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Only human? Immigration and firm productivity in Britain

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Abstract
This paper estimates the impact of migration on productivity by estimating production functions for British firms. We find that much of the apparent higher productivity of migrants is the result of sorting across areas, industries, and firms. If we include firm fixed effects, the estimated productivity advantage of migrants over locals is not significantly different from zero. One possible interpretation of our results is that migrants and locals with similar skills are equally productive; there is nothing distinctive about migrants. However, since productivity estimates are imprecise after controlling for firm fixed effects, we also can't reject the hypothesis that migrants and locals differ in their productivity.

Key words: productivity, migration
JEL: J24; J61

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1 Introduction

Krugman (1997) famously said "Productivity isn't everything, but in the long run, it's almost everything". If immigration affects productivity this is likely to be one of its most important economic effects.

Migration might affect productivity in many ways. Immigration can affect innovation either directly through migrants being innovators (Hunt and Gauthier-Loiselle, 2010) or influencing the incentives for firms to create and adopt new technologies (Lewis, 2013; Clemens et al., 2018; San, 2023). Migrants may also affect entrepreneurship (Waldinger, 1986; Nathan and Lee, 2013; Kerr and Kerr, 2020; Azoulay et al., 2022). If immigration increases the size of the labour force, this may change the capital-labour ratio (depending on how elastic the supply of capital is) and have agglomeration or congestion effects. Or, the subject of this paper, immigration may affect productivity through its effect on the composition of the labour force.

The existing literature on immigration and productivity differs in the nature of the data used and conclusions. Some studies use cross-sections of country-level data (Ortega and Peri, 2014; Alesina et al., 2016) or country-level panels (Boubtane et al., 2016; Jaumotte et al., 2016). Others have explored the effects of immigration on productivity within countries aggregated at regional or region-industry levels (Peri, 2012; Campo et al., 2018; Nam and Portes, 2023). Others (Ottaviano et al., 2018; Mitaritonna et al., 2017) use firm-level data but measure the share of migrants at the local labour market level, instrumenting to address endogeneity concerns about the location decision of migrants. Some studies use matched employer – employee data sets to measure migrant share at the firm-level (Paserman 2013 in Israel, Parrotta et al. 2014 in Denmark, Fabling et al. 2022 in New Zealand, and Ek 2024 in Sweden), though it is then hard to find firm-level instruments to address endogeneity concerns. There are also papers which study the effects of immigration on longer-term prosperity, relating differences in outcomes within countries today to variations in the location of immigration in the distant past (Rocha et al., 2017; Sequira et al., 2021; Murard and Sakalli, 2021).

The conclusions are mixed. Most studies which use firm-level migrant share find negative effects of immigration on labour productivity: Ek (2024) finds that migrants have cultural values associated with lower labour productivity, Paserman (2013) finds a negative relationship between Soviet immigration and firm productivity in Israel, and Parrotta et al. (2014) finds a negative association between ethnic diversity and firm productivity in Denmark. Most studies defining the migrant share at a higher level of aggregation than the firm find positive effects. These effects vary in magnitude from moderate to very large. For example, Ottaviano et al. (2018) is closest to our paper in terms of data used and finds that an immigrant inflow equal to 1% of local employment leads to a 3% rise in firm labour productivity in the UK service sector.

Studies reporting large positive effects sometimes explain it in terms of migration raising the productivity of locals either through complementaries in production or facilitating greater specialization. As will be explained later in the paper, these mechanisms cannot explain the findings; we show that what is identified is the difference in marginal products between migrants and locals so that finding, for example, that a 1 percentage point increase in the migrant share raises productivity by 3% implies that migrants, at the margin, are 4 times as productive as locals. Productivity effects of this magnitude, if true, would transform the debate over the economic impact of migration, which has largely focused on the modest effect of immigration on employment and wages (see among others Card 2001; Borjas 2003; Ottaviano and Peri 2012, and for the UK Dustmann et al. 2005, 2013). As the migrant-local earnings gap is nowhere near productivity gaps of this magnitude, such a finding also raises the question of who receives the extra productivity, a question that the literature on immigration and productivity does not address.

If there are differences between the productivity of immigrants and locals, it is important to understand why. Research should try to explain why immigrants have different productivity though this is often not the focus of the existing literature. A good analogy would be the gender pay gap; we aspire not just to estimate its magnitude (though that is useful) but to understand why it exists. The ideal endpoint of research should be a regression in which the included covariates are sufficiently rich that the coefficient on gender is zero; one would then have explained the gender pay gap in terms of regressors.

This agenda is particularly important in immigration because we do not simply want to know whether immigration is good or bad for productivity but to understand the sorts of migrants who are more productive so that we can better design immigration policy. If the included covariates are sufficiently rich that the coefficients on the migrant dummy variables are zero one would have explained any difference in productivity between migrants and locals in terms of regressors and those findings could, in principle, be used to design immigration policy to influence productivity. Depending on the data available, one may not be able to reach this endpoint and some unexplained productivity gaps might remain; it is also possible that country of birth per se has some effect on productivity. Nevertheless, it is important to see how far one can go in explaining productivity gaps between migrants and locals.

The approach taken in this paper is in the spirit of this research agenda i.e. to investigate how productivity gaps change when controlling for characteristics. We use firm-level financial data from England and Wales for the period 1998-2019 inclusive. Following Ottaviano et al. (2018) and Mitaritonna et al. (2017) we use the migrant share in the local labour market as the key regressor. We define the local labour market using neighbourhood data and commuting patterns following the approach in Manning and Petrongolo (2017). This approach is more precise than existing UK studies (Ottaviano et al., 2018; Campo et al., 2018; Nam and Portes, 2023) and allows us to control for different trends in productivity at higher levels of geographical aggregation. Controlling for geographical productivity trends is important in the UK because London evolves differently from other regions. To address potential endogeneity of the migrant share we use a shift-share type instrument but, different from most of the existing literature, we use distance to the location of Polish resettlement camps after 1945 as the basis for allocating migrants from the EU8 countries[1] as in Viskanic (2018). There was a big increase in the share of migrants from Poland following the expansion of the EU in 2004 and where Poles had been re-settled after 1945 predicts the location of this later cohort.

We estimate firm-level production functions using different control function approaches that have been proposed in the literature (see Mollisi and Rovigatti 2017 for a review). We use different specifications with varying assumptions regarding the endogeneity of the migrant share and other factors of production (labour and capital). In one set of specifications we treat migrants and locals as different types of labour but each group as homogeneous. In another set, we further differentiate by skill leading to four types of labour - high- and low-skill, migrant and local. Using different sets of fixed effects we also investigate the extent to which migrant productivity differentials result from the sorting of immigrants across regions, industries, and firms and the extent to which there remain unexplained gaps. Reporting many results rather than a single headline finding is important to give some idea of the robustness of the results.

Our main conclusions are as follows. First, much of the apparent higher productivity of migrants is the result of sorting across areas, industries, and firms. If we do not differentiate by skill, we

[1] Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, Slovenia

find that migrants are more productive than locals but the gap is much smaller than found in other UK studies, a difference that can be largely explained by our inclusion of area trends rather than just area and time fixed effects. However, when we include firm fixed effects, the estimated productivity advantage of migrants over locals is smaller still and no longer significantly different from zero. When we further differentiate labour by skill, we find that it is high- rather than low-skill migrants that seem the more productive. But, again, these effects are no longer significantly different from zero when we include fixed effects. One possible interpretation of our results is that migrants and locals with similar skills are equally productive; there is nothing distinctive about migrants. However, since productivity estimates are imprecise after controlling for firm fixed effects, we also can't reject the hypothesis that migrants and locals differ in their productivity.

In perfectly competitive labour markets, relative marginal products between different types of workers will equal relative wages (Hellerstein et al., 1999). Since we have information on firm labour costs, we also estimate equations for average earnings in the firm, to see how they are affected by the migrant share. If we do not include firm fixed effects, we find that relative marginal products are higher than relative wages for high-skilled migrants and high-skilled locals, perhaps because of some monopsony power in the labour market (Amior and Manning, 2020; Borjas and Edo, 2023; Amior and Stuhler, 2024). With the inclusion of firm fixed effects estimates become too imprecise to reject the equality of marginal products and relative wages.

The plan of the paper is as follows. The second section describes our data on productivity and migrants. The third section describes our framework and our empirical methodology. The fourth section presents our results on firm-level productivity. Section five looks at the effects of migration on the labour share. Section six concludes.

2 Data

2.1 Firm financial data

The data on firms comes from ARDx, a panel dataset of firms in England and Wales from 1998 to 2019. The ARDx sample is drawn from the Inter-Departmental Business Register (IDBR). Large firms (more than 250 employees) are always part of the sample, but for smaller firms (less than 250 employees) the panel is holed and unbalanced. The ARDx panel contains data on employment and turnover from the Inter-Departmental Business Register (IDBR) and balance sheet accounting information (output, costs, capital expenditures etc.) from the Annual Business Inquiry (ABI) from 1998 - 2008 and the Annual Business Survey (ABS) for subsequent years. ARDx also includes more detailed employment information from the Business Register Employment Survey (BRES). The firm-level ARDx data is our source of data for value-added, output, employment, and capital stock.

We use 'firm' to refer to what in ARDX is called a reporting unit (with identifier ruref)[2]. A reporting unit can be a collection of plants (known as local units with identifier luref).

Linking firms to locations: Less than 1% of firms in the have multiple plants, but these make up around 10% of firms in the ARDx sample because it over-samples large firms which are more likely to be multi-plant. We know the exact location of all plants but because multi-plant firms will match to multiple locations it is hard to define a local labour market for them. In our main specification, we only use firms with one local unit so we are sure about their geographical

[2]In rare cases, a firm is split into two reporting units (e.g. for legal reasons GB and Northern Ireland local units might be split)

location. In a robustness check in Appendix A3, we allocate reporting unit (ruref) values to local units (luref) based on the plant share in firm employment or link reporting units with multiple plants to their modal location.

Measuring firm employment: For all firms, we have employee headcount from the IDBR, both at the local unit and reporting unit level. This is the measure of employment we use in our main regression specification. For less than half of firms in the years 1998 - 2014, we also have the number of employees split by gender and full-time/part-time. In Appendix A4 we use this information to calculate employment full-time equivalents; results using this measure are very similar.

Measuring capital stock: The ARDx capital stock is created using the Perpetual Inventory method to generate reporting unit level capital stocks. [3].

The ARDx panel has an average of 46,000 firms per year leading to a full ARDx sample of 1,009,253 ruref - years. Keeping only single-plant firms takes us to 901,396, of which 569,946 have non-missing values for all our key firm variables (value added, capital stock, and employment). Taking logs (i.e., dropping zero or negative values) of firm value-added, capital stock, and employment takes us to our final regression sample of 526,003 firm-years. Some summary statistics are reported in Table 1.

Table 1: Firm-year level summary statistics, pooling 1998 - 2019.

Variable	Mean	Median	St. Dev	N
Employment	149	14	1,536	682,383
Employment FTE	197	23	1,589	369,064
Turnover	22,867	810	50,0815	682,383
Labour costs	3,193	205	29,588	683,889
Output (gross)	13,515	786	11,5457	377,049
Value added	5,664	349	59,192	600,674
Capital stock	9,835	114	18,5457	652,507
Operating Surplus	2,393	72	40,529	556,779
Capital per FTE	74	11	1,833	307,400
Value Added per FTE	44	25	641	256,637

Financial variables in real throusand £, rounded to the nearest thousand £.
Source: ARDx

2.2 Migrant population data

The firm-level data does not have information on worker characteristics that would allow us to compute firm-level measures of the migrant and skill shares of employment. For measures of labour mix we use the shares in the local labour market (defined later) of the firm. There will be some measurement error in replacing firm-level by market-level shares but this is of the group aggregate form that does not lead to attenuation bias and, in any case, we will use an instrumental variable strategy.

The data for migrant and skill shares comes from three surveys: UK Quarterly Labour Force Survey (QLFS) 1994 - 2003; UK Annual Population Survey (APS) 2004 - 2021; UK decennial census small area statistics (1981, 1991, 2001, 2011, 2021). All these surveys are individual

[3]For more information on how this variable is constructed, refer to the ARDx Capital Stock User Guide.

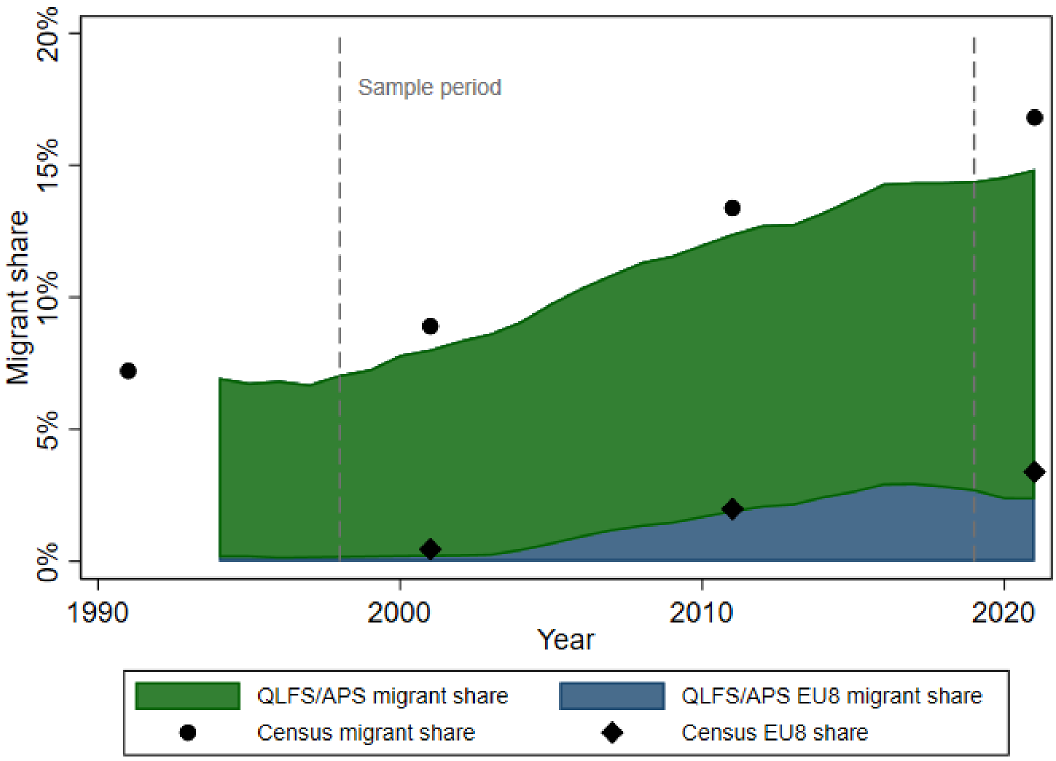
micro-samples with location at the detailed CAS ward geographical level (approximately 8,000 CAS wards in England and Wales). We define migrant status by country of birth. We define two broad skill groups using SOC occupational categories: high-skilled for occupation groups 1 - 3[4] and lower-skilled for all other occupation groups 4 - 9[5]. We use occupation rather than educational attainment as our measure of skill because the QLFS/APS is known to misclassify the education of migrants and because of evidence of occupational down-grading among migrants (Dustmann et al., 2013).

The employee mix data we use in our analysis comes from the QLFS for 1994 - 2003 and the larger APS for 2004 onwards. The sample size is approximately 320,000 respondents for each annual APS dataset and 150,000 for combined annual quarters of the QLFS. These surveys contain weights to allow grossing up to the total population. Figure 1 shows the overall migrant share of the population over the period 1994-2021 from the QLFS/APS. For comparison are the shares from the decennial census which show similar trends. The overall share of migrants in the population grew at a historically fast rate from the late 1990s, especially after the eastward expansion of the EU in 2004. Figure 1 shows that the share of migrants from the EU8 countries increased substantially post-2004; this is the most marked change in our sample period.

[4]Managers, directors and senior officials, professional occupations, and associate professional and technical occupations.

[5]Administrative and secretarial occupations, skilled trades occupations, caring, leisure and other service occupations, process, plant and machine operatives, elementary occupations.

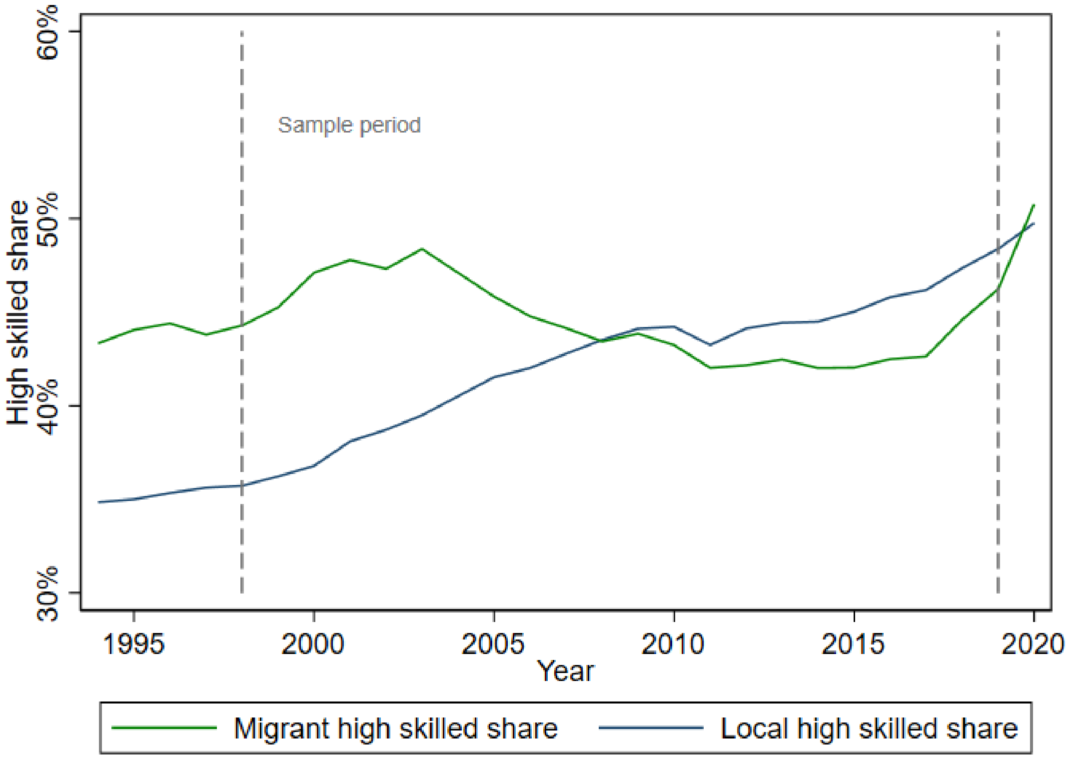
Figure 1: Migrant share of population: England and Wales 1991 - 2021.



