentives to invest in human capital. Hunt finds that immigration (in particular of individuals with less than 12 years of school) increases the probability of finishing 12 years of education, while McHenry analyses a wider class of educational attainment indicators to conclude that low-skill immigration increases schooling investment – an increase that, as the author notes, is either a loss or a benefit depending on whether students choose schooling optimally *ex ante*. In the UK, Geay, McNally, and Telhaj (2013) find that correcting for selection of immigrant children into schools with 'less desirable characteristics' yields neutral or slightly positive spillover effects from non-native English speakers on school performance among natives. Previous work commissioned by the MAC (George et al., 2012), found evidence of complementarities between highly skilled immigrants and natives, and no evidence to suggest that, overall, skilled migration reduced training for natives. However, as far as we know, no quantitative 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[6]. 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:

[6]See here.

- 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 Portes and Forte, 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, Dumont, and Rault, 2016 and Jaumotte, Koloskova, and Saxena, 2016 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 of analysing the impact of migration: we examine the relationship between variation in levels of migration and outcomes of interest across labour markets within Great Britain over the 2004-2015 period. In the literature, labour markets can be defined either by reference to geography, to sector, or to skill group. The latter is not entirely relevant here (since productivity is a firm-level concept) so we only consider geographical and sectoral divisions, plus a hybrid specification which interacts the geographical and sectoral dimensions. In principle, it is important to analyse both geographical and sectoral impacts of immigration, since different causal mechanisms might be expected to have different impacts depending on the nature of the complementarities and spillovers between migrants and natives: different impacts could operate, interact, and dominate at firm, sectoral or geographic level. Unfortunately, however, it proved impossible to construct a sufficiently robust instrumental variable to purse the sector-level analysis, so results are only reported in the Appendix.

Specifically, we define our units of observation as:

- Local Authorities;
- Travel-To-Work Areas;
- Aggregates of 2-digit Standard Industrial Classification (SIC) industries. As noted above, results are only reported in the Appendix.
- Aggregates of 2-digit SIC industries interacted with statistical regions (NUTS2). As noted above, results are only reported in the Appendix.

The independent variable of interest is the number of migrant workers. We start by focusing on aggregate impacts, considering all migrant workers as a homogeneous group, then move on to distinguish the role played by 'skilled' and 'unskilled' migration. We use two different measure of immigrants' skills; the first is based on education data which allows us to 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: we divide 1-digit Standard

Occupational Classification (SOC) codes into 'higher-skill' occupations (divisions 1, 2, 3 and 5) and 'lower-skill' occupations (divisions 4, 6, 7, 8 and 9). //

Furthermore, we introduce an additional level of disaggregation by attempting to assess the impact associated with workers from European Union (EU) and non-EU 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 the UK should continue to give some form of preferential treatment to EU migrants post-Brexit is high on the political and policy agenda.

We specify a linear model in first-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. The principal reason for analysing the data in differences is that this practice should in principle net out the effect of any time-invariant variable in the linear model. Note however that, while year-on-year differences 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 adapt production techniques, ways of working, and management techniques to take advantage of migrants' skills; training might not be undertaken immediately following an immigration shock. Following these considerations, we also consider the cumulative impacts over the entire time period (2004-2015) as an additional outcome variable.

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 theoretically be a substitute for investment, or a complement to it. As a result, 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 and more granular data, 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 or both variables are functions of a third covariate, then a simple regression of productivity or training on immigration may yield biased estimates of the causal impact of migration on productivity. Moreover, crucially, this bias could run in either direction. While there is significant consensus that immigrants select into labour markets with more favourable conditions (lower unemployment, higher wages) thus yielding an obvious reasonable prior on the sign of the bias associated with labour market impact analyses, the direction of such bias in our regression estimates is not obvious. That is, immigration flows might be higher to low productivity sectors, which demand more workers to expand or maintain output; or they might be higher to high productivity sectors which are more attractive and likely to be growing.

Empirically, we 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. The rationale behind 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 cycles 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 in order to benefit from the existent network effects. 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 and, more generally, the counterfactual inflows are not systematically correlated with any omitted variable that might influence the relationship under analysis, the requirements for a valid instrument are credibly satisfied and consistent estimates of the causal impact of immigration on the dependent variables of interest can be calculated.