Source: QLFS 1994 - 2003; APS 2004 - 2021, Census (1991, 2001, 2011, 2021)

The skill mix of the migrant and local labour force has also been changing. Figure 2 shows that the share of the UK-born ('locals') who were high-skilled was rising steadily as later birth cohorts have more education. For migrants the trend is different; in the late 1990s migrants were more highly skilled than the locals. But the gap began to close after EU expansion in 2004 as many of the migrants from Eastern Europe worked in lower-skilled jobs. By the end of our sample period, migrants were less skilled than locals, though this began to reverse again later in the pandemic as many lower-skilled Europeans left the UK.

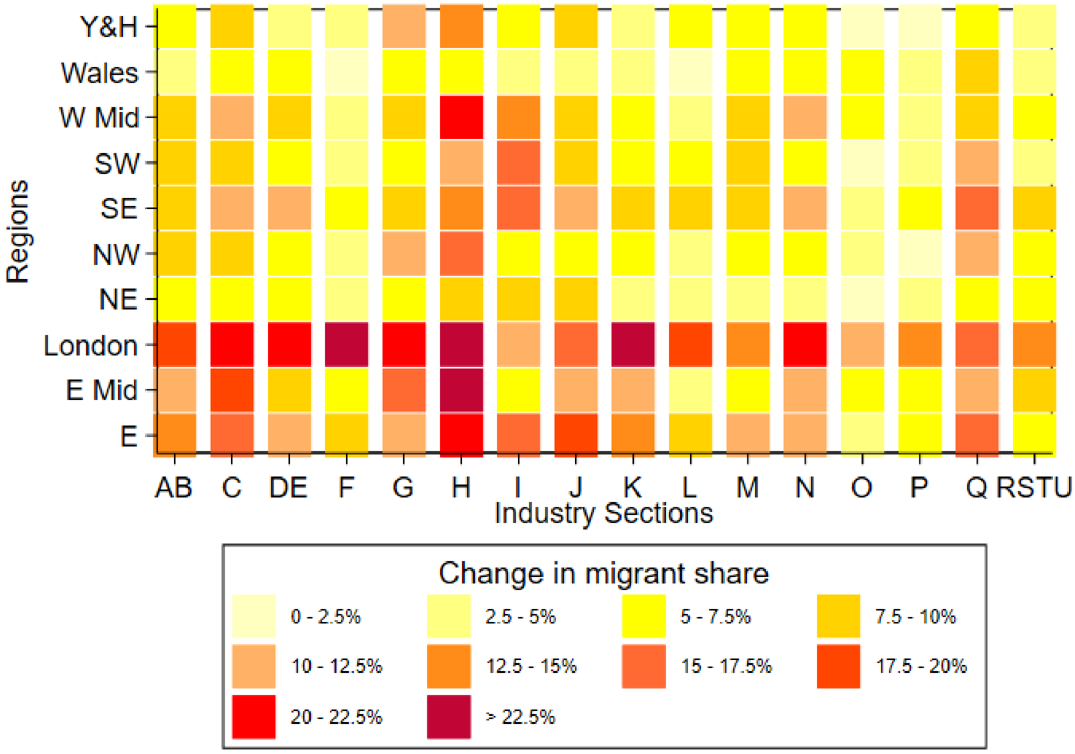
Figure 2: High skilled (occupation groups 1 - 3) share of migrant and local worker: England and Wales 1994 - 2021.



Source: QLFS 1994 - 2003; APS 2004 - 2021

Crucial to our identification strategy is that the change in the migrant share varied with geography and industry. To illustrate this type of variation Figure 3 shows the increase in migrant share over our sample period by government office region of work and broad industry. London saw the the largest increase in migrant share while the industries with the largest increases are transport, hospitality, and healthcare. Our regressions use employee shares defined using narrower definitions of both geography and industry than shown in Figure 3. Specifically, we use variation at the 2-digit industry and CAS ward geographical levels.

Figure 3: Change in migrant share England and Wales between 1998 and 2019, by industry section and work region.



AB: Agriculture, Forestry, Fishing, Mining, Quarrying; C: Manufacturing; DE: Electricity, Gas, Water; F: Construction; G: Wholesale and Retail Trade; H: Transport and Storage; I: Accommodation and Food Services; J: Information and Communication; K: Financial and Insurance Activities; L: Real Estate; M: Professional, Scientific, and Technical; N: Administrative and Support; O: Public Administration and Defence; P: Education; Q: Health; RSTU: Arts, Other Services

Source: QLFS 1998; APS 2019

Table 2 shows the average characteristics of migrant and local workers at the beginning, mid-point and end of our sample period. At the start migrants earned more than locals, in the middle of our sample period they earned similar amounts, and by the end they earned more again, reflecting the change in the skill mix seen in Figure 2. Although migrants sometimes have higher mean earnings, we show later that when control for region of work, industry, and occupation they face a pay penalty of around 5% throughout our sample period.

Table 2: Migrant and local worker characteristics in England and Wales 1998, 2009, and 2019.

	Mean	St.Dev	Mean	St.Dev
1998	Local		Migrant	
Hourly wage	7.75	5.98	8.59	6.89
Gross weekly pay	282.83	235.89	319.35	303.67
Age	38.49	12.34	39.08	11.51
Usual hours	33.56	12.08	34.75	12.26
2009	Local		Migrant	
Hourly wage	12.47	10.28	12.58	9.34
Gross weekly pay	438.55	378.37	456.29	376.10
Age	41.89	2.79	39.23	11.51
Usual hours	33.13	11.31	34.50	11.01
2019	Local		Migrant	
Hourly wage	15.81	23.41	16.29	30.22
Gross weekly pay	555.73	774.50	601.06	1,211.94
Age	42.98	13.22	40.48	10.98
Usual hours	33.52	10.87	34.99	10.28

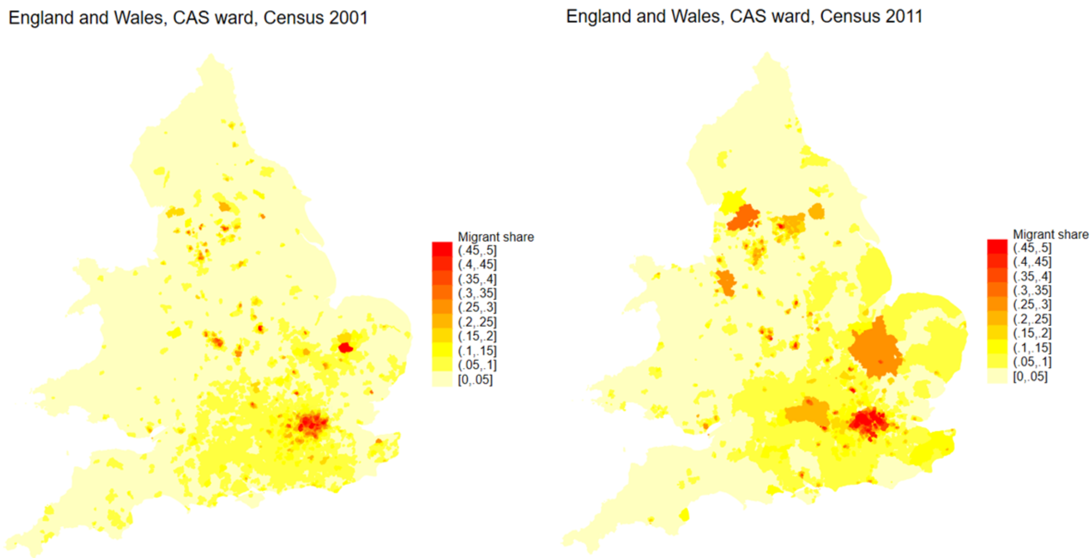
Source: QLFS 1998; APS 2009 & 2019

2.3 Migrant population in a firm's local labour market

Most existing UK studies define the regional dimension of labour markets using 20 broad regions (Nam and Portes, 2023) or 270 commuting zones (called travel-to-work areas, TTWAs, in the UK) (Ottaviano et al., 2018; Campo et al., 2018) to define labour markets. In contrast, our definition is much more local.

Our definition of a neighbourhood is what is called a CAS ward; there are approximately 8,000 in England and Wales with an average population of about 7,000. There are two reasons why we think this is important. The first is that it allows us to control for time-varying effects at the region or TTWA level, something we argue is important because of different trends in productivity across areas. Secondly, there is growing evidence (Manning and Petrongolo, 2017) that labour markets are more local than one might think and existing classifications have boundary effects that do not exist in reality. Migrants are not evenly distributed within TTWAs; they are often overrepresented in more urban areas (Clark and Drinkwater, 2002) and our approach allows us to exploit this variation. Figure 4 shows how using a more local level leads to more variation in the migrant share.

Figure 4: Map of migrant share in England and Wales by CAS ward of residence.



Source: Census (2001, 2011)

We link firms to migrant shares by defining a firm's local labour market as location-industry-year where location is the CAS ward where the firm is located and industry is the firm's 2-digit industry code. From the QLFS and APS we can compute migrant and skill shares among workers living in each ward and working in each industry in each year. However, workers commute between wards and move between industries so it does not make sense to use this as a measure of labour shares for firms located in each ward-industry cell. To address this issue we use 2001 commuting flows to predict labour shares in each destination ward. For each origin ward k and destination ward l, define w_{kl} as the fraction of people who live in k and work in l. To take account of industry switching we use the QLFS (pooling our sample years 1998 - 2019) to compute the fraction of job-changers that transition between each 2-digit industry. For each origin industry g and destination industry h, define a_{gh} as the fraction of people who worked in g and switched to h. This assumes that industry transitions do not vary across areas; but we have too little data to allow for a full interaction of area and industry.

The relationship between the origin ward-industry level supplies (which might be the number of migrants or locals) in ward k industry g at time t $Level^o_{kgt}$ and the destination ward-industry level variable $Level^d_{lht}$ is defined as:

$$Level^d_{lht} = \sum_g \sum_k a_{gh} * w_{kl} * Level^o_{kgt} \tag{1}$$

In our baseline specification, we use labour shares in hours worked in the firm's local labour market (defined by industry and ward). We chose to look at labour shares in hours worked rather than shares in headcount employment since migrants work longer hours (see Table 2) which tends to raise productivity.

Linking labour shares to firms by destination ward l, destination 2-digit SIC industry h, and year t is more precise than other UK studies, which are at TTWA level at best. Nevertheless, we are using a prediction of the migrant share for each firm rather than the actual share. The measurement error from the deviation of the actual from the predicted will not induce attenuation bias if the prediction is the expectation of the actual given covariates, a reasonable assumption given that the average across local firms must be estimated correctly. We also instrument the predicted migrant share as explained in the next section. The studies which use actual firm migrant shares either do not use instruments to account for the endogeneity (Paserman, 2013; Fabling et al., 2022; Ek, 2024) or use variation in the migrant share at local labour market level as an instrument (Parrotta et al. 2014 use commuting zone characteristics as an instrument), which is close to our approach.

2.4 Instrumental variable for employment shares

We largely follow the existing literature and use an Altonji and Card (1989) style shift-share instrument to predict the total hours worked for migrants and locals in each ward-industry-year cell. Specifically, we assume that workers can come from origin regions $c \in (UK, EU8, other)$. Distinguishing between migrants from the EU8 countries and others gives more variation.

First, consider how we predict the labour shares when we do not differentiate by skill. As is usual in shift-share style instruments we assign the total hours worked from region c at time t, X_t^c to wards and industries based on initial shares which are exogenous to firm productivity shocks at time t. With the initial share of workers from origin c in ward k given by θ_k^c and industry g given by θ_g^c, our predictor of the total hours worked in each ward-industry-year-origin-group cell is given by

$$\widetilde{X_{kgt}^c} = \theta_k^c \theta_g^c X_t^c \tag{2}$$

For geographical location, we allocate the share of non-EU8 migrants and locals in each ward k, θ_k^c, using the distribution from the 1981 census.

For EU8 immigration, which is the most important change in the sample period, we use a different approach. Following Viskanic (2018) we use distance to the Polish resettlement camps that were established after WW2 as the predictor for the 'share' of EU8 migrants in different areas. Our proposed mechanism for how the location of these camps affected the location of Eastern European immigrants over 50 years later is the following. After the end of WW2 there was a sizeable population of Poles who had left Poland when it had been over-run by Germany and the Soviet Union in 1939, many of whom fought for the Allies. The 1947 Polish Resettlement Act offered British citizenship to displaced Polish troops and their families. Further immigration was also encouraged to help with post-war reconstruction. In total about 250,000 Poles came to the UK, making them the second-largest migrant group after the Irish. Initially they were housed in the resettlement camps[6], many of which were recently vacated military camps, and many came to settle nearby having found local jobs. These Polish communities established a social infrastructure of clubs, schools and churches[7]. With the hardening of the border between Eastern and Western Europe in the 1950s migration was virtually non-existent until the Iron Curtain came down. But the Polish social infrastructure remained although with an ageing

[6]Data on the location of camps available here are collected by The National Archives, the History of the Polish Ex-combatants Association, and The Sikorski Institute. The final dataset contains the postcodes for 113 resettlement camps across England

[7]see, for example, the Loughborough Polish Social Club established in 1966

community. It is plausible that when Polish immigration re-started the first migrants gravitated to places where there was an existing Polish community. And, as for many migrant groups, later migrants also settled where the pioneers did. Hence, Polish immigration in the 2000s came to be influenced by the location of Polish Resettlement camps at the end of WW2.

The share of migrants from EU8 countries in each ward k is instrumented using the distance to WW2 Polish resettlement camps using the functional form

$$\theta_k^{EU8} = \frac{5 - ln(dist_k)}{\sum_k 5 - ln(dist_k)} \tag{3}$$

where $dist_k$ is the distance between a ward's central point and the nearest WW2 Polish resettlement camp[8].

To assign each origin group to industries we use the share of the group in each 2-digit industry g from the QLFS 1994 - 1997 (before our sample period) θ_g^c. The migrant share in hours workers in each ward-industry-year, s_{kgt}, is hence given by

$$s_{kgt} = \frac{\sum_{c \in (EU8, other)} \theta_k^c \theta_g^c X_t^c}{\sum_{c \in (EU8, other, UK)} \theta_k^c \theta_g^c X_t^c} \tag{4}$$

When we also distinguish by skill level, for UK-born workers the shares of high/lower skilled in each ward, $\theta_k^{UK,skill}$, and in each industry, $\theta_g^{UK,skill}$, are taken from the QLFS 1994 - 97. So total hours by skill level in each ward-industry-year for the UK-born are

$$X_{kgt}^{\widetilde{UK,skill}} = \theta_k^{UK,skill} \theta_g^{UK,skill} X_t^{UK,skill} \tag{5}$$

For migrants, we instead use the fact that migrants from each origin region differ in skill composition because of the nature of the visa system: EU migrants have free movement in our sample period, so EU8 migrants who didn't face visa requirements are more likely to be lower-skilled. The predictor of migrant total hours by skill level in each ward-industry-year is

$$X_{kgt}^{\widetilde{Migrant,skill}} = \sum_{c \in (EU8, other)} \theta_k^c \theta_g^c X_t^{c,skill} \tag{6}$$

All IVs are transformed to the destination ward (l) or ward-industry (l, h) level using 2001 commuter flow and industry switching from the QLFS (see Section 2.3). We then use these to instrument labour shares in hours worked.

The exclusion restriction holds if both our 'shifts' (aggregate hours worked by workers from each region), ward 'shares' (location of resettlement camps or location of other migrants and UK-born workers in 1981), and industry 'shares' (industry of workers from each region in 1994 - 97) are orthogonal to local productivity shocks at time t. Since we're using narrowly defined labour markets, national flows are unlikely endogenous. We also include time-location (TTWA) and time-industry fixed effects in our main specification. So 'shares' only need to be exogenous conditional on these controls.

[8] 5 is chosen because this gives us a positive numerator for all wards and works well in practice. Shares add to one by construction

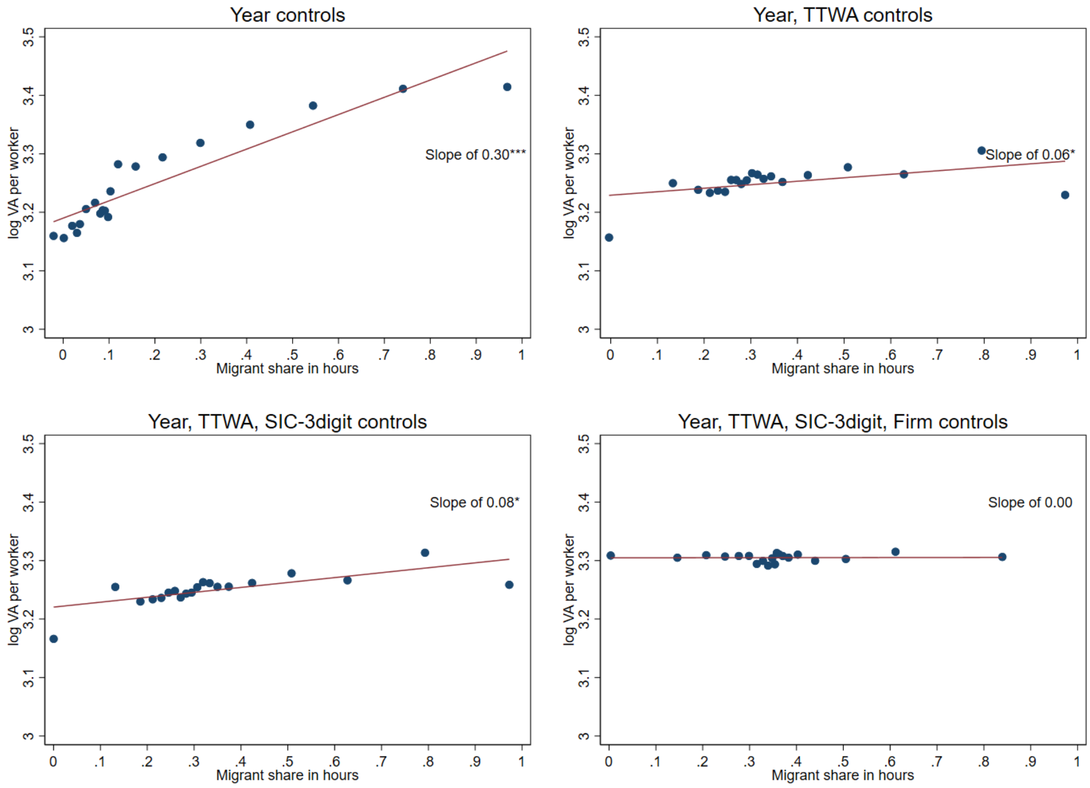
Jaeger et al. (2018) express concern that shift-share instruments conflate the long and short-run responses to local immigration shocks. They suggest using both current and lagged instruments to address the overlapping response problem. We included lags of the instrument in Appendix A5 with similar results.

2.5 Stylised facts on productivity and immigration

We start our analysis by presenting some crude correlations between productivity (log value-added per worker) and the migrant share in hours in a firm's local labour market. The top-left panel of Figure 5 shows a binscatter when we only control for time effects. There is a very strong positive correlation between the migrant share in hours in a firm's labour market and the firm's log value-added output per worker. This is likely driven by migrants sorting into the most productive regions - notably, London has the highest migrant share and the highest output per worker. The sorting of migrants towards London could be taken as a productivity-augmenting effect of migration as it might raise value-added per worker through a simple composition effect. However, a full consideration of this claim would have to address whether migration into high-productivity areas causes locals to be less likely to locate there (on the possible displacement effect of migrants on locals see inter alia Card 2001; Borjas 2006; Amior 2021 Possible displacement effects is an interesting topic but not addressed this paper which focuses on whether, conditional on observables, migrants have different productivity from locals.

The top-right panel of Figure 5 controls for TTWA fixed effects; the relationship between migrant share and firm value added per worker becomes weaker though still significantly positive. Further controlling for the firm's industry (the bottom-left panel) makes little difference. But if we go further and control for firm fixed effects then the relationship disappears entirely (the bottom-right panel). Although the binscatters in Figure 5 do not control for other covariates and do not adjust for the potential endogeneity of the migrant share, the general conclusion from our estimates will be similar.

Figure 5: Correlation between migrant share in hours and log value-added per worker at the firm level. Binscatter n = 20. Cluster robust standard errors at CAS ward level.



3 A framework for modelling the effect of immigration on firm productivity

This section presents a production function that guides our empirical analysis. Suppose firms produce value-added output with a production function of the following form:

$$Y = AK^{\alpha} \cdot F(L_1, ..., L_n)^{\beta} \tag{7}$$

where Y denotes total value-added, A captures total factor productivity, K is capital, $L_1, ..., L_n$ are the different types of labour used in production and $F(\cdot)$ is a labour aggregate that we assume to be homogeneous of degree 1[9]. Using the homogeneity of $F(\cdot)$ we can rewrite (7) as:

$$Y = AK^{\alpha} \cdot L^{\beta} \cdot F(s_1, ..., s_n)^{\beta} \tag{8}$$

where $L = \sum_j L_j$ denotes total employment and $s_j = \frac{L_j}{L}$ denotes the share of type L_j in total employment. Taking logs of (8) and expressing in per worker terms leads to:

[9]The assumption of homogeneity of $F(\cdot)$ is not restrictive given the presence of β

$$\ln\left(\frac{Y}{L}\right) = \ln(A) + \alpha\ln(\frac{K}{L}) + (\alpha+\beta-1)\ln(L) + \beta\ln\left(F(s_1,...,s_n)\right) \tag{9}$$

The shares must add to one so one of them can be eliminated and then write (9) as:

$$\ln\left(\frac{Y}{L}\right) = \ln(A) + \alpha\ln(\frac{K}{L}) + (\alpha+\beta-1)\ln(L) + \beta\ln\left(F(s_1,...,s_{n-1},1-\sum_{j=1}^{n-1}s_j)\right) \tag{10}$$

Immigration can affect both the level and the mix of employment. Both changes in employment level and employment mix resulting from immigration can cause shifts in firm productivity [10]. In this paper we will focus on employment mix: a shift from locals to migrants holding total employment fixed.

Note that (10) implies that an increase in the share of one type of labour at the expense of the base category raises by an amount equal to the difference between the marginal product of that type of labour and the reference group - this idea was used by Hellerstein et al. (1999) to explain gender and ethnicity gaps. The intuition is simple. Imagine reducing employment by one local - output falls by their marginal product. Now imagine replacing them with one migrant - output rises by their marginal product. Whether output is higher or lower after the replacement depends on the difference in marginal product. This is true whatever the nature of substitutability or complementarity between migrants and locals. One cannot (as the literature sometimes does) explain a finding that a higher migrant share raises productivity as a finding that migrants are complements to locals in production. If one finds that a 1 percentage point rise in the migrant share raises productivity by 1% this is a finding that the marginal product of migrants is twice the marginal product of locals.

To turn (10) into an estimable model take a first-order Taylor series approximation of (10) about some share s^* leading to:

$$\ln\left(\frac{Y}{L}\right) \approx \ln(A) + \alpha\ln(\frac{K}{L}) + (\alpha+\beta-1)\ln(L) + \beta\sum_{j=1}^{n-1}\frac{F_j^*-F_n^*}{F^*}\cdot(s_j-s_j^*) \tag{11}$$

where $F_j = \frac{\partial F}{\partial L_j}$ denotes the partial derivative of F with respect to s_j and an * on the variable denotes the variable at the point of the approximation.

Our main parameters of interest μ^j are the re-scaled (divided by β) coefficients on the s_j's and are given by

$$\mu^j = \frac{F_j^*-F_n^*}{F^*} \tag{12}$$

Each μ_j captures the relative productivity difference between labour type L_j and the omitted type L_n.

Equation (11) makes it clear that what is being estimated in the production function literature with labour shares on the right-hand side is the marginal product of each labour type relative

[10]If immigration leads to a lower capital-labour ratio this will tend to reduce productivity but this channel is not the subject of this paper which aims to estimate the productivity of migrants relative to locals. See Borjas 2019, for a discussion of the impact of migration in a standard growth model and Dew-Becker and Gordon 2012 for a study that finds a negative relationship between labour force growth and productivity growth

to average productivity. The linearity of the shares in the estimating equation (11) might seem to make assumptions about the substitutability/complementarity of labour types. However, (11) is a first-order approximation to an arbitrary production function[11] which allows for such substitutability/complementarity. But it will be a closer approximation if the labour types are perfect substitutes i.e. a Cobb-Douglas production function where different labour types are perfect substitutes in production but possibly supply different efficiency units of labour:

$$Y = AK^{\alpha}[\sum(1+\mu^j)L^j]^{\beta} \tag{13}$$

Concerns that a first-order Taylor series is a bad approximation and so produces misleading conclusions can be alleviated by estimating a more flexible functional form e.g. a second-order approximation which is the translog. This is done in Appendix A1 and the results are discussed in the robustness section below.

3.1 Empirical strategy

From the production function framework outlined above, our estimating equation for value-added output per capita in firm f and year t is:

$$\ln(\frac{Y}{L})_{ft} = \beta_0 + \beta_1 \ln(\frac{K}{L})_{ft} + \beta_2 \ln(L)_{ft} + \sum_j \beta_j s^j_{ft} + \upsilon_{ft} \tag{14}$$

There is a large literature on estimating production functions (see Mollisi and Rovigatti 2017 for a review) which is generally acknowledged to be hard because of the potential endogeneity of input choices which means that (14) cannot be reliably estimated by OLS. The literature on estimating production functions is typically concerned about endogenous choices of capital and labour as they are potentially correlated with productivity shocks observed by the firm but not by the researcher. In addition, capital stock estimated using the perpetual inventory method is likely to be measured imperfectly (Collard-Wexler and De Loecker, 2016) leading to attenuation bias. We follow the production function literature in using control function approaches (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015) to deal with the endogeneity of capital and labour. These control function approaches use some other firm decision (investment or intermediate inputs) to control for productivity shocks. We also present the results which use the Collard-Wexler and De Loecker (2016) approach for controlling for measurement error in capital stock using lagged investment to instrument for capital.

In addition to these endogeneity problems standard in the production function literature, we also potentially have endogeneity of the labour share variables. Most existing production function estimates do not regard migrants and locals as separate labour inputs but that is critical for this paper. So we need to instrument the employment shares for the same reason factor inputs have to be instrumented. The nature of the bias may be different; although there are good reasons why firms which experience positive productivity shocks will have more capital and labour, it is less clear how this might affect the migrant share of their employment. The migrant share might be positively correlated with the productivity shock if, for example, migrants move to areas with more productive firms, or negatively correlated if less productive firms hire more migrants. In addition, our estimate of the migrant share is noisy, so should be instrumented to correct for

[11] In our derivation we have assumed for simplicity separability between technology, capital and the labour aggregate but the approximation does not require this

attenuation bias. We use the shift-share style instrumental variable described in section 2.4 to account for the potential endogeneity of the employment shares.

We also report estimates with a range of fixed effects. All our specifications control for year fixed effects; our preferred specifications include controls for year-TTWA, year-3-digit industry specific productivity shocks and firm effects. Controlling for year-TTWA interactions is important because, as Figure 3 shows, the increase in the migrant share is generally much larger in London than elsewhere. If one just includes TTWA and year effects then if London has a different trend from the rest of the country one is effectively ascribing this to the impact of immigration when there are lots of other reasons why the London economy evolved differently. See Appendix C for a more detailed explanation on why this can explain many of the large productivity effects estimated in the existing literature. Being able to include TTWA-year interactions is an advantage of our more local approach to defining labour markets.

Our approach is to report several different methods that have been proposed to deal with these estimation issues and see whether our estimates of the impact of immigration are robust to different methods. Although this means we report a lot of estimates, it is important to have some idea of the robustness of results to avoid potential issues with cherry-picking specifications.

4 Results

For all regressions in this main results section, the dependent variable is firm log real value-added output per worker measured from ARDx data; the regressors are firm log employment and firm log real capital stock per worker measured from ARDx data and employment shares measured from the QLFS/APS at the firm local labour market level described in section 2.3.

4.1 No differentiation by skill level

We first treat all migrants and locals as homogeneous not distinguishing by skill level.

4.1.1 First stages

First stages for our IV are reported in Table 3. Migrant shares at the firm's destination ward-industry level are instrumented using the shift-share IVs defined in section 2.4 above. The first stage is strong, significant at the 0.1% level, robust to the inclusion of firm fixed effects, and robust to using control function approaches; Table 3 shows the first stage when using the Ackerberg et al. (2015) (ACF) control function approach but all control function first stages are of a similar magnitude and significant at the 0.1% level.

Table 3: First stage for the migrant share in hours worked.

	(1)	(2)	(3)	(4)
Migrant share IV	1.340***	1.002***	1.992***	1.542***
	(0.0301)	(0.0729)	(0.0364)	(0.177)
Labour	0.00544***	0.00108		
	(0.000339)	(0.00145)		
Capital per worker	-0.000178	-0.0000434	0.00108	0.00558
	(0.000144)	(0.000470)	(0.00216)	(0.00565)
N	526,003	280,732	24,597	21,663
Fixed Effects				
Firm		✓		✓
Year-TTWA-Ind	✓	✓	✓	✓
Control Function				
	None	None	ACF	ACF

Cluster robust standard errors in parentheses, clustered at the CAS ward level.
Year-TTWA-Ind: Full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.1.2 Treating labour and capital as exogenous

Table 4 presents estimates of our value-added production function where firm labour and capital are treated as exogenous. The top panel also treats the migrant share as exogenous (so is an OLS regression) while the bottom panel instruments the migrant share. From the regression coefficient estimates we can back out the production function parameters described in section 3: capital share (α), labour share (β) and the relative productivity of migrants (μ).

The first column shows that if only year effects are included the OLS estimate implies that migrants are 38% more productive than locals. The IV estimate is larger implying that migrants are over twice as productive as locals. The difference between the OLS and IV estimates could be because when firms experience a negative productivity shock they hire more migrants. This could be because low-productivity firms struggle to offer wages that are attractive to locals causing them to turn to migrants who may have lower reservation wages. The difference between OLS and IV estimates could also arise because instrumenting reduces attenuation bias from measurement error in the migrant share. These productivity differentials are conditional on the overall level of employment; the estimates imply that a higher capital-labour ratio raises productivity and immigration might also affect this variable.

The migrant-local productivity differentials reduce when we add more fixed effects though the IV estimates always remain above the OLS estimates. With TTWA and industry (3-digit SIC) controls interacted with year fixed effects (column 2), the IV estimate implies that migrants are 55% more productive than local workers and that a 1pp increase in migrant share in hours worked is associated with a 0.5% increase in output per worker. This is not as large as many other estimates in the literature (E.g., Ottaviano et al. 2018 find an effect of 1pp increase in migrant share leading to a 3% rise in productivity) but is still economically significant. Even with the inclusion of CAS ward fixed effects (column 3), migrants are found to be significantly more productive than local workers. However, when we control for firm fixed effects (column 4) the estimated migrant-local productivity gap is smaller and not significantly different from zero. Sorting across areas and firms seems important in determining productivity differentials.

Although including firm fixed effects may alleviate some endogeneity problems, the estimated coefficients on labour and capital in column 4 are implausibly low. Low coefficients on capital and employment when adding firm fixed effects is a known problem in production function estimation - see (Nickell, 1981). Griliches and Mairesse (2012) argue this is largely attributable to measurement error which survives the within-firm transformation, this accentuates division bias and attenuates estimates. In the next section, we address this issue by instrumenting for firm labour and capital.

Table 4: Value-added per worker regression results.

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Migrant Share	0.336***	0.0694***	0.00462	0.00478
	(0.0540)	(0.0191)	(0.00983)	(0.00892)
Labour	-0.00457*	0.0215***	0.00485	-0.463***
	(0.00227)	(0.00209)	(0.00259)	(0.00983)
Capital per worker	0.120***	0.113***	0.111***	0.0342***
	(0.00236)	(0.00249)	(0.00238)	(0.00263)
N	526,003	525,903	525,902	280,732
r2	0.114	0.213	0.237	0.820
Implied α	0.120***	0.113***	0.111***	0.0342***
	(0.00236)	(0.00249)	(0.00238)	(0.00263)
Implied β	0.876***	0.909***	0.894***	0.503***
	(0.00421)	(0.00415)	(0.00466)	(0.0107)
Implied μ	0.384***	0.0764***	0.00517	0.00950
	(0.0630)	(0.0212)	(0.0110)	(0.0177)
	(1) IV	(2) IV	(3) IV	(4) IV
Migrant Share	1.143***	0.499***	0.319*	0.0185
	(0.103)	(0.101)	(0.155)	(0.0746)
Labour	-0.00738**	0.0194***	0.00494	-0.463***
	(0.00259)	(0.00233)	(0.00261)	(0.00983)
Capital per worker	0.122***	0.113***	0.111***	0.0342***
	(0.00250)	(0.00248)	(0.00238)	(0.00264)
N	526,003	525,903	525,902	280,732
r2	0.0559	0.0645	0.0624	0.0875
Implied α	0.122***	0.113***	0.111***	0.0342***
	(0.00250)	(0.00248)	(0.00238)	(0.00264)
Implied β	0.871***	0.906***	0.894***	0.503***
	(0.00475)	(0.00444)	(0.00468)	(0.0107)
Implied μ	1.313***	0.550***	0.357*	0.0368
	(0.124)	(0.113)	(0.173)	(0.148)
Fixed Effects				
Firm				✓
CAS Ward			✓	
Year-TTWA-Ind		✓	✓	✓
Year	✓	✓	✓	✓

Cluster robust standard errors in parentheses, clustered at the CAS ward level.
Year-TTWA-Ind: Full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.1.3 Treating labour and capital as endogenous

The previous section treated labour and capital as exogenous; this section reports estimates treating them as endogenous using a variety of methods proposed in the production function literature to deal with their endogeneity. Table 5 presents estimates of our value-added production function using control function approaches: Olley and Pakes (1996) (OP), Levinsohn and Petrin (2003) (LP), Ackerberg et al. (2015) (ACF). We also present the results which use the Collard-Wexler and De Loecker (2016) (CWDL) approach for controlling for measurement error in capital stock using lagged investment to instrument for capital.

The advantage is that we control for endogeneity issues in factor inputs, but this comes at the cost of fewer observations because we need lagged values of investment or intermediates and the ARDx panel is short for most firms in our sample.

The capital and labour coefficients change little with the control function approaches, suggesting the endogeneity of factor inputs problem is not severe in our sample. The attenuation of the coefficients on employment and capital in column 4 of Table 4 is less severe. In line with Collard-Wexler and De Loecker (2016) our capital coefficients are much higher when using the CWDL approach. We similarly instrument for firm employment in the 'LIV' columns using the firm's local labour market shift-share IV defined in section 2.4[12] instead of employment lags, in conjunction with the ACF control function approach.

The top panel of results in Table 5 include year-TTWA and year-industry fixed effects. Comparing the estimates in Table 5 with those in the bottom panel of Table 4, the estimated migrant share effect is lower across all control function estimates but still significantly positive. Our preferred specification, the ACF with firm employment instrumented using our shift-share IV (column 5), implies that migrants are 20% more productive than local workers.

However, as for Table 4, the migrant share effects are much smaller (though still positive) and become insignificant with the inclusion of firm fixed effects (these estimates are shown in the bottom panel of Table 5). The estimated coefficients on the capital-labour ratio and total employment remain plausible and significant even with the inclusion of firm fixed effects so it is not the case that the inclusion of firm fixed effects attenuates all coefficients. We can't reject the hypothesis that the positive effect of migration on productivity comes from the sorting of migrants to firms with higher underlying fixed productivity.

[12] Labour IV = log(migrant employment IV + local employment IV) in the destination ward and 2-digit industry of the firm. When there is more than one firm in each destination ward-industry, distribute instrumented labour to each firm based on the lagged employment share of each firm in ward-industry total employment.

Table 5: Value-added per worker regression results. Control function approach with IV for migrant share.