We adopt a specification of the shift-share instrument similar to Bianchi, Buonanno, and Pinotti, 2012: specifically, the 'shift' is the aggregate inflow from origin a to all countries except the UK; this flow is then allocated across sub-national labour markets on the base of the historical concentration (the 'share')[7] – i.e. concentration of non-native population as captured by the 1991 Census. We rely on inflows to countries other than the UK as immigration to the UK from any set of areas of origin 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: for example, labour-demand shocks in London may significantly affect national migration inflows and spill over other geographical areas, therefore compromising the instrument's validity. For this reason, the 'shift' component of the instrument in this paper considers migration inflows which can plausibly assumed to be exogenous: the maintained assumption that ensures validity is that the 'relative attractiveness' of different UK labour markets does not systematically affect migration to other countries. Note that, while there exists evidence that relative attractiveness of hosting countries is relevant to the choice of destination of the immigrant (Bertoli and Moraga, 2013), validity in our study relies on the credible assumption that changes in performance of UK local authority/occupation labour markets (rather than country-wide economic performance) are not systematically related to the choice of which country, among a number of countries *other than the UK*, to migrate to.

4.1 Data

Our key independent variable is the number of migrants in employment in each labour market. We construct these figures from the Annual Population Survey Secure Access 2004-2016 data set (APS henceforth) provided by the UK Data Service: each wave of the survey comprises

[7]In other specifications in the literature, the shift is constructed as 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; since we do not however observe exact inflows to the specific cells, we resort to this alternative approach that excludes UK immigration entirely.

between 300,000 and 400,000 individual observations from 4 quarters of the Longitudinal Labour Force Survey, plus minor local sample boosts sponsored by governmental agencies. The survey includes, among many others, the following individual characteristics:

- Country of birth;
- Industry (2-digit SIC92) of employment[8];
- Local Authority and Region of residence and employment;
- Highest Educational Degree;
- Occupation (SOC).

Using this information, we define as migrant workers those born outside the UK (that is, we use country of birth, as is standard in the literature, rather than country of nationality). We then associate workers with their local authority or region of employment rather than residence, in order to avoid measurement error resulting from cross-border commuting. Immigrant concentration variables for each labour market cell are computed as share of the overall employed population (estimated from APS) in the labour market; we then disaggregate immigration into inflows with diverse characteristics (e.g. tertiary- vs below-tertiary-educated; EU vs non-EU origin).

We define tertiary-educated immigrants as those whose highest educational attainment is at least college degree or equivalent, and below-tertiary-education immigrants those with high-school degree or less. As for occupations, we define immigrants in high-skill occupations those employed in SOC codes 1,2, 3 or 5; codes 4, 6, 7, 8, 9 are defined as 'low-skill' occupations.

Our dependent variable intended to capture productivity is Gross Value Added (GVA) per employment contract. Data on GVA (£ millions, current prices) are obtained from the December 2017 ONS release (Office for National Statistics, 2017)[9]. The data set provides (at

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

[9] Available on the ONS website at this link.

the time of writing) 1998-2016 yearly estimates of GVA by Local Authority and 2-digit SIC07 Industry-by-Region cells; the data set is based upon 7 components from the Business Register Employment Survey (BRES) and the Annual Business Survey (ABS).
These GVA figures are then matched with estimates of the number of employment contracts by labour market cell from the BRES[10], data for which is available for the 1998-2015 period at same level of disaggregation as GVA data, to compute GVA per employment contract as the ratio of the two figures. We favour a measure of GVA that is standardised by the number of contracts rather than population (a more common denominator in GVA summary statistics) as we believe that number of contracts is a superior proxy for measure of the labour market, as it inherently takes into account the demographics and tightness of the labour market as well as individuals having multiple jobs.

The second dependent variable of interest is training: to gauge its extent, we consider the APS questions regarding any form of on- and off-the-job training acquired by the worker in the last three months, and we use the (weighted) percentage of natives in each labour market who respond positively to this question to form a measure of the pervasiveness of training.

As a partial robustness check for immigration stocks, we construct an alternative measure of migration inflows, using National Insurance Number (NINo) registrations. Natives, as well as immigrants who have been resident in the UK as children, automatically receive a 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; these data allow us to construct a variable measuring migration inflows by local authority of residence and country of origin. Note that, however, there is no information on sector, occupation or skill level: NINo data can only act as a partial sense check for the analysis based on local authority cells.

In constructing the above variables and the shift-share instrument, we employed multiple data

[10] Available on the NOMIS website. More precisely, estimates from 1998 to 2008 are computed from Annual Business Inquiry – replaced, from 2009 onward, by BRES.

sources covering different time periods and mapped relevant information on the definition of labour markets (e.g. industry of employment) between different standards, which unavoidably resulted in a number of compromises.