No Firm Fixed Effects	(1) OP	(2) LP	(3) ACF	(4) CWDL	(5) LIV
Migrant Share	0.435^{***}	0.123^{**}	0.183^{**}	0.174^{**}	0.183^{**}
	(0.0361)	(0.0414)	(0.0628)	(0.0660)	(0.0629)
Labour	0.00300	0.0181^{***}	0.0239^{***}	0.0188^{***}	0.0180^{*}
	(0.00206)	(0.00269)	(0.00426)	(0.00447)	(0.00835)
Capital per worker	0.101^{***}	0.0636^{***}	0.0926^{***}	0.266^{***}	0.0926^{***}
	(0.00285)	(0.00418)	(0.00712)	(0.0235)	(0.00712)
N	97,667	45,699	24,597	22,823	24,597
r2	0.107	0.159	0.162	0.139	0.162
Implied α	0.101^{***}	0.0636^{***}	0.0926^{***}	0.266^{***}	0.0926^{***}
	(0.00285)	(0.00418)	(0.00712)	(0.0235)	(0.00712)
Implied β	0.902^{***}	0.955^{***}	0.931^{***}	0.753^{***}	0.925^{***}
	(0.00348)	(0.00500)	(0.00829)	(0.0245)	(0.0109)
Implied μ	0.482^{***}	0.129^{**}	0.197^{**}	0.231^{**}	0.197^{**}
	(0.0401)	(0.0434)	(0.0675)	(0.0882)	(0.0678)
Firm Fixed Effects	(1) OP	(2) LP	(3) ACF	(4) CWDL	(5) LIV
Migrant Share	0.0411	0.0573	0.0853	0.0859	0.0774
	(0.0869)	(0.140)	(0.177)	(0.196)	(0.150)
Labour	-0.343^{***}	-0.236^{***}	-0.291^{***}	-0.183^{**}	-0.0983
	(0.0276)	(0.0335)	(0.0495)	(0.0614)	(0.211)
Capital per worker	0.0733^{***}	0.0916^{***}	0.0945^{***}	0.338^{***}	0.143^{**}
	(0.00863)	(0.0118)	(0.0225)	(0.0889)	(0.0542)
N	69,371	34,916	21,663	20,150	21,663
r2	0.0781	0.0460	0.0438	0.0131	0.0318
Implied α	0.0733^{***}	0.0916^{***}	0.0945^{***}	0.338^{***}	0.143^{**}
	(0.00863)	(0.0118)	(0.0225)	(0.0889)	(0.0542)
Implied β	0.584^{***}	0.672^{***}	0.615^{***}	0.478^{***}	0.759^{***}
	(0.0242)	(0.0300)	(0.0413)	(0.0772)	(0.159)
Implied μ	0.0705	0.0853	0.139	0.180	0.102
	(0.149)	(0.209)	(0.287)	(0.408)	(0.202)

Cluster robust standard errors in parentheses, clustered at the CAS ward level.
All specifications include fixed effects for the full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2 Differentiation by skill

The estimates of the previous section do not differentiate by skill of either migrants or locals. To investigate this we divide workers into two groups by occupation: higher-skilled (soc occupational groups 1 - 3) and lower-skilled (everyone else) [13].

We now have four types of labour: low-skilled locals (who will be our reference group), low-skilled migrants and high-skilled migrants and locals.

4.2.1 First stages

We need instruments for all of the employment shares which is demanding. We use the shift-share IVs defined in section 2.4. Table 6 shows the first stage relationships between the migrant and

[13] We define skill by occupation rather than education because the UK QLFS/APS is known to misclassify the education of migrants and because there is also occupational downgrading of migrants (Dustmann et al., 2016)

local shares by skill level remain strong. Although there are some significant cross-correlations, all the instruments predominantly pick out the 'correct' employment share.

Table 6: First stage regression results for the migrant share in hours worked, by skill level.

	(1) Migrant-low	(2) Migrant-high	(3) Local-high	(4) Migrant-low	(5) Migrant-high	(6) Local-high
No Control Function	**No Firm Fixed Effects**			**Firm Fixed Effects**		
Migrant-low IV	1.263***	0.0149	-0.467***	1.115***	-0.136*	-0.288***
	(0.0302)	(0.0241)	(0.0363)	(0.0486)	(0.0557)	(0.0755)
Migrant-high IV	-0.411***	1.248***	1.053***	-0.297***	0.993***	1.098***
	(0.0264)	(0.0770)	(0.0616)	(0.0689)	(0.0733)	(0.0874)
Local-high IV	-0.102***	0.0119	1.479***	-0.0439	-0.00568	2.351***
	(0.0214)	(0.0208)	(0.0298)	(0.0385)	(0.0360)	(0.0684)
N	526,003	526,003	526,003	280,732	280,732	280,732
ACF Control Function	**No Firm Fixed Effects**			**Firm Fixed Effects**		
Migrant-low IV	1.811***	0.150***	-0.711***	1.483***	0.0314	-0.634**
	(0.0405)	(0.0266)	(0.0716)	(0.171)	(0.133)	(0.205)
Migrant-high IV	-0.423***	1.008***	1.436***	-0.518*	0.973**	1.449***
	(0.0595)	(0.0390)	(0.105)	(0.226)	(0.310)	(0.288)
Local-high IV	-0.180***	0.0774***	1.667***	-0.0254	-0.0108	2.445***
	(0.0313)	(0.0205)	(0.0553)	(0.120)	(0.114)	(0.213)
N	24,597	24,597	24,597	21,663	21,663	21,663

Cluster robust standard errors in parentheses, clustered at the CAS ward level.
All specifications include fixed effects for the full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2.2 Treating labour and capital as exogenous

In line with the approach of the previous section, we first show estimates where labour and capital are treated as exogenous. The top panel of Table 7 presents OLS estimates of our value-added production function while the bottom panel presents IV estimates.

When the only controls are year effects (column 1) the OLS estimates (the top panel) imply that both high- and low-skilled migrants are more productive than low-skilled locals. The IV estimates in the bottom panel suggest high-skilled migrants are much more productive than high-skilled locals but low-skilled migrants have similar productivity to low-skilled locals. When including year-TTWA and year-industry fixed effects the effects are smaller and in both OLS and IV specifications lower-skilled migrants are not more productive than lower-skilled locals, suggesting any positive productivity effects of immigration are driven by the high-skilled.

However, when including either ward fixed effects (column 3) or firm fixed effects (column 4), none of the coefficients are significant though the point estimates imply high-skilled migrant workers are more productive. It should be noted that in the specifications with ward or firm fixed effect, high-skill locals are not found to be significantly more productive than low-skilled locals, contrary to expectation. This perhaps indicates that these are very demanding specifications.

Table 7: Value-added per worker regression results, by skill level.

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Migrant-low share	0.158***	-0.00738	-0.00865	0.00191
	(0.0303)	(0.0145)	(0.0121)	(0.0110)
Migrant-high share	0.682***	0.191***	0.0245	0.00353
	(0.0778)	(0.0327)	(0.0144)	(0.0139)
Local-high share	0.171***	0.0165*	0.00250	-0.00473
	(0.0151)	(0.00740)	(0.00645)	(0.00634)
Labour	-0.00207	0.0215***	0.00485	-0.463***
	(0.00219)	(0.00210)	(0.00259)	(0.00983)
Captal per worker	0.121***	0.113***	0.111***	0.0342***
	(0.00240)	(0.00248)	(0.00238)	(0.00263)
N	526,003	525,903	525,902	280,732
r2	0.118	0.213	0.237	0.820
Implied α	0.121***	0.113***	0.111***	0.0342***
	(0.00240)	(0.00248)	(0.00238)	(0.00263)
Implied β	0.877***	0.909***	0.894***	0.503***
	(0.00419)	(0.00416)	(0.00466)	(0.0107)
Implied μ^{M-low}	0.181***	-0.00812	-0.00968	0.00380
	(0.0350)	(0.0159)	(0.0136)	(0.0218)
Implied μ^{M-high}	0.777***	0.211***	0.0274	0.00703
	(0.0915)	(0.0365)	(0.0161)	(0.0276)
Implied $\mu^{Loc-high}$	0.195***	0.0182*	0.00279	-0.00941
	(0.0178)	(0.00815)	(0.00722)	(0.0126)
	(1) IV	(2) IV	(3) IV	(4) IV
Migrant-low shares	0.0872	-0.00548	-0.0146	-0.00157
	(0.0936)	(0.0811)	(0.0977)	(0.0860)
Migrant-high share	1.878***	0.892***	0.132	0.100
	(0.111)	(0.109)	(0.186)	(0.149)
Local-high share	0.384***	0.119*	0.0389	0.0394
	(0.0520)	(0.0535)	(0.0384)	(0.0456)
Labour	0.000729	0.0207***	0.00484	-0.462***
	(0.00254)	(0.00222)	(0.00260)	(0.00990)
Captal per worker	0.124***	0.113***	0.111***	0.0343***
	(0.00246)	(0.00246)	(0.00238)	(0.00264)
N	526,003	525,903	525,902	280,732
r2	0.0605	0.0637	0.0645	0.0867
Implied α	0.124***	0.113***	0.111***	0.0343***
	(0.00246)	(0.00246)	(0.00238)	(0.00264)
Implied β	0.877***	0.908***	0.894***	0.503***
	(0.00466)	(0.00428)	(0.00467)	(0.0107)
Implied μ^{M-low}	0.0994	-0.00604	-0.0164	-0.00312
	(0.107)	(0.0893)	(0.109)	(0.171)
Implied μ^{M-high}	2.141***	0.982***	0.147	0.199
	(0.133)	(0.122)	(0.208)	(0.296)
Implied $\mu^{Loc-high}$	0.438***	0.131*	0.0435	0.0783
	(0.0598)	(0.0591)	(0.0429)	(0.0905)
Fixed Effects				
Firm				✓
CAS Ward			✓	
Year-TTWA-Ind		✓	✓	✓
Year	✓	✓	✓	✓

Cluster robust standard errors in parentheses, clustered at the CAS ward level.
Year-TTWA-Ind: Full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2.3 Treating labour and capital as endogenous

Table 8 presents estimates of our value-added production function where labour and capital are treated as endogenous and migrant and local shares are differentiated by skill level.

The top panel includes year-TTWA and year-industry fixed effects while the bottom also includes firm fixed effects. Without firm fixed effects, low-skilled migrants are estimated to be slightly less productive than low-skilled locals but the differences are never significant. However high-skilled migrants are estimated to be more productive than high-skilled locals, with a significant difference in coefficient estimates under all specifications (at the 0.1% level). In our preferred specification, the ACF with firm employment instrumented using our shift-share IV (column 5), high-skilled migrants are around 80% more productive than lower-skilled locals, whilst high-skilled locals are around 20% more productive.

The inclusion of firm fixed effects (the bottom panel) reduces the magnitudes of the productivity advantage for high-skill migrants and finds that low-skill migrants are less productive than low-skill locals. Again the estimated effects are never significantly different from zero.

Table 8: Value-added per worker regression results, by skill level. Control function approach with IV for labour shares.

No Firm Fixed Effects	(1) OP	(2) LP	(3) ACF	(4) CWDL	(5) LIV
Migrant-low share	-0.0233	-0.0253	-0.0174	-0.0818	-0.0215
	(0.0653)	(0.0923)	(0.131)	(0.134)	(0.131)
Migrant-high share	1.099***	0.598**	0.739**	0.830**	0.744**
	(0.0935)	(0.205)	(0.277)	(0.286)	(0.276)
Local-high share	0.347***	0.177**	0.188*	0.184*	0.183
	(0.0488)	(0.0684)	(0.0948)	(0.0901)	(0.0937)
Labour	0.00406	0.0189***	0.0248***	0.0194***	0.0175*
	(0.00209)	(0.00273)	(0.00433)	(0.00456)	(0.00847)
Captal per worker	0.100***	0.0632***	0.0933***	0.263***	0.0933***
	(0.00287)	(0.00420)	(0.00718)	(0.0237)	(0.00718)
N	97,667	45,699	24,597	22,823	24,597
r2	0.0892	0.148	0.151	0.125	0.151
Implied α	0.100***	0.0632***	0.0933***	0.263***	0.0933***
	(0.00287)	(0.00420)	(0.00718)	(0.0237)	(0.00718)
Implied β	0.904***	0.956***	0.931***	0.756***	0.924***
	(0.00353)	(0.00504)	(0.00835)	(0.0247)	(0.0111)
Implied μ^{M-low}	-0.0258	-0.0264	-0.0187	-0.108	-0.0232
	(0.0722)	(0.0966)	(0.141)	(0.177)	(0.141)
Implied μ^{M-high}	1.216***	0.626**	0.793**	1.098**	0.805**
	(0.104)	(0.215)	(0.298)	(0.380)	(0.298)
Implied $\mu^{Loc-high}$	0.384***	0.186**	0.202*	0.243*	0.198
	(0.0539)	(0.0715)	(0.102)	(0.115)	(0.102)
Firm Fixed Effects	(1) OP	(2) LP	(3) ACF	(4) CWDL	(5) LIV
Migrant-low share	-0.102	-0.0371	-0.266	-0.228	-0.267
	(0.122)	(0.203)	(0.254)	(0.268)	(0.208)
Migrant-high share	0.208	0.127	0.118	0.102	0.185
	(0.197)	(0.377)	(0.502)	(0.524)	(0.429)
Local-high share	0.0871	0.0375	0.0373	0.0614	-0.0470
	(0.0731)	(0.0991)	(0.119)	(0.122)	(0.110)
Labour	-0.341***	-0.236***	-0.287***	-0.184**	-0.0862
	(0.0277)	(0.0335)	(0.0493)	(0.0610)	(0.223)
Capital per worker	0.0737***	0.0914***	0.0968***	0.332***	0.148*
	(0.00867)	(0.0119)	(0.0227)	(0.0889)	(0.0577)
N	69,371	34,916	21,663	20,150	21,663
r2	0.0722	0.0452	0.0376	0.00990	0.0376
Implied α	0.0737***	0.0914***	0.0968***	0.332***	0.148*
	(0.00867)	(0.0119)	(0.0227)	(0.0889)	(0.0577)
Implied β	0.585***	0.672***	0.616***	0.484***	0.766***
	(0.0244)	(0.0300)	(0.0410)	(0.0772)	(0.167)
Implied μ^{M-low}	-0.173	-0.0552	-0.432	-0.470	-0.348
	(0.208)	(0.302)	(0.412)	(0.547)	(0.280)
Implied μ^{M-high}	0.356	-0.190	0.192	0.211	0.242
	(0.335)	(0.560)	(0.815)	(1.081)	(0.545)
Implied $\mu^{Loc-high}$	0.149	0.0558	0.0606	0.127	-0.0613
	(0.125)	(0.147)	(0.193)	(0.253)	(0.142)

Cluster robust standard errors in parentheses, clustered at the CAS ward level.
All specifications include fixed effects for the full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Overall, the results that differentiate employment by skill are similar to the results that didn't;

any productivity advantage to migrants is not robust to the inclusion of firm fixed effects. The point estimates generally provide some support for the view that high-skill migrants are, as expected, more productive than lower-skilled migrants though, again, the differences are not always significantly different from zero.

4.3 Robustness checks

Although we have reported a wide range of specifications, the Appendix reports a variety of robustness checks and further analysis.

Appendix A1 estimates translog production functions which can be thought of as a second-order approximation to an arbitrary production function. With a translog production function the relative marginal products vary with the shares of different labour types so one cannot make simple statements about relative productivity. We de-mean the regressors so the coefficients on the main effects can be interpreted as the relative productivities at the sample means. Only results without firm fixed effects are reported; nothing is significant if they are included as the specification is too demanding. Without firm fixed effects results for the translog are similar to our main results. There is some evidence for positive complementaries between migrants and capital (Lewis, 2011, 2013) and between high-skilled migrant and high-skilled local shares, though not between migrants and firm employment (Kemeny and Cooke, 2018).

Appendix A2 investigates how the coefficient on the migrant share varies when we impose different values for the capital and labour coefficients in the production function. Given that our main focus of interest is the coefficient on the migrant share this approach is one way to deal with the possible problem of attenuation bias on the labour and capital coefficient when firm fixed effects are included. We find that the migrant share effect is higher when imposing higher labour shares, though the results are generally in line with those reported in the main part of the paper.

Appendix A3 includes firms with multiple plants allocating capital stock and value-added at the firm-level to plants based on the plant's share in total firm employment. The results are very similar to our main specification.

Appendix A4 uses information on the share of full-time workers that is available for a shorter sample to construct a measure of full-time equivalent workers. Results are very similar to our main specifications.

Appendix A5 uses the methods of Blundell and Bond (2000) to estimate a dynamic production function. Using this method we again find a positive migrant productivity effect which disappears with the inclusion of firm fixed effects.

Appendix B investigates heterogeneity in the migrant share productivity effect by industry and region. There is some evidence that the productivity advantage of migrants is bigger in the East of England, London, and the South East and in service industries but the effects are not robust to including firm fixed effects.

4.4 Discussion and reconciliation with other studies

Previous studies in the UK which have looked at the relationship between migration and firm productivity find large effects. Our findings imply that controlling for TTWA specific trends the effects are more modest. Further controlling for firm fixed effects there is no significant productivity difference between migrants and locals. Appendix C shows that controlling for TTWA specific trends is essential in this period in the UK, since both productivity and migrant share in London are diverging from other areas. Our use of a more locally defined migrant share measure allows us to include controls like TTWA trends and so fully tease out this geographical sorting effect. With firm controls, our estimates are not precise enough to discern whether migrants and locals are equally productive – but migrants are sorting into more productive firms – or whether migrants themselves have slightly higher marginal products. Either way, most of the 'raw' marginal productivity difference between migrants and locals is the result of sorting.

Sorting is an important mechanism by which migration might affect productivity. For example, one could argue that the tendency of migrants to locate in London where productivity is higher is a positive impact of migration. However, a thorough evaluation of the effect of sorting would need to estimate the displacement effect of locals as a results of immigration. For example, we would have to check that migration to London has raised the total share of the population in London rather than just the share of migrants. Our empirical exercise is not suited to that though this is an interesting question for future research (for studies on this for the US see, amongst others, Card 2001; Borjas 2006 Amior 2021).

If migrants are more productive than locals the natural next question is who benefits from the extra output. Is it the migrants themselves? Or workers as a whole? Or firms through higher profits? The next section investigates this.

5 The effects of migration on the labour share

If labour markets are perfectly competitive with workers paid their marginal products a change in the mix of employment should have the same effect on productivity and average wages as pointed out by Hellerstein et al. (1999). However, if there is discrimination or imperfect competition which cause wages to deviate from marginal products in ways that differ across labour types, the wage and productivity effects may be different. In this case there will also be effects on profits.

To compare the productivity and wage effects of migration consider the following equation for the labour share, the ratio of total labour costs to value-added output:

$$\begin{aligned}\frac{LabourCosts}{VA} &= \frac{\sum L^j w^j}{AK^\alpha[\sum(1+\mu^j)L^j]^\beta} \\ &= \frac{w^1 L \sum(1+d^j)s^j}{AK^\alpha L^\beta[\sum(1+\mu^j)s^j]^\beta}\end{aligned} \tag{15}$$

Log linearising this can be written as:

$$\ln(\frac{Lab.Cost}{VA}) \approx \ln(w^1) - \ln(A) - \alpha\ln(K) + (1-\beta)\ln(L) + \sum s^j(d^j - \beta\mu^j) \tag{16}$$

Because the employment share variables must add to one, we must choose a base category which we assume to be type 1 labour. d^j is the wage advantage of type j labour over the base category. This yields the estimating equation:

$$\ln(\frac{Lab.Cost}{VA})_{ft} = \beta_0 + \beta_1\ln(K)_{ft} + \beta_2\ln(L)_{ft} + \sum_j \beta_j s^j_{ft} + \upsilon_{ft} \tag{17}$$

The coefficients on the employment share variables represent the difference between the wage and marginal product for that labour type relative to the base category. For example, a positive coefficient implies a gap between the wage and marginal product that is bigger than for the base category of labour.

Table 9 presents estimates for the log labour share treating migrants as homogeneous. We present results treating labour and capital as exogenous and also using our preferred control function approach (i.e., ACF control function approach, shift-share IV for labour shares, and shift-share IV for firm employment).

The results in Table 9 without firm fixed effects have a significant negative effect of the migrant share on the log labour share in value added implying that the gap between wages and marginal products is larger for migrants than locals. Intuitively, the negative coefficient on migrant share implies a higher migrant share increases firm value-added more than it increases labour costs. Therefore, some of the productivity improvements are captured by firms. That might explain why businesses frequently lobby in favour of a more relaxed immigration policy (Donnelly et al., 2020). With firm fixed effects the estimates are not significantly different from zero though with the control function approach the estimated coefficient is similar to that found without firm fixed effects.

Table 9: Regression of log labour costs as share of value-added output on migrant share in hours worked. IV for migrant share.

	(1) IV	(2) IV	(3) IV	(4) LIV	(5) LIV	(6) LIV
	No Control Function			**ACF + Labour IV**		
Migrant share	-0.320***	-0.0552**	-0.0898	-0.544***	-0.165***	-0.184
	(0.0126)	(0.0201)	(0.0572)	(0.0259)	(0.0484)	(0.134)
Capital	-0.0163***	-0.0115***	0.00445***	-0.0645***	-0.0261***	0.0273
	(0.000576)	(0.000542)	(0.00131)	(0.00464)	(0.00573)	(0.0287)
Labour	0.163***	0.149***	0.0680***	0.0954***	0.0330**	0.0316
	(0.00121)	(0.00125)	(0.00491)	(0.0102)	(0.0128)	(0.238)
N	410039	409915	234006	27939	27053	22703
r2	0.117	0.0976	0.00233	0.123	0.0691	-0.00984
Fixed Effects						
Firm			✓			✓
Year-TTWA-Ind		✓	✓		✓	✓
Year	✓	✓	✓	✓	✓	✓

Cluster robust standard errors in parentheses, clustered at the CAS ward level.
Year-TTWA-Ind: Full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10 does a similar exercise but now differentiates migrants and locals by skill. Without firm fixed effects the coefficients on both high-skilled migrants and locals are significantly negative implying a larger gap between wages and marginal products for these groups than for the base group (low-skill locals). With the inclusion of year, TTWA, and industry controls (columns 2 and 5), the estimated effect is similar for both migrant and local high-skilled workers. With the inclusion of firm fixed effects the magnitude of the impacts is similar in the control function approach but not significantly different from zero.

Table 10: Regression of log labour costs as share of value-added output on labour share in hours worked, by skill level, IV for skill shares

	(1) IV	(2) IV	(3) IV	(4) LIV	(5) LIV	(6) LIV
	No Control Function			**ACF + Labour IV**		
Migrant - low share	-0.109***	-0.0298	0.0290	-0.152*	-0.132	-0.206
	(0.0284)	(0.0310)	(0.0570)	(0.0662)	(0.0824)	(0.114)
Migrant - high share	-0.485***	-0.107*	-0.00847	-0.923***	-0.189	-0.207
	(0.0283)	(0.0416)	(0.102)	(0.0615)	(0.136)	(0.259)
Local - high share	-0.233***	-0.132***	-0.0296	-0.276***	-0.177**	-0.107
	(0.0200)	(0.0235)	(0.0296)	(0.0519)	(0.0664)	(0.0656)
Capital	-0.0171***	-0.0114***	0.00440***	-0.0641***	-0.0295***	0.0127
	(0.000582)	(0.000541)	(0.00131)	(0.00462)	(0.00600)	(0.0282)
Labour	0.161***	0.148***	0.0679***	0.0925***	0.0399**	0.134
	(0.00121)	(0.00126)	(0.00492)	(0.0101)	(0.0135)	(0.233)
N	410039	409915	234006	27939	27053	22703
r2	0.118	0.0961	0.00361	0.129	0.0666	-0.0346
Fixed Effects						
Firm			✓			✓
Year-TTWA-Ind		✓	✓		✓	✓
Year	✓	✓	✓	✓	✓	✓

Cluster robust standard errors in parentheses, clustered at the CAS ward level.
Year-TTWA-Ind: Full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To conclude, there is perhaps some evidence that wages differ from marginal products for some groups, and so firms benefit when the share of workers from these groups rises, but these differences are not significantly different from zero when firm fixed effects are included.

5.0.1 Evidence from the labour force survey

The equations above consider how the labour share in value added varies with the migrant share. Because of the nature of the firm-level data, we cannot see whether any productivity gains that accrue to workers go to locals or migrants. If, for example, all productivity differences are reflected in individual wages, one should find that the productivity effect of the migrant share is equal to the wage differential between migrants and locals at the individual level. In this section, we briefly explore migrant-native wage differentials in log hourly earnings using QLFS data to shed some light on how the estimated effects 'add-up'. In these earnings equations, the regressors are chosen to mimic those included the productivity regressions rather than controls more traditionally included in earnings functions (such as age, gender, race and education). However, we cannot include firm fixed effects in these earnings functions using QLFS data. The first column of Table 11 shows that migrants earn about 4.7% less than natives when controlling for year-TTWA-industry effects. The same regression with log value added per worker as the dependent variable (column (2) of Table 6) has a positive effect on the migrant share implying, if correct, that either native wages or profits must be higher. The second column of Table 11 differentiates by skill. Low-skill migrants are found to earn about 5% less than low-skill natives but high-skill migrants earn much the same as high-skill natives.

We can also use the QLFS to investigate whether apparent differences in productivity between migrants and locals in the production function estimates are the consequence of using a definition of skill that is too crude. For example, it could be that within our high-skill category, migrants are concentrated in higher-paid occupations. Columns (3)-(5) of Table 11 investigate this by including more detailed occupational controls. We find that the more detailed the occupational controls the smaller the wage gap between migrants and natives but the impact is very small. Overall, the evidence from wage differentials suggests that, conditional on year, area, industry and occupation, migrants are being paid slightly less than locals. If migrants raise productivity they do not seem to be getting the returns themselves.

Table 11: Regression of log hourly pay on dummies for migrant status and skill group.

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
Migrant	-0.0467***	-0.0514***	-0.0415***	-0.0417***	-0.0369***
	(0.00328)	(0.00284)	(0.00274)	(0.00271)	(0.00265)
High skilled		0.534***			
		(0.00200)			
High skilled migrant		0.0365***	0.0203***	0.0178***	0.0106*
		(0.00482)	(0.00472)	(0.00464)	(0.00447)
N	569,284	569,191	569,191	569,191	569,191
r2	0.269	0.431	0.457	0.466	0.484
Fixed Effects					
Year-TTWA-Ind	✓	✓	✓	✓	✓
Soc - 1 digit			✓		
Soc - 2 digit				✓	
Soc - 3 digit					✓

Cluster robust standard errors in parentheses, clustered at the cas ward level.
Year-TTWA-Ind: Full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6 Conclusion

This paper estimates the impact of migration on productivity by estimating production functions for British firms. We report a wide range of specifications to give some idea of the robustness of our results. Our main conclusions are as follows. First, that much of the apparent higher productivity of migrants is the result of sorting across areas, industries, and firms. If we do not differentiate by skill, we find that migrants are more productive than locals but the gap is much smaller than found in other UK studies, a difference that can be largely explained by our inclusion of area trends rather than just area and time fixed effects. However, when we include firm fixed effects, the estimated productivity advantage of migrants over locals is smaller still and no longer significantly different from zero. When we further differentiate labour by skill, we find that it is high- rather than low-skill migrants that seem the more productive. But, again, these effects are no longer significantly different from zero when we include fixed effects. One possible interpretation of our results is that migrants and locals with similar skills are equally productive; there is nothing distinctive about migrants. However, since productivity estimates are imprecise after controlling for firm fixed effects, we also can't reject the hypothesis that migrants and locals differ in their productivity.

References

Ackerberg, D. A., Caves, K., and Frazer, G. (2015). Identification Properties of Recent Production Function Estimators. Econometrica, 83(6). https://doi.org/10.3982/ecta13408

Alesina, A., Harnoss, J., and Rapoport, H. (2016). Birthplace diversity and economic prosperity. Journal of Economic Growth, 21(2). https://doi.org/10.1007/s10887-016-9127-6

Altonji, J. G., and Card, D. (1989). The effects of immigration on the labour market outcomes of less-skilled natives. NBER Working Paper No. 3123. https://doi.org/10.3386/w3123

Amior, M. (2021). Immigration, Local Crowd-Out and Undercoverage Bias. CEP Discussion Paper No 1669. https://cep.lse.ac.uk/pubs/download/dp1669.pdf

Amior, M. and Manning, A. (2020). Monopsony and the Wage Effects of Migration. CEP Discussion Paper No. 1690. https://cep.lse.ac.uk/pubs/download/dp1690.pdf

Amior, M. and Stuhler, J. (2024). Immigration, monopsony and the distribution of firm pay. CEP Discussion Paper No. 1971. https://cep.lse.ac.uk/pubs/download/dp1971.pdf

Azoulay, P., Jones, B. F., Kim, J. D., and Miranda, J. (2022). Immigration and Entrepreneurship in the United States. American Economic Review: Insights, 4(1). https://doi.org/10.1257/aeri.20200588

Blundell, R., and Bond, S. (2000). GMM Estimation with persistent panel data: An application to production functions. Econometric Reviews, 19(3). https://doi.org/10.1080/07474930008800475

Borjas, G. J. (2003). The labour demand curve is downward sloping: Reexamining the impact of immigration on the labour market. Quarterly Journal of Economics, 118(4). https://doi.org/10.1162/003355303322552810

Borjas, G. J. (2006). Native internal migration and the labour market impact of immigration. Journal of Human Resources, 41(2). https://doi.org/10.3368/jhr.xli.2.221

Borjas, G. J. (2019), Immigration and Economic Growth (May 2019). NBER Working Paper No. 25836. https://ssrn.com/abstract=3387192

Borjas, G. J. and Edo, A. (2023). Monopsony, Efficiency, and the Regularization of Undocumented Immigrants. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4519218

Boubtane, E., Dumont, J. C., and Rault, C. (2016). Immigration and economic growth in the OECD countries 1986-2006. Oxford Economic Papers, 68(2). https://doi.org/10.1093/oep/gpw001

Campo, F., Forte, G., and Portes, J. (2018). The Impact of Migration on Productivity and Native-Born Workers' Training. IZA DP No. 11833. https://doi.org/10.2139/ssrn.3261692

Card, D. (2001). Immigrant inflows, native outflows, and the local labour market impacts of higher immigration. Journal of labour Economics, 19(1). https://doi.org/10.1086/209979

Clark, K., and Drinkwater, S. (2002). Enclaves, neighbourhood effects and employment outcomes: Ethnic minorities in England and Wales. Journal of Population Economics, 15(1). https://doi.org/10.1007/PL00003839

Clemens, M. A., Lewis, E. G., and Postel, H. M. (2018). Immigration restrictions as active labour market policy: Evidence from the Mexican Bracero exclusion. In American Economic Review, 108(6). https://doi.org/10.1257/aer.20170765

Collard-Wexler, A., and De Loecker, J. (2016). Production Function Estimation and Capital Measurement Error. NBER Working Paper No. 22437. https://ssrn.com/abstract=2813885

Dew-Becker, I., and Gordon, R. J. (2012). The Role of labour-Market Changes in the Slowdown of European Productivity Growth. Review of Economics and Institutions, 3(2). https://doi.org/10.5202/rei.v3i2.74

Donnelly, M. J., Islam, M. M., and Savoie, J. (2020). The public face of interest group lobbying on immigration: Who responds to and who ignores what they say. Journal of European Social Policy, 30(5). https://doi.org/10.1177/0958928720954685

Dustmann, C., Fabbri, F., and Preston, I. (2005). The impact of immigration on the British labour market. Economic Journal, 115(507). https://doi.org/10.1111/j.1468-0297.2005.01038.x

Dustmann, C., Frattini, T., and Preston, I. P. (2013). The effect of immigration along the distribution of wages. Review of Economic Studies, 80(1). https://doi.org/10.1093/restud/rds019

Dustmann, C., Schönberg, U., and Stuhler, J. (2016). The Impact of Immigration: Why Do Studies Reach Such Different Results? Journal of Economic Perspectives, 30 (4): 31-56. https://doi.org/10.1257/jep.30.4.31

Eberhardt, M. and Helmers, C. (2010). Untested Assumptions and Data Slicing: A Critical Review of Firm-Level Production Function Estimators. Economics Series Working Papers 513, University of Oxford, Department of Economics. https://ideas.repec.org/s/oxf/wpaper.html

Ek, A. (2024). Cultural Values and Productivity. Journal of Political Economy, 132(1). https://doi.org/10.1086/726239

Fabling, R., Maré, D. C., and Stevens, P. (2022). Migration and Firm-Level Productivity. IZA DP No. 15482. https://doi.org/10.2139/ssrn.4188293

Griliches, Z., and Mairesse, J. (2012). Production Functions: The Search for Identification. In Econometrics and Economic Theory in the 20th Century. https://doi.org/10.1017/ccol521633230.006

Hellerstein, J. K., Neumark, D., and Troske, K. R. (1999). Wages, productivity, and worker characteristics: Evidence from plant-level production functions and wage equations. Journal of labour Economics, 17(3). https://doi.org/10.1086/209926

Hunt, J., and Gauthier-Loiselle, M. (2010). How much does immigration boost innovation. American Economic Journal: Macroeconomics, 2(2). https://doi.org/10.1257/mac.2.2.31

Jaeger, D. A., Ruist, J., and Stuhler, J. (2018). Shift-Share Instruments and the Impact of Immigration. NBER Working Papers 24285. https://doi.org/10.2139/ssrn.3117311

Jaumotte, F., Koloskova, K., and Saxena, S., C. (2016). Impact of Migration on Income Levels in Advanced Economies. IMF Spillover Notes 2016/008, International Monetary Fund. https://ideas.repec.org/p/imf/imfsns/2016-008.html

Kemeny, T., and Cooke, A. (2018). Spillovers from immigrant diversity in cities. Journal of Economic Geography, 18(1). https://doi.org/10.1093/jeg/lbx012

Kerr, S. P., and Kerr, W. (2020). Immigrant Entrepreneurship in America: Evidence from the Survey of Business Owners 2007 and 2012. Research Policy, 49(3): 103918. https://doi.org/10.1016/j.respol.2019.103918

Krugman, P. (1997) The Age of Diminished Expectations, MIT Press. https://ideas.repec.org/b/mtp/titles/0262611341.html

Levinsohn, J., and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. Review of Economic Studies, 70(2). https://doi.org/10.1111/1467-937X.00246

Lewis, E. (2011). Immigration, Skill Mix, and Capital Skill Complementarity. The Quarterly Journal of Economics, 126(2), 1029–1069. https://doi.org/10.1093/qje/qjr011

Lewis, E. (2013). Immigration and production technology. In Annual Review of Economics, Vol. 5:165-191. https://doi.org/10.1146/annurev-economics-080612-134132

Manning, A., and Petrongolo, B. (2017). How local are labour markets? Evidence from a spatial job search model. American Economic Review, 107(10). https://doi.org/10.1257/aer.20131026

Mitaritonna, C., Orefice, G., and Peri, G. (2017). Immigrants and firms' outcomes: Evidence from France. European Economic Review, 96. https://doi.org/10.1016/j.euroecorev.2017.05.001

Mollisi, V., and Rovigatti, G. (2017). Theory and Practice of TFP Estimation: The Control Function Approach Using Stata. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2916753

Murard, E., and Sakalli, S. O. (2021). Mass Refugee Inflow and Long-Run Prosperity: Lessons from the Greek Population Resettlement. IZA DP No. 11613. https://doi.org/10.2139/ssrn.3209707

Nam, H., and Portes, J. (2023). Migration and Productivity in the UK: An Analysis of Employee Payroll Data. IZA DP No. 16472. https://doi.org/10.2139/ssrn.4584949

Nathan, M., and Lee, N. (2013). Cultural diversity, innovation, and entrepreneurship: Firm-level evidence from London. Economic Geography, 89(4). https://doi.org/10.1111/ecge.12016

Nickell, S. (1981). Biases in Dynamic Models with Fixed Effects. Econometrica, 49(6). https://doi.org/10.2307/1911408

Olley, G. S., and Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. Econometrica, 64(6). https://doi.org/10.2307/2171831

Ortega, F., and Peri, G. (2014). Openness and income: The roles of trade and migration. Journal of International Economics, 92(2). https://doi.org/10.1016/j.jinteco.2013.11.008

Ottaviano, G. I. P., and Peri, G. (2012). Rethinking the effect of immigration on wages. Journal of the European Economic Association, 10(1). https://doi.org/10.1111/j.1542-4774.2011.01052.x

Ottaviano, G. I. P., Peri, G., and Wright, G. C. (2018). Immigration, trade and productivity in services: Evidence from U.K. firms. Journal of International Economics, 112. https://doi.org/10.1016/j.jinteco.2018.02.007

Parrotta, P., Pozzoli, D., and Pytlikova, M. (2014). labour diversity and firm productivity. European Economic Review, 66. https://doi.org/10.1016/j.euroecorev.2013.12.002

Paserman, M. D. (2013). Do high-skill immigrants raise productivity? Evidence from Israeli manufacturing firms, 1990-1999. IZA Journal of Migration, 2(1). https://doi.org/10.1186/2193-9039-2-6

Peri, G. (2012). The effect of immigration on productivity: Evidence from U.S. States. Review of Economics and Statistics, 94(1). https://doi.org/10.1162/RESTa00137

Rice, P., Venables, A. J., and Patacchini, E. (2006). Spatial determinants of productivity: Analysis for the regions of Great Britain. Regional Science and Urban Economics, 36(6). https://doi.org/10.1016/j.regsciurbeco.2006.03.006

Rocha, R., Ferraz, C., and Soares, R. R. (2017). Human capital persistence and development. American Economic Journal: Applied Economics, 9(4). https://doi.org/10.1257/app.20150532

San, S. (2023). labour Supply and Directed Technical Change: Evidence from the Termination of the Bracero Program in 1964. American Economic Journal: Applied Economics, 15(1). https://doi.org/10.1257/app.20200664

Sequira, S., Nunn, N., and Qian, N. (2021). Immigrants and the making of America. Review of Economic Studies, 87(1). https://doi.org/10.1093/RESTUD/RDZ003

Valero, A., and Van Reenen, J. (2019). The UK Economy: Policies for Investment and Productivity Growth. CEP Election Analysis Papers.