The geographical matching yields 380 Local Authorities, resulting from mapping the about 390 Local Authorities in APS and ONS GVA data sets into the Local Authorities available in the 1991 Census data set (100% sample information[11]), 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 GVA data sets. Finally, we map Local Authorities into 173 groups of TTWAs: in fact, although TTWA information is available for the 1991 Census, we are unable to exactly match TTWAs due to the boundary changes that they underwent in the last two decade[12].

The sectoral mapping provides 39 aggregates of 2-digit SIC industries, resulting from the mapping between 1991 Census 2-digit SIC80 industry aggregates, 2-digit SIC92 in the APS and 2-digits SIC07 aggregates in the GVA data set. Matching between 2-digit SIC80 (1991 Census) and 2-digit SIC92 (APS) is based on the proportional Labour Force Survey SIC mapping proposed by Jennifer Smith[13]; matching between 2-digit SIC92 (APS) and 2-digit SIC07 (GVA) is possible from APS data directly, as a look-up variable for the two standards is provided from 2008 onward. As a result of the mapping, there are thus $10 \times 39 = 390$ Industry-by-Region cells.

4.2 Specification

The analysis of the short-term of the impact of immigration on productivity is based on the following linear regression in 1-year first-differences, estimated over the 2004-2015 period:

$$\frac{\Delta(gva_{c,t}/emp_{c,t})}{gva_{c,t-1}/emp_{c,t-1}} = \alpha_0 + \alpha_1 \Delta \frac{imm_{c,t}}{emp_{c,t}} + \alpha_2 \frac{\Delta emp_{c,t}}{emp_{c,t-1}} + \tau^{\intercal}\mu + \epsilon_{c,t} \tag{1}$$

[11]Available on the NOMIS website under 1991 Census - Local Base Statistics.
[12]In what follows we will often refer to 'TTWA' rather than 'group of TTWAs' for simplicity.
[13]Information available at this link.

where outcome variable, $\frac{\Delta(gva_{c,t}/emp_{c,t})}{gva_{c,t-1}/emp_{c,t-1}}$, is the yearly growth in GVA per employment contract. The set of explanatory variables includes a constant; the change in the share of immigrants over employed population in c, $\Delta\frac{imm_{c,t}}{emp_{c,t}}$; a control of labour market growth, $\frac{\Delta emp_{c,t}}{emp_{c,t-1}}$; and τ, a column vector of year fixed effects. The coefficient α_2 in (1) can thus be interpreted as the growth in GVA per contract (in percentage points) associated with a one percentage point increase in the immigrant share of the employed population in the relevant labour market, after controlling for market growth and year FE. Standard errors are clustered at c level in order to account for autocorrelation at the labour market level.

To examine the differential impact of high-/low-skilled and EU/non-EU migration we adopt a similar approach, only with two separate independent variables and two coefficients of interest, β_1 and β_2 in equations (2), (3) below:

$$\frac{\Delta(gva_{c,t}/emp_{c,t})}{gva_{c,t-1}/emp_{c,t-1}} = \beta_0 + \beta_1\Delta\frac{TerEd\text{-}imm_{c,t}}{emp_{c,t}} + \beta_2\Delta\frac{BTerEd\text{-}imm_{c,t}}{emp_{c,t}} + \beta_3\frac{\Delta emp_{c,t}}{emp_{c,t-1}} + \tau^{\intercal}\mu + \epsilon_{c,t} \quad (2)$$

$$\frac{\Delta(gva_{c,t}/emp_{c,t})}{gva_{c,t-1}/emp_{c,t-1}} = \beta_0 + \beta_1\Delta\frac{EU\text{-}imm_{c,t}}{emp_{c,t}} + \beta_2\Delta\frac{non\text{-}EU\text{-}imm_{c,t}}{emp_{c,t}} + \beta_3\frac{\Delta emp_{c,t}}{emp_{c,t-1}} + \tau^{\intercal}\mu + \epsilon_{c,t} \quad (3)$$

In order to account for the short- and long-term impacts of immigration differing (e.g. due to change in investment in and use of complementary/substitute factors of production) we also estimate specification (1) over the 2004-2015 difference, omitting time fixed effects as we rely on one observation per labour market (note all clusters have unit size, so clustered standard errors are identical to heteroscedasticity-robust standard errors). That is, denoting by $\tilde{\Delta}$ the 2015-2004 difference, we estimate

$$\frac{\tilde{\Delta}[gva_c/emp_c]}{emp_{c,2004}/gva_{c,2004}} = \gamma_0 + \gamma_1\tilde{\Delta}\frac{imm_c}{emp_c} + \gamma_2\frac{\tilde{\Delta}emp_c}{emp_{c,2004}} + \epsilon_c \quad (4)$$