Viskanic, M. (2018). Fear and Loathing on the Campaign Trail: Did Immigration Cause Brexit? SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2941611

Waldinger, R. (1986). Immigrant enterprise: A critique and reformulation. Theory and Society, 15(1–2). https://doi.org/10.1007/BF00156934

Appendix - for Online Publication Only

A Robustness

A.1 Translog production function

Our estimated production functions can be thought of as a first-order approximation to an arbitrary production function. However the first-order approximation cannot estimate complementaries that have been argued to be important between labour and capital (Lewis, 2011, 2013) or migrants and locals (Kemeny and Cooke, 2018). To investigate this we estimate a translog production function which can be thought of as a 2nd order Taylor approximation to general unknown production function). The translog model for N inputs:

$$\ln Y = \beta_0 + \sum_{i=1}^{N} \beta_i \ln X_i + \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \beta_{ij} \ln X_i \ln X_j \tag{18}$$

With a translog marginal products depend on the factor inputs in a complicated way making it hard to interpret results. In the translog estimates reported below each variable is expressed as the deviation from its mean (demeaned). Tha main effects can then be interpreted as relative producitivty effects at the sample mean.

In Table 12 below we show regression with (i) only capital and labour interactions, (ii) capital and labour also interacted with migrant share, and (iii) full translog interaction.

We find some evidence of significant interaction effects between migrant share and capital. Whilst Cobb-Douglas is rejected, the marginal effects of capital, labour and migrant share evaluated at the mean are similar to those in our main results section.

Table 12: Log value-added per worker translog regression results, all covariates demeaned.

	(1) OLS (i)	(2) OLS (ii)	(3) OLS (iii)	(4) IV (i)	(5) IV (ii)	(6) IV (iii)
Migrant share	0.0645***	0.0531**	0.0743***	0.476***	0.473***	0.124
	(0.0179)	(0.0170)	(0.0209)	(0.0935)	(0.0899)	(0.193)
Migrant share^2			-0.0422			0.760
			(0.0501)			(0.539)
Migrant share - k		0.0474***	0.0474***		0.155***	0.156***
		(0.00600)	(0.00599)		(0.0115)	(0.0114)
Migrant share - l		-0.0239***	-0.0240***		-0.0443**	-0.0458**
		(0.00593)	(0.00589)		(0.0148)	(0.0155)
Labour	0.0202***	0.0209***	0.0209***	0.0180***	0.0196***	0.0199***
	(0.00185)	(0.00176)	(0.00176)	(0.00204)	(0.00177)	(0.00175)
Capital per worker	0.160***	0.160***	0.160***	0.160***	0.159***	0.159***
	(0.00300)	(0.00267)	(0.00266)	(0.00298)	(0.00208)	(0.00208)
l^2	-0.0120***	-0.0120***	-0.0120***	-0.0118***	-0.0117***	-0.0117***
	(0.000635)	(0.000629)	(0.000629)	(0.000614)	(0.000602)	(0.000601)
k^2	0.0203***	0.0202***	0.0202***	0.0203***	0.0200***	0.0199***
	(0.000549)	(0.000523)	(0.000522)	(0.000543)	(0.000477)	(0.000476)
k - l	0.0129***	0.0129***	0.0129***	0.0130***	0.0129***	0.0128***
	(0.000588)	(0.000589)	(0.000590)	(0.000588)	(0.000603)	(0.000609)
N	525903	525903	525903	525903	525903	525903
r2	0.239	0.240	0.240	0.0957	0.0906	0.0879
Fixed Effects						
Year-TTWA-Ind	✓	✓	✓	✓	✓	✓

Cluster robust standard errors in parentheses, clustered at the cas ward level.
Year-TTWA-Ind: Full interation between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 13 below we differentiate by skill level. We find a strong positive interaction between high-skilled migrant labour and capital. Unlike Lewis (2011, 2013) we also find positive interactions between lower-skilled migrant labour and capital. There is also a significant positive interaction between high-skilled migrants and high-skilled locals.

The full translog interaction specification (iii) using our labour share IV is omitted because first stages are no longer significant (with too many instruments the ‘wrong’ instrument is picked up by each variable). All other first stages are significant and pick out the ‘correct’ variable.

In addition none of our translog estimates include firm fixed effects as none of the estimated coefficients are significantly different from zero in this case.

Table 13: Log value-added per worker translog regression results, all covariates demeaned. By skill level.

	(1) OLS (i)	(2) OLS (ii)	(3) OLS (iii)	(4) IV (i)	(5) IV (ii)
M-low share	-0.00680	-0.0163	0.0639^{*}	-0.00292	-0.0278
	(0.0137)	(0.0143)	(0.0313)	(0.0750)	(0.0692)
M-high share	0.181^{***}	0.166^{***}	0.158^{***}	0.869^{***}	0.891^{***}
	(0.0307)	(0.0285)	(0.0397)	(0.103)	(0.0996)
N-high share	0.0180^{*}	0.0101	0.0365^{**}	0.126^{*}	0.120^{*}
	(0.00715)	(0.00717)	(0.0138)	(0.0502)	(0.0483)
M-low - l		-0.0144^{*}	-0.0144^{*}		0.0604
		(0.00671)	(0.00669)		(0.0311)
M-high - l		-0.0381^{***}	-0.0367^{***}		-0.112^{***}
		(0.00960)	(0.00956)		(0.0264)
N-high - l		-0.00924^{**}	-0.00849^{*}		0.0245
		(0.00358)	(0.00357)		(0.0188)
M-low - k		0.0303^{***}	0.0304^{***}		0.115^{***}
		(0.00533)	(0.00536)		(0.0209)
M-high - k		0.0935^{***}	0.0942^{***}		0.185^{***}
		(0.00934)	(0.00937)		(0.0206)
N-high - k		0.0310^{***}	0.0313^{***}		0.127^{***}
		(0.00263)	(0.00264)		(0.0127)
M-low - M-high			0.136		
			(0.206)		
M-low - N-high			0.209		
			(0.116)		
M-high - N-high			0.639^{***}		
			(0.148)		
M-low^2			-0.0220		
			(0.0663)		
M-high^2			0.268^{*}		
			(0.114)		
N-high^2			0.100^{***}		
			(0.0279)		
Labour	0.0203^{***}	0.0210^{***}	0.0208^{***}	0.0196^{***}	0.0204^{***}
	(0.00185)	(0.00174)	(0.00174)	(0.00196)	(0.00173)
Capital per worker	0.160^{***}	0.160^{***}	0.160^{***}	0.160^{***}	0.160^{***}
	(0.00299)	(0.00246)	(0.00246)	(0.00296)	(0.00198)
l^2	-0.0120^{***}	-0.0120^{***}	-0.0120^{***}	-0.0120^{***}	-0.0119^{***}
	(0.000631)	(0.000624)	(0.000624)	(0.000612)	(0.000602)
k^2	0.0203^{***}	0.0203^{***}	0.0202^{***}	0.0202^{***}	0.0202^{***}
	(0.000547)	(0.000512)	(0.000511)	(0.000542)	(0.000476)
$k - l$	0.0129^{***}	0.0132^{***}	0.0132^{***}	0.0128^{***}	0.0142^{***}
	(0.000588)	(0.000589)	(0.000591)	(0.000587)	(0.000625)
N	525903	525903	525903	525903	525903
r2	0.239	0.241	0.241	0.0947	0.0869
Fixed Effects					
Year-TTWA-Ind	✓	✓	✓	✓	✓

Cluster robust standard errors in parentheses, clustered at the cas ward level.
Year-TTWA-Ind: Full interation between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.2 Sensitivity to labour and capital coefficients

The production function coefficient estimates on capital α and labour β are not of first-order importance to us; we're interested in the migrant share effect. One way of testing the robustness of our results is hence to see whether these hold over a range of plausible labour and capital coefficients (see Eberhardt and Helmers 2010 for an overview of production function parameter estimates using various methods in the UK).

Tables 14 and 15 present some estimates imposing values of the labour and capital share. Across all specifications, the migrant share effect is positive and significant without the inclusion of firm fixed effect, controlling for year-TTWA and year - 3-digit industry fixed effects. The migrant share effect is stronger when labour has a higher share in production. With the inclusion of firm fixed effects, there is no combination of labour and capital for which migrant share effects are significant.

Table 14: IV regressions of value-added per worker with imposed capital and labour coefficients.

Constant returns to scale	(1)	(2)	(3)	(4)	(5)	(6)
	$\alpha = 0.1$	$\alpha = 0.1$	$\alpha = 0.2$	$\alpha = 0.2$	$\alpha = 0.3$	$\alpha = 0.3$
	$\beta = 0.9$	$\beta = 0.9$	$\beta = 0.8$	$\beta = 0.8$	$\beta = 0.7$	$\beta = 0.7$
Migrant share	0.515***	0.0506	0.488***	0.0244	0.461***	-0.00182
	(0.104)	(0.0767)	(0.0944)	(0.0810)	(0.0858)	(0.0882)
N	525903	280732	525903	280732	525903	280732
r2	-0.00668	-0.000213	-0.00577	-0.0000381	-0.00450	-0.00000139
Increasing returns to scale	(1)	(2)	(3)	(4)	(5)	(6)
	$\alpha = 0.2$	$\alpha = 0.2$	$\alpha = 0.3$	$\alpha = 0.3$	$\alpha = 0.4$	$\alpha = 0.4$
	$\beta = 0.9$	$\beta = 0.9$	$\beta = 0.8$	$\beta = 0.8$	$\beta = 0.7$	$\beta = 0.7$
Migrant share	0.552***	0.0137	0.525***	-0.0125	0.499***	-0.0387
	(0.103)	(0.0807)	(0.0938)	(0.0881)	(0.0856)	(0.0978)
N	525903	280732	525903	280732	525903	280732
r2	-0.00669	-0.00000746	-0.00534	-0.0000213	-0.00395	-0.000128
Decreasing returns to scale	(1)	(2)	(3)	(4)	(5)	(6)
	$\alpha = 0.05$	$\alpha = 0.05$	$\alpha = 0.1$	$\alpha = 0.1$	$\alpha = 0.15$	$\alpha = 0.15$
	$\beta = 0.8$	$\beta = 0.8$	$\beta = 0.7$	$\beta = 0.7$	$\beta = 0.6$	$\beta = 0.6$
Migrant share	0.432***	0.0798	0.386***	0.0720	0.340***	0.0642
	(0.0968)	(0.0779)	(0.0891)	(0.0794)	(0.0825)	(0.0815)
N	525903	280732	525903	280732	525903	280732
r2	-0.00524	-0.000540	-0.00439	-0.000429	-0.00348	-0.000327
Fixed Effects						
Firm		✓		✓		✓
Year-TTWA-Ind	✓	✓	✓	✓	✓	✓

Cluster robust standard errors in parentheses, clustered at the cas ward level.
Year-TTWA-Ind: Full interation between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: IV regressions on VA per worker with imposed capital coefficients and labour coefficients. By skill level.

Constant returns to scale	(1) $\alpha = 0.1$ $\beta = 0.9$	(2) $\alpha = 0.1$ $\beta = 0.9$	(3) $\alpha = 0.2$ $\beta = 0.8$	(4) $\alpha = 0.2$ $\beta = 0.8$	(5) $\alpha = 0.3$ $\beta = 0.7$	(6) $\alpha = 0.3$ $\beta = 0.7$
M-low share	-0.0287	0.0483	0.0560	0.0188	0.141	-0.0107
	(0.0829)	(0.0896)	(0.0766)	(0.0933)	(0.0729)	(0.100)
M-high share	0.936***	0.105	0.827***	0.105	0.719***	0.105
	(0.111)	(0.152)	(0.105)	(0.159)	(0.102)	(0.172)
N-high share	0.0822	0.0170	0.155**	0.00569	0.229***	-0.00561
	(0.0549)	(0.0479)	(0.0512)	(0.0493)	(0.0499)	(0.0522)
N	525903	280732	525903	280732	525903	280732
r2	-0.00812	-0.000467	-0.00569	-0.000343	-0.00411	-0.000314
Increasing returns to scale	(1) $\alpha = 0.2$ $\beta = 0.9$	(2) $\alpha = 0.2$ $\beta = 0.9$	(3) $\alpha = 0.3$ $\beta = 0.8$	(4) $\alpha = 0.3$ $\beta = 0.8$	(5) $\alpha = 0.4$ $\beta = 0.7$	(6) $\alpha = 0.4$ $\beta = 0.7$
M-low share	-0.00446	0.00380	0.0803	-0.0257	0.165*	-0.0552
	(0.0836)	(0.0924)	(0.0787)	(0.0994)	(0.0763)	(0.109)
M-high share	0.971***	0.104	0.862***	0.104	0.754***	0.104
	(0.114)	(0.159)	(0.108)	(0.171)	(0.106)	(0.188)
N-high share	0.0216	-0.00811	0.0949	-0.0194	0.168**	-0.0307
	(0.0563)	(0.0486)	(0.0537)	(0.0517)	(0.0534)	(0.0562)
N	525903	280732	525903	280732	525903	280732
r2	-0.00848	-0.000383	-0.00522	-0.000421	-0.00324	-0.000511
Decreasing returns to scale	(1) $\alpha = 0.05$ $\beta = 0.8$	(2) $\alpha = 0.05$ $\beta = 0.8$	(3) $\alpha = 0.1$ $\beta = 0.7$	(4) $\alpha = 0.1$ $\beta = 0.7$	(5) $\alpha = 0.15$ $\beta = 0.6$	(6) $\alpha = 0.15$ $\beta = 0.6$
M-low share	0.0196	0.0855	0.0921	0.0782	0.165*	0.0710
	(0.0782)	(0.0915)	(0.0737)	(0.0928)	(0.0715)	(0.0950)
M-high share	0.775***	0.107	0.649***	0.108	0.523***	0.108
	(0.105)	(0.155)	(0.102)	(0.157)	(0.102)	(0.161)
N-high share	0.246***	0.0434	0.350***	0.0446	0.453***	0.0459
	(0.0514)	(0.0498)	(0.0494)	(0.0504)	(0.0495)	(0.0514)
N	525903	280732	525903	280732	525903	280732
r2	-0.00589	-0.000812	-0.00603	-0.000756	-0.00752	-0.000697
Fixed Effects						
Firm		✓		✓		✓
Year-TTWA-Ind	✓	✓	✓	✓	✓	✓

Cluster robust standard errors in parentheses, clustered at the cas ward level.
Year-TTWA-Ind: Full interation between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Regression data from ARDx (ONS, 2023a) linked to QLFS (ONS, 2023b) and APS (ONS, 2023c).

A.3 Including larger multi-plant firms

For the main results section our data only includes those firms which have a unique plant so that we can precisely estimate the local migrant share. However, this excludes larger firms which operate at multiple plants. This is a small share of firms in our full ARDx sample (10%) but much larger share of sample employment (45%).

For each plant we have information on employment and revenue but not capital stock or value-added. So to estimate plant-level production functions, we allocate firm capital stock and value-added to plants based on the plant's share in total firm employment. Note that this is essentially assigning the same productivity to all of a firm's plants. Results at the plant level are reported in Table 16 using a shift-share IV to instrument for each plant's local migrant share in columns (1) - (8) and in columns (4) - (8) further using the ACF control function approach combined with the shift-share IV for plant employment. Plant-level migrant share effects are lower than those at the firm level. But unlike our firm-level estimates, the migrant share effect remains significant, albeit small, with the inclusion of firm fixed effects.

In Table 17 we estimate production functions at the firm level but keep in the sample those firms with multiple plants, assigning them the migrant share in the ward-industry where they have the most plants (dropping firms which have no modal ward - industry). These results are very similar to our main specification.

Table 16: Value-added per worker regression results at the plant (luref) level.

	(1) IV	(2) IV	(3) IV	(4) IV	(5) ACF-LIV	(6) ACF-LIV	(7) ACF-LIV	(8) ACF-LIV
Migrant share	0.0149^{***}	0.264^{***}			-0.000366	0.173^{**}		
	(0.00433)	(0.0407)			(0.0175)	(0.0640)		
M-low share			0.0108	0.0536			0.0781	0.0489
			(0.00752)	(0.0343)			(0.0417)	(0.134)
M-high share			0.0286^{**}	0.542^{***}			-0.104	0.274
			(0.00949)	(0.0497)			(0.0565)	(0.231)
Loc-high share			0.00709	0.0122			0.0378	0.0290
			(0.00709)	(0.0277)			(0.0264)	(0.116)
Labour	-0.0000495	0.0548^{***}	-0.0000361	0.0549^{***}	0.000565	0.0230^{***}	0.000621	0.0216^{***}
	(0.000709)	(0.00106)	(0.000710)	(0.00105)	(0.00193)	(0.00522)	(0.00196)	(0.00521)
Capital per Worker	0.0583^{***}	0.108^{***}	0.0583^{***}	0.108^{***}	0.0178^{***}	0.0261^{***}	0.0180^{***}	0.0254^{***}
	(0.000881)	(0.000605)	(0.000882)	(0.000612)	(0.00320)	(0.00475)	(0.00317)	(0.00474)
N	2405057	2647558	2405057	2647558	45717	46348	45717	46348
r2	0.0181	0.0767	0.0181	0.0747	0.00846	0.192	0.00182	0.194
Fixed Effects								
Firm	✓		✓		✓		✓	
Year-TTWA-Ind	✓	✓	✓	✓	✓	✓	✓	✓

Cluster robust standard errors in parentheses, clustered at the cas ward level.
Year-TTWA-Ind: Full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Value-added per worker regression results at the firm level, with multi-plant firms located in their modal ward - industry.

	(1) IV	(2) IV	(3) IV	(4) IV	(5) ACF - LIV	(6) ACF - LIV	(7) ACF - LIV	(8) ACF - LIV
Migrant share	-0.0173	0.530^{***}			-0.0427	0.212^{*}		
	(0.0583)	(0.0903)			(0.162)	(0.101)		
M-low share			-0.0403	-0.0773			-0.178	-0.0335
			(0.0658)	(0.0640)			(0.236)	(0.165)
M-high share			-0.00511	1.005^{***}			0.112	0.830^{*}
			(0.0973)	(0.0928)			(0.447)	(0.333)
Loc-high share			-0.0282	-0.0285			-0.0259	0.146
			(0.0344)	(0.0315)			(0.0993)	(0.0973)
Labour	-0.441^{***}	0.0174^{***}	-0.441^{***}	0.0181^{***}	-0.0481	0.0167	-0.0505	0.0159
	(0.00943)	(0.00281)	(0.00946)	(0.00282)	(0.218)	(0.0122)	(0.224)	(0.0120)
Capital per worker	0.0341^{***}	0.114^{***}	0.0341^{***}	0.113^{***}	0.158^{**}	0.0949^{***}	0.158^{**}	0.0952^{***}
	(0.00243)	(0.00251)	(0.00243)	(0.00247)	(0.0589)	(0.0105)	(0.0604)	(0.0105)
N	307568	553579	307568	553579	23282	26266	23282	26266
r2	0.0838	0.0643	0.0837	0.0602	0.0264	0.160	0.0232	0.148
Fixed Effects								
Firm	✓		✓		✓		✓	
Year-TTWA-Ind	✓	✓	✓	✓	✓	✓	✓	✓

Cluster robust standard errors in parentheses, clustered at the cas ward level.
Year-TTWA-Ind: Full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.4 Firm employment measured in full-time equivalent workers

In the main results section, we use raw headcount employment to measure labour. However, ideally, we would want to measure labour in terms of full-time equivalent (FTE) workers. Data on full/part-time workers is available for the years 1998 - 2014, from which we can estimate firm-level FTE workers. Tables 18 to 21 below replicate our main results from Section 5 measuring firm labour in FTE workers.

To do this for each year-industry (SIC07 2-digit) and TTWA, we link in median full-time and part-time hours measured from the QLFS/APS. For an estimate of total annual hours worked at the firm level (X_{ft}), we use the total number of male / female full / part time employees at the firm level multiplied by the median hours worked each week by male / female full / part workers in the same industry (SIC07 2 digit), TTWA, and year, multiplied by the weeks in a year (52). For each of $type \in (M - ft, M - pt, F - ft, F - ft)$, total working hours at the firm level:

$$X_{ft} = \sum_{type} N_{ft}^{type} * h_{industry,ttwa,t}^{type} * 52 \tag{19}$$

To measure total employment in full-time equivalents (FTE), we divide total hours worked at the firm by the median full-time hours per year.

Table 18: Value-added per FTE worker regression results.

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Migrant Share	0.283^{***}	0.0302	0.00795	0.0193
	(0.0465)	(0.0171)	(0.0113)	(0.0102)
Labour (FTE)	-0.0330^{***}	-0.0153^{***}	-0.0249^{***}	-0.352^{***}
	(0.00184)	(0.00169)	(0.00182)	(0.0112)
Captal per worker (FTE)	0.0668^{***}	0.0607^{***}	0.0591^{***}	0.0243^{***}
	(0.00109)	(0.00117)	(0.00114)	(0.00281)
N	235,205	234,966	234,893	154,962
r2	0.102	0.240	0.283	0.787
Implied α	0.0668^{***}	0.0607^{***}	0.0591^{***}	0.0243^{***}
	(0.00109)	(0.00117)	(0.00114)	(0.00281)
Implied β	0.900^{***}	0.924^{***}	0.916^{***}	0.624^{***}
	(0.00238)	(0.00234)	(0.00250)	(0.0114)
Implied μ	0.314^{***}	0.0327	0.00868	0.0309
	(0.0518)	(0.0185)	(0.0124)	(0.0162)
	(1) IV	(2) IV	(3) IV	(4) IV
Migrant Share	1.163^{***}	0.359^{***}	0.0900	0.0286
	(0.0925)	(0.0804)	(0.173)	(0.0774)
Labour (FTE)	-0.0360^{***}	-0.0163^{***}	-0.0249^{***}	-0.351^{***}
	(0.00190)	(0.00175)	(0.00182)	(0.0112)
Captal per worker (FTE)	0.0694^{***}	0.0609^{***}	0.0591^{***}	0.0243^{***}
	(0.00119)	(0.00117)	(0.00114)	(0.00281)
N	235,205	234,966	234,893	154,962
r2	0.00201	0.0354	0.0387	0.0564
Implied α	0.0694^{***}	0.0609^{***}	0.0591^{***}	0.0243^{***}
	(0.00119)	(0.00117)	(0.00114)	(0.00281)
Implied β	0.895^{***}	0.923^{***}	0.916^{***}	0.624^{***}
	(0.00257)	(0.00241)	(0.00250)	(0.0114)
Implied μ	1.300^{***}	0.389^{***}	0.0982	0.0458
	(0.105)	(0.0874)	(0.189)	(0.124)
Fixed Effects				
Firm				✓
CAS Ward			✓	
Year-TTWA-Ind		✓	✓	✓
Year	✓	✓	✓	✓

Cluster robust standard errors in parentheses, clustered at the CAS ward level.
Year-TTWA-Ind: Full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: Value-added per FTE worker regression results. Control function approach - IV for migrant share and FEs.

No Firm Fixed Effects	(1) OP	(2) LP	(3) ACF	(4) CWDL	(5) LIV
Migrant Share	0.347***	0.109**	0.227***	0.226***	0.218***
	(0.0346)	(0.0403)	(0.0624)	(0.0629)	(0.0610)
Labour (FTE)	0.0109***	0.0312***	0.0381***	0.0367***	0.0399***
	(0.00192)	(0.00256)	(0.00416)	(0.00421)	(0.00818)
Captal per worker (FTE)	0.0863***	0.0626***	0.0796***	0.199***	0.0765***
	(0.00278)	(0.00415)	(0.00719)	(0.0232)	(0.00706)
N	88691	41730	21320	21320	22109
r2	0.0820	0.148	0.155	0.142	0.156
Implied α	0.0863***	0.0626***	0.0796***	0.199***	0.0765***
	(0.00278)	(0.00415)	(0.00719)	(0.0232)	(0.00706)
Implied β	0.925***	0.969***	0.958***	0.837***	0.963***
	(0.00332)	(0.00485)	(0.00815)	(0.0239)	(0.0104)
Implied μ	0.376***	0.112**	0.237***	0.270***	0.226***
	(0.0375)	(0.0417)	(0.0652)	(0.0756)	(0.0631)
	(1)	(2)	(3)	(4)	(5)
Firm Fixed Effects	OP	LP	ACF	CWDL	LIV
Migrant Share	-0.0217	0.00504	0.0611	0.0603	0.0796
	(0.0780)	(0.120)	(0.160)	(0.160)	(0.163)
Labour (FTE)	-0.0625***	0.00121	-0.00147	0.00852	0.102
	(0.0185)	(0.0234)	(0.0382)	(0.0386)	(0.264)
Captal per worker (FTE)	0.107***	0.0999***	0.117***	0.145*	0.150
	(0.00562)	(0.00864)	(0.0164)	(0.0609)	(0.0830)
N	62574	31800	18811	18811	19476
r2	0.0304	0.00974	0.0110	0.00957	-0.00161
Implied α	0.107***	0.0999***	0.117***	0.145*	0.150
	(0.00562)	(0.00864)	(0.0164)	(0.0609)	(0.0830)
Implied β	0.831***	0.901***	0.882***	0.864***	0.952***
	(0.0156)	(0.0202)	(0.0288)	(0.0546)	(0.182)
Implied μ	-0.0262	0.00559	0.0693	0.0698	0.0836
	(0.0939)	(0.133)	(0.181)	(0.185)	(0.168)

Cluster robust standard errors in parentheses, clustered at the CAS ward level.
All specifications include fixed effects for the full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20: Value-added per FTE worker regression results, by skill level.

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Migrant-low share	0.134**	-0.0352	-0.0145	0.0165
	(0.0430)	(0.0210)	(0.0134)	(0.0120)
Migrant-high share	0.611***	0.157***	0.0368*	0.0144
	(0.0548)	(0.0222)	(0.0178)	(0.0171)
Local-high share	0.186***	0.0325***	0.0000521	0.00827
	(0.0164)	(0.00814)	(0.00712)	(0.00676)
Labour (FTE)	-0.0313***	-0.0152***	-0.0249***	-0.352***
	(0.00181)	(0.00169)	(0.00182)	(0.0112)
Captal per worker (FTE)	0.0675***	0.0607***	0.0591***	0.0243***
	(0.00110)	(0.00116)	(0.00114)	(0.00281)
N	235,205	234,966	234,893	154,962
r2	0.109	0.241	0.283	0.787
Implied α	0.0675***	0.0607***	0.0591***	0.0243***
	(0.00110)	(0.00116)	(0.00114)	(0.00281)
Implied β	0.901***	0.924***	0.916***	0.624***
	(0.00237)	(0.00234)	(0.00250)	(0.0114)
Implied $\mu M - low$	0.149**	-0.0381	-0.0158	0.0264
	(0.0478)	(0.0227)	(0.0146)	(0.0192)
Implied $\mu M - high$	0.678***	0.170***	0.0402*	0.0230
	(0.0611)	(0.0242)	(0.0195)	(0.0274)
Implied $\mu N - high$	0.206***	0.0352***	0.0000569	0.0132
	(0.0183)	(0.00881)	(0.00778)	(0.0108)
	(1) IV	(2) IV	(3) IV	(4) IV
Migrant-low shares	0.143	-0.196**	-0.207	-0.0959
	(0.0908)	(0.0674)	(0.128)	(0.0912)
Migrant-high share	1.948***	1.011***	0.344	0.0300
	(0.141)	(0.150)	(0.265)	(0.146)
Local-high share	0.650***	0.199***	0.0587	0.0924*
	(0.0519)	(0.0484)	(0.0442)	(0.0467)
Labour (FTE)	-0.0284***	-0.0151***	-0.0249***	-0.352***
	(0.00193)	(0.00176)	(0.00183)	(0.0112)
Captal per worker (FTE)	0.0706***	0.0603***	0.0590***	0.0244***
	(0.00118)	(0.00116)	(0.00114)	(0.00283)
N	235,205	234,966	234,893	154,962
r2	-0.00209	0.0230	0.0351	0.0535
Implied α	0.0706***	0.0603***	0.0590***	0.0244***
	(0.00118)	(0.00116)	(0.00114)	(0.00283)
Implied β	0.901***	0.925***	0.916***	0.624***
	(0.00259)	(0.00241)	(0.00251)	(0.0114)
Implied $\mu M - low$	0.159	-0.212**	-0.226	-0.154
	(0.101)	(0.0728)	(0.140)	(0.146)
Implied $\mu M - high$	2.162***	1.093***	0.376	0.0481
	(0.157)	(0.163)	(0.290)	(0.233)
Implied $\mu N - high$	0.721***	0.216***	0.0641	0.148*
	(0.0576)	(0.0524)	(0.0482)	(0.0749)
Fixed Effects				
Firm				✓
CAS Ward			✓	
Year-TTWA-Ind		✓	✓	✓
Year	✓	✓	✓	✓

Cluster robust standard errors in parentheses, clustered at the CAS ward level.
Year-TTWA-Ind: Full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21: Value-added per FTE worker regression results, by skill level. Control function approach with IV for labour shares.

	(1)	(2)	(3)	(4)	(5)
No Firm Fixed Effects	OP	LP	ACF	CWDL	LIV
Migrant-low share	-0.101	-0.0291	0.0779	0.0664	0.0755
	(0.0633)	(0.0906)	(0.129)	(0.130)	(0.126)
Migrant-high share	0.983***	0.580**	0.684*	0.707*	0.685**
	(0.0931)	(0.200)	(0.277)	(0.279)	(0.263)
Local-high share	0.299***	0.177**	0.240**	0.241**	0.221*
	(0.0465)	(0.0658)	(0.0879)	(0.0885)	(0.0865)
Labour (FTE)	0.0122***	0.0321***	0.0393***	0.0378***	0.0395***
	(0.00195)	(0.00261)	(0.00421)	(0.00426)	(0.00831)
Captal per worker (FTE)	0.0863***	0.0625***	0.0806***	0.196***	0.0774***
	(0.00281)	(0.00418)	(0.00725)	(0.0234)	(0.00711)
N	88691	41730	21320	21320	22109
r2	0.0820	0.148	0.155	0.142	0.156
Implied α	0.0863***	0.0625***	0.0806***	0.196***	0.0774***
	(0.00281)	(0.00418)	(0.00725)	(0.0234)	(0.00711)
Implied β	0.925***	0.969***	0.958***	0.837***	0.963***
	(0.00332)	(0.00485)	(0.00815)	(0.0239)	(0.0104)
Implied $\mu M - low$	-0.109	-0.0300	0.0812	0.0790	0.0785
	(0.0684)	(0.0935)	(0.135)	(0.155)	(0.131)
Implied $\mu M - high$	1.062***	0.598**	0.714*	0.840*	0.712**
	(0.101)	(0.206)	(0.289)	(0.332)	(0.273)
Implied $\mu N - high$	0.323***	0.183**	0.250**	0.286**	0.230*
	(0.0502)	(0.0678)	(0.0916)	(0.106)	(0.0901)
	(1)	(2)	(3)	(4)	(5)
Firm Fixed Effects	OP	LP	ACF	CWDL	LIV
Migrant-low share	-0.117	-0.0246	-0.0197	-0.0209	-0.0365
	(0.106)	(0.163)	(0.205)	(0.205)	(0.200)
Migrant-high share	0.174	0.0451	0.0338	0.0358	0.131
	(0.173)	(0.303)	(0.439)	(0.439)	(0.446)
Local-high share	-0.102	0.00260	-0.0194	-0.0209	-0.00810
	(0.0639)	(0.0823)	(0.112)	(0.111)	(0.110)
Labour (FTE)	-0.0602**	0.00128	-0.00145	0.00737	0.0903
	(0.0187)	(0.0235)	(0.0382)	(0.0388)	(0.274)
Captal per worker (FTE)	0.108***	0.0999***	0.117***	0.142*	0.147
	(0.00568)	(0.00864)	(0.0165)	(0.0615)	(0.0863)
N	62574	31800	18811	18811	19476
r2	0.0304	0.00974	0.0110	0.00957	-0.00161
Implied α	0.108***	0.0999***	0.117***	0.142*	0.147
	(0.00568)	(0.00864)	(0.0165)	(0.0615)	(0.0863)
Implied β	0.832***	0.901***	0.881***	0.865***	0.943***
	(0.0158)	(0.0203)	(0.0288)	(0.0549)	(0.188)
Implied $\mu M - low$	-0.141	-0.0273	-0.0224	-0.0242	-0.0387
	(0.127)	(0.180)	(0.233)	(0.237)	(0.213)
Implied $\mu M - high$	0.209	0.0500	0.0383	0.0414	0.139
	(0.208)	(0.336)	(0.499)	(0.507)	(0.465)
Implied $\mu N - high$	-0.123	0.00288	-0.0220	-0.0242	-0.00859
	(0.0768)	(0.0913)	(0.127)	(0.129)	(0.117)

Cluster robust standard errors in parentheses, clustered at the CAS ward level.
All specifications include fixed effects for the full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.5 Dynamic panel production function estimators

Blundell and Bond (2000) identify conditions which allow lagged levels of endogenous variables to be valid instruments for the endogenous first differences. We apply this idea to our production function estimation setting. Blundell and Bond (2000) generalise the fixed effects model to allow ω_{ft} to vary across time. The error term is composed of an observable and random component.

$$y_{ft} = \beta_0 + \beta_1 k_{ft} + \beta_2 l_{ft} + \sum_j \beta_j s^j_{ft} + \omega_{ft} + \epsilon_{ft} \tag{20}$$

The key difference with control function approaches is that we assume ω_{ft} follows a linear process

$$\omega_{ft} = \rho\omega_{ft-1} + \xi_{ft} \tag{21}$$

Estimate by ρ-differencing and setting sample moments based on the assumptions that: ϵ_{ft} is uncorrelated with all input choices and migrant share, k_{ft} is chosen in the period before ω_{ft} is observed and l_{ft} is chosen in the period that ω_{ft} is observed.

$$y_{ft} = \rho y_{ft-1} + (1-\rho)\beta_0 + \beta_1(k_{ft} - \rho k_{ft-1}) + \beta_2(l_{ft} - \rho l_{ft-1}) + \sum_j \beta_j (s^j_{ft} - \rho s^j_{ft-1}) + \xi_{ft} + (\epsilon_{ft} - \rho\epsilon_{ft-1}) \tag{22}$$

This means we don't need scalar unobservable and strict monotonicity assumptions that are required by OP/LP/ACF for the inversion of the investment / intermediate input demand equation. Dynamic panel literature can also allow additional fixed effects.

The estimates using this methodology are very similar to those in the main part of the paper.

Table 22: Dynamic panel approaches - Value added per worker - migrant share only.

	(1) IV-FE	(2) IV-FE	(3) System GMM
Migrant share	-0.0793	-0.0417	0.0539
	(0.0611)	(0.0909)	(0.0521)
Migrant share t-1	0.198***	0.138	0.129*
	(0.0571)	(0.0832)	(0.0594)
Labour	-0.511***	-0.495***	-0.732***
	(0.0146)	(0.0242)	(0.0776)
Labour t-1	0.518***	0.274***	0.243***
	(0.0145)	(0.0204)	(0.0213)
Capital (per worker)	0.0446***	0.0250***	0.0219
	(0.00311)	(0.00679)	(0.0145)
Capital (per worker) t-1	-0.0201***	-0.00980*	-0.00946
	(0.00250)	(0.00459)	(0.00550)
VA (per worker) t-1	0.680***	0.130***	0.180***
	(0.00870)	(0.0142)	(0.0239)
N	83503	58949	38346
r2	0.482	0.0812	
Fixed Effects			
Firm		✓	
Year-TTWA-Ind	✓	✓	✓
Implied α	0.0766***	0.0175**	0.0152
	(0.00386)	(0.00639)	(0.0162)
Implied β	0.943***	0.728***	0.388***
	(0.00729)	(0.0193)	(0.0926)
Implied μ	0.392**	0.152	0.575*
	(0.137)	(0.174)	(0.290)

Standard errors in parentheses
Year-TTWA-Ind: Full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 23: Dynamic panel approaches - Log real value added per worker - by skill.