The specifications adopted for the training analysis follow an identical approach throughout, replicating equations (1), (2), (3) and (4) with a different dependent variable. For example, (1) becomes

$$\frac{\Delta\ trained\ natives_{c,t}}{employed\ natives_{c,t-1}} = \delta_0 + \delta_1\Delta\frac{imm_{c,t}}{emp_{c,t}} + \delta_2\frac{\Delta emp_{c,t}}{emp_{c,t-1}} + \tau^{\intercal}\mu + \epsilon_{c,t} \quad (5)$$

$\frac{\Delta \ trained \ natives_{c,t}}{employed \ natives_{c,t-1}}$ being the year-on-year change in the stock of trained natives over native employed population in the past period.

4.2.1 Shift-Share Instrument

As for the first stage instrument, the counterfactual migration inflow to labour market c is defined as:

$$\Delta Imm_{c,t}^{IV} \equiv \sum_{a=1}^{25} \widehat{\Delta M_{a,c,t}} = \sum_{a=1}^{25} S_{a,c}^{1991} \times \Delta M_{a,t}^{OECD} \tag{6}$$

That is, the predicted migration inflow from area of origin a to labour market c at time t, $\widehat{\Delta M_{a,c,t}}$, 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 UK Census share of immigrants from a in c over the UK total.

The $\Delta M_{a,t}^{OECD}$ component is derived from the OECD International Migration Flows Database[14], collecting information on yearly inflows for each origin-OECD destination pair, spanning the 2000-2015 period. We match the OECD data with the set of 25 areas of origin identifiable from the 1991 Census[15], and consider a set of 15 substantially diverse OECD destinations[16] representing a group of countries comparable to UK in terms of development, all with an experience of substantial migration inflows for the last two decades.

The final instrument $\Delta Imm_{c,t}^{IV}$ is the sum of predicted inflows from all 25 areas of origin. While most of the specifications in the migration literature standardise the instrument with a lagged measure of labour market population, we avoid doing so as this may induce spurious

[14] Available on the OECD website: https://stats.oecd.org/Index.aspx?DataSetCode=MIG.

[15] 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.

[16] 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.

correlation between an otherwise irrelevant instrument and the endogenous immigration share via a common denominator (see Clemens and Hunt, 2017). As an alternative, the authors suggest including labour market population growth as an additional (exogenous) covariate: we follow this approach, including $\frac{\Delta emp_{c,t}}{emp_{c,t-1}}$ in all specifications. The first stage specification in all[17] Two-Stage Least Squares estimators is

$$\Delta \frac{imm_{c,t}}{emp_{c,t}} = \kappa_0 + \kappa_1 \Delta Imm_{c,t}^{IV} + \kappa_2 \frac{\Delta emp_{c,t}}{emp_{c,t-1}} + \tau^\intercal \mu + \eta_{c,t} \tag{7}$$

5 Results: Productivity

5.1 OLS estimates

Table 1 shows OLS estimates of GVA per head regressed on migration at a geographical level: by Local Authorities in the upper panel, by Travel To Work Areas in the lower panel. Columns 2 and 4 disaggregate immigrants into those with tertiary education and those without. Table 2 performs the same analysis, disaggregating immigrants into those in high and low skilled occupations.

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 percentage point (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 growth in GVA per head and immigration in the short term. A 1 p.p. increase in immigration at TTWA level, for example, is associated with a negligible and insignificant increase in GVA per head, amounting to around 0.026 p.p. (Panel B, Column 1). This is also the case when immigrants

[17] As explained above, Year FE are not included in 2015-2004 FD specification.

are disaggregated by education or occupational level.

Over the longer term, there is some evidence of a correlation between immigration and GVA growth, particularly at TTWA level, where a 1 percentage point increase in the migrant share is associated with a 0.54% increase in GVA per head. Disaggregating the results by the type of immigrant supports this, but does not show any consistent pattern. In any case, even to the extent that this provides some tentative evidence that migration is associated with higher productivity at geographical level, the direction of causality is unclear.

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.	Unit of aggregation: Local Authorities [n=380]			
Δ(*Imm./Emp. Pop.*)	0.0174		0.259	
	(0.0310)		(0.169)	
Δ(*Ter. Ed. Imm./ Emp. Pop.*)		0.0887		0.851***
		(0.0545)		(0.184)
Δ(*Below-Ter. Ed. Imm./ Emp. Pop.*)		-0.00731		-0.304
		(0.0315)		(0.205)
Observations	4,180	4,180	380	380
R^2	0.489	0.490	0.261	0.318
EXP. VAR.	Unit of aggregation: Travel-to-Work Areas [n=173]			
Δ(*Imm./Emp. Pop.*)	0.0267		0.544**	
	(0.0395)		(0.249)	
Δ(*Ter. Ed. Imm./ Emp. Pop.*)		0.115		1.311***
		(0.0957)		(0.398)
Δ(*Below-Ter. Ed. Imm./ Emp. Pop.*)		0.00783		0.216
		(0.0411)		(0.267)
Observations	1,903	1,903	173	173
R^2	0.496	0.497	0.214	0.236

Notes: 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 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.	Unit of aggregation: Local Authorities [n=380]			
Δ(*Imm./Emp. Pop.*)	0.0174		0.259	
	(0.0310)		(0.169)	
Δ(*High Sk. Occ. Imm./ Emp. Pop.*)		0.0976*		0.957**
		(0.0562)		(0.380)
Δ(*Low Sk. Occ. Imm./ Emp. Pop.*)		-0.0581		0.381
		(0.0396)		(0.338)
Observations	4,180	4,180	380	380
R^2	0.489	0.490	0.261	0.274
EXP. VAR.	Unit of aggregation: Travel-to-Work Areas [n=173]			
Δ(*Imm./Emp. Pop.*)	0.0267		0.544**	
	(0.0395)		(0.249)	
Δ(*High Sk. Occ. Imm./ Emp. Pop.*)		0.0518		0.849
		(0.103)		(0.790)
Δ(*Low Sk. Occ. Imm./ Emp. Pop.*)		-0.0496		0.908**
		(0.0346)		(0.443)
Observations	1,903	1,903	173	173
R^2	0.496	0.497	0.214	0.219

Notes: 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 2: ***Immigration and GVA per head. OLS estimates. 2004-2015***

In general, OLS results do not give strong evidence of any impact, positive or negative, of migration on productivity, because unobserved and time-varying labour market-specific characteristics may still simultaneously affect both migration and productivity, leading to a bias in the estimated effect. 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 employ the instrumental variable approach detailed in Section 4.2.1.

5.2 Instrumental variable: first stage estimates

Table 3 presents first stage estimates of the endogenous migration variables using the shift-share instrument for both Local Authorities and Travel to Work Areas. In Columns 1 and 4 we perform the first stage regressions of the model taking the share of all immigrants in the employed population by labour market as endogenous for, respectively, the short and long term analysis. In Columns 2, 3, 5 and 6 we estimate similar first stage equations taking the share of high and low education immigrants as endogenous.

The point estimates for the Local Authorities specification, in Columns 1 and 4 of the upper panel, exhibit statistically significant 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, Stock, et al. (1997) suggest as a rule of thumb to identify a strong enough first stage. This suggests it is a strong and appropriate instrument for estimation. Similarly, the first stage of share of tertiary-educated and below-tertiary-educated immigrants (Columns 2 and 5, 3 and 6) show significant coefficients, with F-statistics well above 10 for both short and long term analysis. The lower panel shows the same estimates for Travel to Work Areas. Here, the results are somewhat weaker, with the F-statistic below 10 for all immigrants, although well above 10 when immigrants are disaggregated by level of education. Table 4 repeats this procedure, disaggregating immigrants by occupational skill level; the results are similar, but somewhat weaker, with the instrument generally performing well at local authority level but less so at TTWA level, particularly in respect of low skilled immigration.

	(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.	Unit of aggregation: Local Authorities [n=380]					
IV-Δ(*Imm./Emp. Pop.*)	9.85e-08***	2.53e-07***	-1.40e-07***	9.87e-08***	2.33e-07***	-1.06e-07***
	(2.37e-08)	(2.07e-08)	(2.35e-08)	(2.52e-08)	(2.18e-08)	(2.91e-08)
Observations	4,180	4,180	4,180	380	380	380
R^2	0.008	0.064	0.016	0.080	0.551	0.227
First stage F-Statistic	17.33	149.71	35.63	15.33	114.55	13.35
EXP. VAR.	Unit of aggregation: Travel-to-Work Areas [n=173]					
IV-Δ(*Imm./Emp. Pop.*)	8.44e-09***	1.54e-08***	-7.11e-09***	6.76e-09**	1.39e-08***	-6.32e-09***
	(2.93e-09)	(3.16e-09)	(1.24e-09)	(3.01e-09)	(3.24e-09)	(1.80e-09)
Observations	1,903	1,903	1,903	173	173	173
R^2	0.008	0.052	0.011	0.067	0.320	0.028
First stage F-Statistic	8.32	23.58	32.98	5.05	18.32	12.4

Notes: 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.

Table 3: ***First Stage Regressions, Education Division. 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(*High Sk. Occ. Imm./ Emp. Pop.*)	Δ(*Low Sk. Occ. Imm./ Emp. Pop.*)	Δ(*Imm./ Emp. Pop.*)	Δ(*High Sk. Occ. Imm./ Emp. Pop.*)	Δ(*Low Sk. Occ. Imm./ Emp. Pop.*)
EXP. VAR.	Unit of aggregation: Local Authorities [n=380]					
IV-Δ(*Imm./Emp. Pop.*)	9.85e-08***	7.76e-08***	5.03e-08***	9.87e-08***	6.51e-08***	3.44e-08**
	(2.37e-08)	(1.41e-08)	(1.43e-08)	(2.52e-08)	(1.39e-08)	(1.63e-08)
Observations	4,180	4,180	4,180	380	380	380
R^2	0.008	0.007	0.009	0.080	0.233	0.102
First stage F-Statistic	17.33	30.4	12.47	15.33	21.87	4.44
EXP. VAR.	Unit of aggregation: Travel-to-Work Areas [n=173]					
IV-Δ(*Imm./Emp. Pop.*)	8.44e-09***	5.23e-09***	2.52e-09***	6.76e-09**	4.10e-09***	5.78e-10
	(2.93e-09)	(7.74e-10)	(9.59e-10)	(3.01e-09)	(6.89e-10)	(1.02e-09)
Observations	1,903	1,903	1,903	173	173	173
R^2	0.008	0.010	0.010	0.067	0.178	0.102
First stage F-Statistic	8.32	45.67	6.92	5.05	35.52	.32

[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.

Table 4: ***First Stage Regressions, Skill Division. 2004-2015***

As noted above, first stage estimates clearly show that there is strong 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. However, specifications using industries, or industries by region, do not perform well and therefore second stage estimates are likely to yield unreliable estimates of the parameters of interest.

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 specifications using Local Authorities and TTWAs. In what follows, we therefore present results using these specifications.

Similarly, specifications that disaggregated between EU and non-EU migration did not perform well, and are hence omitted in the results below. This may reflect that our instrument – based as it is on historic migration patterns – is ill-suited to instrument the large increase in EU migration flows that occurred after 2004, since these were of a distinctly different character to pre-2004 flows.

Results using alternative labour market specifications and disaggregating between EU and non-EU migrants are reported in the Appendix, but given these considerations we would caution against regard them as reliable evidence of causal impact.

5.3 Instrumental variable: second stage estimates

Table 5 presents second stage estimates analogous to Table 1. At the LA level, a 1 p.p. increase in the share of immigrants over one year is significantly associated with a 2.95 p.p. increase in GVA per head (Column 1, Panel A); the long term estimate, 2.96 p.p., is almost identical. Similar results are found at TTWA level, with the long-term estimate here being somewhat larger than the short-term one, although none of the estimates are significantly different from each other. All 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, Koloskova, and Saxena (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 1.14 p.p. increase in GVA per head, for unskilled migrants the association is -1.96 p.p. 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.

Dep. Var.: Growth in GVA per head						
	(1)	(2)	(3)	(4)	(5)	(6)
	Short-term analysis: 1-year diff.			Long-term analysis: 11-years diff.		
EXP. VAR.	Unit of aggregation: Local Authorities [n=380]					
Δ(*Imm./Emp. Pop.*)	2.948***			2.962***		
	(0.939)			(1.054)		
Δ(*Ter. Ed. Imm./ Emp. Pop.*)		1.144***			1.021***	
		(0.214)			(0.289)	
Δ(*Below-Ter. Ed. Imm./ Emp. Pop.*)			-1.956***			-0.872
			(0.423)			(0.721)
Observations	4,180	4,180	4,180	380	380	380
EXP. VAR.	Unit of aggregation: Travel-to-Work Areas [n=173]					
Δ(*Imm./Emp. Pop.*)	2.661***			3.389***		
	(0.495)			(1.002)		
Δ(*Ter. Ed. Imm./ Emp. Pop.*)		1.466***			1.761***	
		(0.126)			(0.339)	
Δ(*Below-Ter. Ed. Imm./ Emp. Pop.*)			-2.940***			-0.996
			(0.698)			(1.019)
Observations	1,903	1,903	1,903	173	173	173

[1] Robust standard errors in parentheses (clustered at labor market level in Columns 1, 2 and 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.

Table 5: ***Immigration and GVA per head. 2SLS estimates. 2004-2015***

Dep. Var.: Growth in GVA per head						
	(1)	(2)	(3)	(4)	(5)	(6)
	Short-term analysis: 1-year diff.			Long-term analysis: 11-years diff.		
EXP. VAR.	Unit of aggregation: Local Authorities [n=380]					
Δ(*Imm./Emp. Pop.*)	2.948***			2.962***		
	(0.939)			(1.054)		
Δ(*High SK. Occ. Imm./ Emp. Pop.*)		3.785***			4.339***	
		(0.919)			(1.262)	
Δ(*Low SK. Occ. Imm./ Emp. Pop.*)			5.635***			7.529*
			(2.045)			(4.083)
Observations	4,180	4,180	4,180	380	380	380
EXP. VAR.	Unit of aggregation: Travel-to-Work Areas [n=173]					
Δ(*Imm./Emp. Pop.*)	2.661***			3.389***		
	(0.495)			(1.002)		
Δ(*High SK. Occ. Imm./ Emp. Pop.*)		4.326***			5.046***	
		(0.493)			(1.023)	
Δ(*Low SK. Occ. Imm./ Emp. Pop.*)			8.817***			32.53
			(2.268)			(51.81)
Observations	1,903	1,903	1,903	173	173	173

[1] Robust standard errors in parentheses (clustered at labor market level in Columns 1, 2 and 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.

Table 6: ***Immigration and GVA per head. 2SLS estimates. 2004-2015***

Table 6, analogous to Table 2, disaggregates by occupational skill level. In contrast to Table 5, it suggests that both immigrants in both high- and low-skill-occupation are associated with increases in GVA per head. However, again, the first stage results suggest that we should treat the results, particularly for lower skilled immigration, with caution.

As noted above, as a robustness check, 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.

6 Results: Training

6.1 OLS estimates

The OLS estimates in Table 7 and 8 show an overall negative correlation between immigration and native-born workers' training at both Local Authority and TTWA level in the short term. For the short-term analysis in Column 1, we find a significant and negative correlation between total immigration and training: a 1 p.p. increase in the migrants' share is associated with a fall of about 0.08 p.p. in the share of natives who report having undertaken training in the last three months. This is statistically significant, but fairly small. Over the long term, we find no significant association.

Disaggregating immigration by either educational or occupation is inconclusive, although it suggests that higher-skill or more educated migrants may be associated with an increase in native workers' training: for example, at both LA and TTWA level, a 1 p.p. increase in more educated immigrants in associated with approximately a 0.4 p.p. increase in training for native workers.

Again, 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. It is also the case that possible mechanisms exist by which migration could increase the incentives for natives to acquire skills via training. Again, we proceed to construct instrumental variable estimates to establish causality.

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.	Unit of agg: Local Authorities [n=380]			
Δ(*Imm./Emp. Pop.*)	-0.0795***		0.126	
	(0.0191)		(0.0830)	
Δ(*Ter. Ed. Imm./ Emp. Pop.*)		0.0481		0.430***
		(0.0676)		(0.109)
Δ(*Below-Ter. Ed. Imm./ Emp. Pop.*)		-0.124***		-0.162**
		(0.0216)		(0.0704)
Observations	4,180	4,180	380	380
R^2	0.059	0.061	0.039	0.167
EXP. VAR.	Unit of agg: Travel-to-Work Areas [n=173]			
Δ(*Imm./Emp. Pop.*)	-0.0825**		-0.00452	
	(0.0337)		(0.106)	
Δ(*Ter. Ed. Imm./ Emp. Pop.*)		-0.134		0.369***
		(0.113)		(0.130)
Δ(*Below-Ter. Ed. Imm./ Emp. Pop.*)		-0.0714**		-0.164
		(0.0294)		(0.106)
Observations	1,903	1,903	173	173
R^2	0.108	0.109	0.037	0.104

[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. 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.	Unit of agg: Local Authorities [n=380]			
Δ(*Imm./Emp. Pop.*)	-0.0795***		0.126	
	(0.0191)		(0.0830)	
Δ(*High Sk. Occ. Imm./ Emp. Pop.*)		-0.0174		0.953***
		(0.0541)		(0.225)
Δ(*Low Sk. Occ. Imm./ Emp. Pop.*)		-0.0533*		0.0487
		(0.0303)		(0.144)
Observations	4,180	4,180	380	380
R^2	0.059	0.057	0.039	0.142
EXP. VAR.	Unit of agg: Travel-to-Work Areas [n=173]			
Δ(*Imm./Emp. Pop.*)	-0.0825**		-0.00452	
	(0.0337)		(0.106)	
Δ(*High Sk. Occ. Imm./ Emp. Pop.*)		-0.166		0.516*
		(0.117)		(0.272)
Δ(*Low Sk. Occ. Imm./ Emp. Pop.*)		-0.0604		-0.162
		(0.0370)		(0.200)
Observations	1,903	1,903	173	173
R^2	0.108	0.108	0.037	0.064

[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 8: ***Immigration and Natives' Training. OLS estimates. 2004-2015***

6.2 Instrumental Variable: Second Stage Estimates

As for the productivity analysis, in Tables 9 and 10 we only present 2SLS estimates at Local Authority and TTWA level, since for the other labour market definitions we do not get a strong enough first stage for our instrumental variable.

The tables show consistently positive, and generally (but not always) significant impacts of migration on the training of native workers. For example, at local authority level, a 1 p.p. increase in the migrant share is associated with a 10.1 p.p. increase in native workers' training; at TTWA level, the (more precisely estimated) impact is 4.5 p.p. Over the long-term, the estimated impacts are still positive, but much smaller, and arguably more plausible; at Local Authority level, the estimated impact is 0.99 p.p, and at TTWA level 0.51 p.p.

Disaggregating by educational or occupational skill level does not yield a consistent pattern, although again the long term estimates are lower, and perhaps more plausible, than the short-term ones. The strongest results are those that show a positive impact, over the long-term, of migrants in high skilled occupations on the training of natives.

Dep. Var.: $\Delta(Trained\ Natives)_{t,t-1}/Employed\ Native\ Pop._{t-1}$						
	(1)	(2)	(3)	(4)	(5)	(6)
	Short-term analysis: 1-year diff.			Long-term analysis: 11-years diff.		
EXP. VAR.	Unit of agg: Local Authorities [n=380]					
$\Delta(Imm./Emp.\ Pop.)$	10.08**			0.987**		
	(4.193)			(0.482)		
$\Delta(Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$		3.855***			0.252	
		(1.304)			(0.162)	
$\Delta(Below\text{-}Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$			-7.153***			0.435
			(2.479)			(0.641)
Observations	4,180	4,180	4,180	380	380	380
EXP. VAR.	Unit of agg: Travel-to-Work Areas [n=173]					
$\Delta(Imm./Emp.\ Pop.)$	4.496***			0.510*		
	(0.805)			(0.270)		
$\Delta(Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$		2.439***			0.152*	
		(0.362)			(0.0875)	
$\Delta(Below\text{-}Ter.\ Ed.\ Imm./$ $Emp.\ Pop.)$			-5.686***			0.421
			(1.588)			(0.379)
Observations	1,903	1,903	1,903	173	173	173

[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 9: ***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)	(5)	(6)
	Short-term analysis: 1-year diff.			Long-term analysis: 11-years diff.		
EXP. VAR.	Unit of agg: Local Authorities [n=380]					
Δ(*Imm./Emp. Pop.*)	10.08**			0.987**		
	(4.193)			(0.482)		
Δ(*High SK. Occ. Imm./ Emp. Pop.*)		12.85***			1.419***	
		(3.415)			(0.461)	
Δ(*Low SK. Occ. Imm./ Emp. Pop.*)			19.81*			1.035
			(11.09)			(1.408)
Observations	4,180	4,180	4,180	380	380	380
EXP. VAR.	Unit of agg: Travel-to-Work Areas [n=173]					
Δ(*Imm./Emp. Pop.*)	4.496***			0.510*		
	(0.805)			(0.270)		
Δ(*High SK. Occ. Imm./ Emp. Pop.*)		7.298***			0.887***	
		(1.230)			(0.290)	
Δ(*Low SK. Occ. Imm./ Emp. Pop.*)			15.42***			2.635
			(4.006)			(5.960)
Observations	1,903	1,903	1,903	173	173	173

[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 10: ***Immigration and Natives' Training. 2SLS estimates. 2004-2015***

7 Conclusions and policy implications

Our results suggest that immigration has a positive and significant impact (in both the statistical and economic senses) 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. So far we have been unable to construct reliable estimates of impacts at a sectoral level, or to disaggregate between EU and non-EU migration.

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, substantial and significant, as measured at a geographical level; this finding appears robust, and consistent with other evidence in the literature that also find large positive impacts at aggregate 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 our analysis of training, although our view is that these results are less robust. Again, we find some evidence of a positive impact of migration on training, and little or no evidence to suggest significant negative impacts. Concern about the negative impacts of migration on training, in aggregate, are not substantiated by our analysis. However, our results here are less consistent and should be treated with caution; we would not place too much weight on any specific quantitative estimates here.

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.

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Appendix

{ *To be added.* }