	(1) IV	(2) IV-FE	(3) System GMM
M-low share	-0.253**	-0.160	0.0500
	(0.0876)	(0.114)	(0.0707)
M-low share t-1	0.213*	0.0621	0.171*
	(0.0866)	(0.134)	(0.0758)
M-high share	0.139	0.224	0.0454
	(0.111)	(0.192)	(0.0818)
M-high share t-1	0.200*	0.246	0.0601
	(0.101)	(0.162)	(0.0984)
Loc-high share	-0.0135	-0.122*	0.0115
	(0.0412)	(0.0614)	(0.0412)
Loc-high share t-1	0.139***	-0.0212	-0.0189
	(0.0398)	(0.0597)	(0.0377)
Labour	-0.511***	-0.494***	-0.724***
	(0.0146)	(0.0243)	(0.0782)
Labour t-1	0.518***	0.276***	0.243***
	(0.0144)	(0.0205)	(0.0214)
Capital (per worker)	0.0445***	0.0262***	0.0221
	(0.00311)	(0.00695)	(0.0145)
Capital (per worker) t-1	-0.0200***	-0.00986*	-0.00945
	(0.00252)	(0.00463)	(0.00549)
VA (per worker) t-1	0.677***	0.130***	0.180***
	(0.00862)	(0.0144)	(0.0239)
N	83503	58949	38346
r2	0.479	0.0670	
Fixed Effects			
Firm		✓	
Year-TTWA-Ind	✓	✓	✓
Implied α	0.0758***	0.0188**	0.0154
	(0.00379)	(0.00660)	(0.0162)
Implied β	0.945***	0.730***	0.398***
	(0.00715)	(0.0193)	(0.0934)
Implied μ - Loc h	0.413***	-0.226	-0.0224
	(0.122)	(0.138)	(0.193)
Implied μ - Mh	1.111***	0.741	0.323
	(0.295)	(0.410)	(0.411)
Implied μ - Ml	-0.132	-0.155	0.678
	(0.166)	(0.239)	(0.353)

Standard errors in parentheses
Year-TTWA-Ind: Full interaction between year-TTWA and year-SIC 3-digit industry.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Heterogeneity

In this section, we use the full sample 1998 - 2019 and regress log real value-added output per worker on log firm employment, log real capital stock per worker, and labour shares in hours worked, instrumented using our shift-share IV. To maintain a large enough sample size to see varying effects by industry and region we do not use the control function approaches nor can we include firm fixed effects.

B.1 By industry

Table 24: Number and percentage of firms in each industry section in our regression sample.

	Industry Sections	
	N	%
AB	3,055	0.58
C	136,656	25.94
DE	4,171	0.79
F	46,669	8.86
G	108,660	20.62
H	23,127	4.39
I	9,553	1.81
J	33,550	6.37
K	247	0.05
L	16,094	3.05
M	62,081	11.78
N	45,005	8.54
P	2,787	0.53
Q	3,264	0.62
RSTU	31,973	6.07
Total	526,892	100.00

AB: Agriculture, Forestry, Fishing, Mining, Quarrying; C: Manufacturing; DE: Electricity, Gas, Water; F: Construction; G: Wholesale and Retail Trade; H: Transport and Storage; I: Accommodation and Food Services; J: Information and Communication; K: Financial and Insurance Activities; L: Real Estate; M: Professional, Scientific, and Technical; N: Administrative and Support; O: Public Administration and Defence; P: Education; Q: Health; RSTU: Arts, Other Services

Estimate a combined model with a separate slope for each industry. Chow test rejects the null that coefficients on capital per worker and labour are equal across industries (at the 1% level) across all specifications.

For the migrant share effect, with firm fixed effects, the coefficient estimates don't vary significantly by industry (and are insignificant across the board). Without firm fixed effects, the migrant share effect is significantly different across industries (at the 1% level). The migrant share effect is highest in the service industries and insignificant in manufacturing (our largest sector). Part of the reason why the effects found by Ottaviano et al. (2018) are so large is that they focus solely on services.

Table 25: Value-added per worker IV regression results, by industry.

	(1) IV		(2) IV	
Migrant Share				
AB	1.922*	(0.847)	-0.407	(0.591)
C	-0.0979	(0.0559)	0.0365	(0.0860)
DE	0.326	(0.471)	-0.687	(0.374)
F	0.647***	(0.147)	-0.0713	(0.227)
G	0.427***	(0.130)	0.0540	(0.122)
H	0.560**	(0.201)	-0.0101	(0.261)
I	0.678***	(0.0920)	-0.140	(0.221)
J	0.810***	(0.0927)	-0.117	(0.230)
L	1.289***	(0.134)	0.264	(0.294)
M	0.797***	(0.112)	0.0724	(0.293)
N	0.484**	(0.175)	0.344*	(0.157)
P	-0.577*	(0.266)	-1.883	(1.257)
Q	0.220	(0.219)	-1.767	(3.301)
RSTU	0.864***	(0.152)	-0.420	(0.295)
Employment				
AB	-0.0736	(0.0408)	-0.470***	(0.0904)
C	0.0638***	(0.00276)	-0.410***	(0.0111)
DE	-0.0559*	(0.0252)	-0.430***	(0.0439)
F	0.0295***	(0.00434)	-0.526***	(0.0250)
G	0.0741***	(0.00427)	-0.466***	(0.0166)
H	0.0245**	(0.00746)	-0.444***	(0.0328)
I	-0.0394***	(0.0115)	-0.635***	(0.107)
J	0.0379***	(0.00793)	-0.428***	(0.0251)
L	-0.00333	(0.0137)	-0.502***	(0.0341)
M	-0.000702	(0.00530)	-0.483***	(0.0246)
N	-0.0657***	(0.00633)	-0.513***	(0.0206)
P	0.0412*	(0.0172)	-0.499**	(0.161)
Q	-0.0507*	(0.0212)	-0.398**	(0.144)
RSTU	-0.0632***	(0.00694)	-0.563***	(0.0259)
Capital				
AB	0.199***	(0.0268)	0.0768***	(0.0200)
C	0.0718***	(0.00157)	0.0208***	(0.00309)
DE	0.218***	(0.0175)	0.0959***	(0.0271)
F	0.103***	(0.00374)	0.0416***	(0.00764)
G	0.0895***	(0.00259)	0.0291***	(0.00482)
H	0.105***	(0.00522)	0.0278*	(0.0116)
I	0.0784***	(0.00659)	0.0241	(0.0248)
J	0.147***	(0.00754)	0.0591***	(0.0108)
L	0.131***	(0.00765)	0.0487***	(0.0105)
M	0.142***	(0.00470)	0.0485***	(0.00729)
N	0.155***	(0.00481)	0.0437***	(0.00684)
P	0.123***	(0.0175)	-0.00714	(0.0382)
Q	0.0565***	(0.0140)	0.196	(0.115)
RSTU	0.112***	(0.00390)	0.0304***	(0.00775)
N	525656		280580	
r2	0.0702		0.0828	
Chow-test p-values				
Migrant share	0.0000		0.1485	
Labour	0.0000		0.0000	
Captal per worker	0.0000		0.0000	
Fixed Effects				
Firm			✓	
Year - TTWA - Ind	✓		✓	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B.2 By region

Table 26: Number and percentage of firms in each region.

	Region	
	N	%
North East	17,047	3.24
North West	61,354	11.64
Yorkshire	51,796	9.83
East Midlands	43,233	8.21
West Midlands	55,166	10.47
East of England	55,201	10.48
London	87,666	16.64
South East	83,361	15.82
South West	47,791	9.07
Wales	24,277	4.61
Total	526,892	100.00

For regressions which don't include firm fixed effects, capital and labour coefficients vary significantly by region (at the 1% level) as does the migrant share effect, which is highest in London and the South East.

Table 27: Value-added per worker IV regression results, by region.

	(1) IV		(2) IV	
Migrant Share				
North East	0.231	(0.251)	0.377	(0.371)
North West	0.233	(0.181)	-0.132	(0.236)
Yorkshire	-0.0995	(0.126)	-0.000513	(0.210)
East Midlands	-0.128	(0.0758)	-0.0186	(0.190)
West Midlands	0.0867	(0.0883)	0.151	(0.160)
East of England	0.627^{**}	(0.208)	-0.136	(0.165)
London	0.780^{***}	(0.141)	0.104	(0.131)
South East	1.021^{***}	(0.186)	-0.113	(0.212)
South West	0.105	(0.292)	-0.183	(0.543)
Wales	-0.418	(0.304)	0.539	(0.553)
Employment				
North East	0.0128	(0.00931)	-0.462^{***}	(0.0254)
North West	0.0312^{***}	(0.00416)	-0.461^{***}	(0.0191)
Yorkshire	0.0298^{***}	(0.00532)	-0.416^{***}	(0.0168)
East Midlands	0.0351^{***}	(0.00442)	-0.445^{***}	(0.0141)
West Midlands	0.0166^{**}	(0.00557)	-0.442^{***}	(0.0144)
East of England	0.00996	(0.00554)	-0.469^{***}	(0.0139)
London	-0.00381	(0.00658)	-0.489^{***}	(0.0159)
South East	0.0246^{***}	(0.00450)	-0.468^{***}	(0.0123)
South West	0.0393^{***}	(0.00505)	-0.459^{***}	(0.0157)
Wales	0.0251^{***}	(0.00634)	-0.486^{***}	(0.0196)
Capital				
North East	0.104^{***}	(0.00815)	0.0335^{***}	(0.00994)
North West	0.101^{***}	(0.00271)	0.0354^{***}	(0.00536)
Yorkshire	0.0951^{***}	(0.00289)	0.0252^{***}	(0.00578)
East Midlands	0.0944^{***}	(0.00290)	0.0434^{***}	(0.00846)
West Midlands	0.0998^{***}	(0.00330)	0.0199^{***}	(0.00551)
East of England	0.107^{***}	(0.00404)	0.0323^{***}	(0.00582)
London	0.152^{***}	(0.00677)	0.0466^{***}	(0.00759)
South East	0.121^{***}	(0.00343)	0.0384^{***}	(0.00494)
South West	0.0966^{***}	(0.00308)	0.0236^{***}	(0.00534)
Wales	0.0891^{***}	(0.00425)	0.0273^{***}	(0.00817)
N	525656		280580	
r2	0.0630		0.0858	
Chow-test p-values				
Migrant share	0.0000		0.5653	
Labour	0.0003		0.0792	
Captal per worker	0.0000		0.6669	
Fixed Effects				
Firm			✓	
Year - TTWA - Ind	✓		✓	

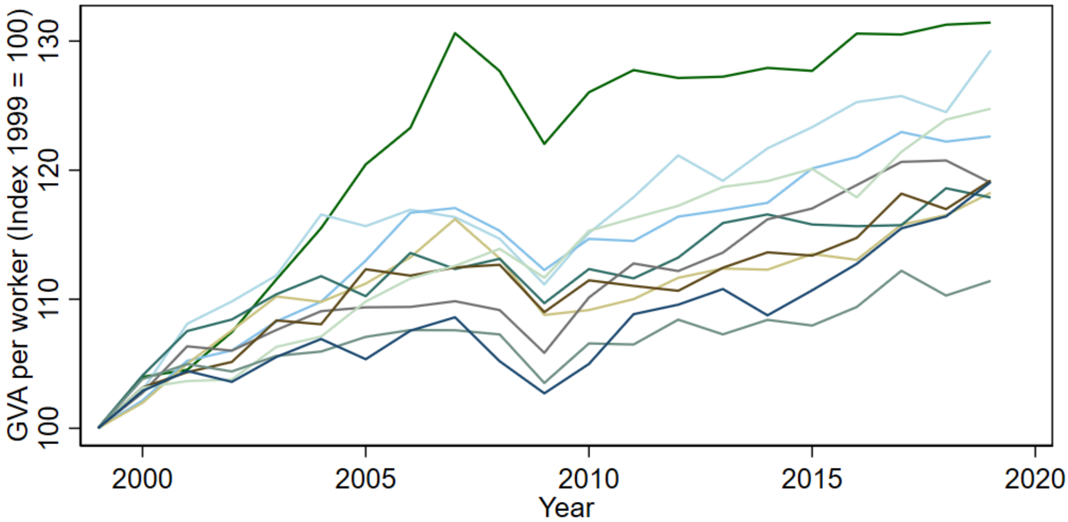
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C Reconciliation With Results in Other UK Studies

Other UK studies which look at the relationship between productivity and migrant share at some higher level of geographical aggregation than the firm find large positive effects. Ottaviano et al. (2018) look at the service sector 2001 - 2007 and regress firm-level gross value added per worker on the share of migrants in a firm's TTWAs. Campo et al. (2018) look at the relationship between migrant share and gross value-added per job within each TTWA in 2004 - 2016. Nam and Portes (2023) look at the relationship between migrant share and labour productivity at the region – sector level in the UK 2014 - 2019. These studies find positive, significant, and large effects of immigration on productivity, with an immigrant inflow equal to 1% of local employment leading to around a 3% rise in labour productivity in all three cases. In the case of Ottaviano et al. (2018), the effect remains significant with the inclusion of firm fixed effects.

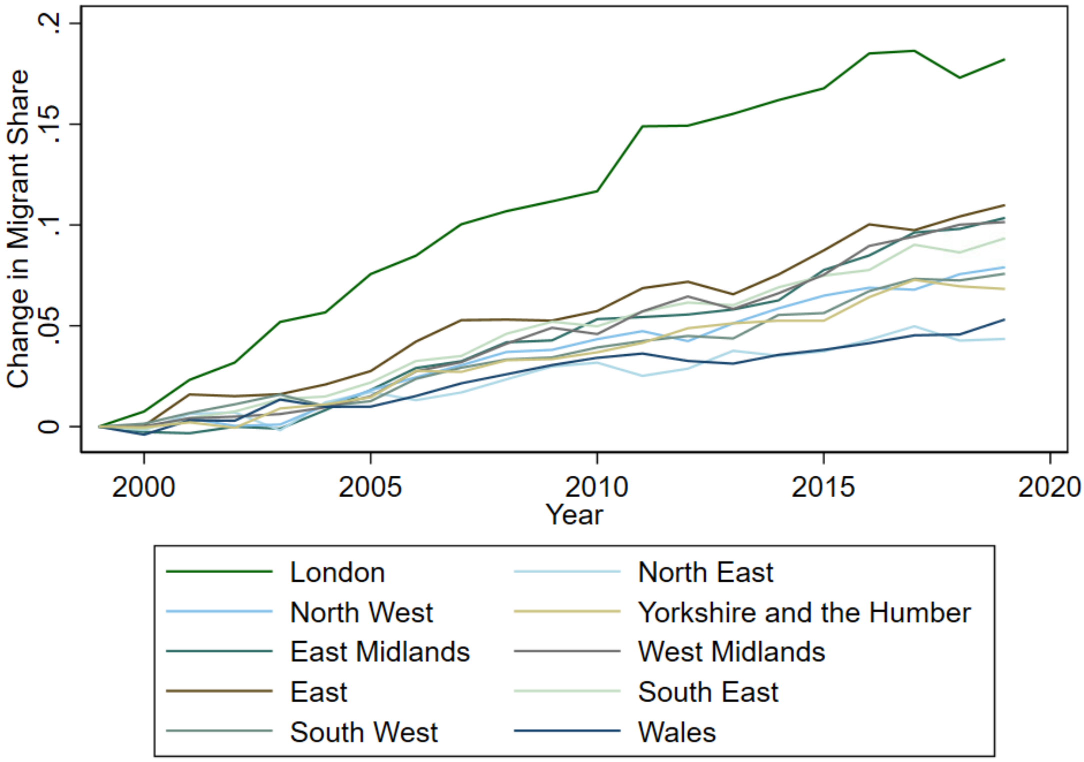
How do we reconcile these results with our own? In Table 28 we estimate the firm level production function with the level at which migrant share is measured becoming increasingly imprecise (ward - industry, ward, TTWA). When the migrant share is measured at the TTWA level, as in the UK studies cited above, the estimated effect of productivity is larger and remains significant with the inclusion of firm fixed effects. However, the effect is no longer significant when we additionally control for a linear TTWA trend. One potential explanation is that productivity in London is diverging from productivity in other TTWAs. This trend is apparent in the ONS regional productivity time series as shown in Figure 6, especially in the years leading up to the financial crisis. Figure 7 shows that in the same period, migrant share also increased more in London than elsewhere. So, without controlling for TTWA productivity trends, rising productivity in London is attributed to immigration, when in fact there could be other explanations (Rice et al., 2006). Another way of showing this is that when we omit London from our regression sample the migrant share effect is no longer significant with firm fixed effects in any of the specifications.

Figure 6: Output per job by government office region, Chained volume measure (CVM), Index 1999 = 100



Source: Office for National Statistics' Regional labour productivity estimates.

Figure 7: Migrant share in employment by government office region, change since 1999.



Source: QLFS 1994 - 2003; APS 2004 - 2021.

Table 28: Value-added per worker IV regression results.

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV	(7) IV	(8) IV
Migrant share at the CAS ward - industry level.								
Migrant share	1.143***	0.483***	0.00824	0.0491	0.853***	0.126**	-0.00825	0.0470
	(0.0225)	(0.0346)	(0.0705)	(0.0726)	(0.0428)	(0.0410)	(0.0803)	(0.0772)
Labour	-0.00738***	0.0195***	-0.451***	-0.452***	0.00107	0.0241***	-0.439***	-0.441***
	(0.00169)	(0.00167)	(0.00816)	(0.00821)	(0.00174)	(0.00172)	(0.00840)	(0.00842)
Capital per worker	0.122***	0.112***	0.0344***	0.0345***	0.112***	0.101***	0.0308***	0.0309***
	(0.00122)	(0.00120)	(0.00203)	(0.00203)	(0.00120)	(0.00118)	(0.00205)	(0.00205)
N	526,003	526,002	280,938	280,938	438,363	438,362	240,007	240,007
r2	0.0561	0.0649	0.0853	0.0852	0.0600	0.0655	0.0839	0.0841
	(9) IV	(10) IV	(11) IV	(12) IV	(13) IV	(14) IV	(15) IV	(16) IV
Migrant share at the CAS ward level.								
Migrant share	1.548***	0.708***	-0.00646	0.106	1.470***	0.281***	-0.180	0.00819
	(0.0291)	(0.0588)	(0.142)	(0.173)	(0.0550)	(0.0843)	(0.211)	(0.258)
Labour	-0.00167	0.0211***	-0.451***	-0.452***	0.00464**	0.0243***	-0.439***	-0.441***
	(0.00167)	(0.00166)	(0.00815)	(0.00820)	(0.00171)	(0.00171)	(0.00839)	(0.00840)
Capital per worker	0.122***	0.112***	0.0344***	0.0345***	0.112***	0.101***	0.0308***	0.0309***
	(0.00121)	(0.00120)	(0.00203)	(0.00203)	(0.00119)	(0.00117)	(0.00205)	(0.00205)
N	526,892	526,891	281,530	281,530	439226	439225	240581	240581
r2	0.0906	0.0704	0.0852	0.0853	0.0804	0.0659	0.0837	0.0841
	(17) IV	(18) IV	(19) IV	(20) IV	(21) IV	(22) IV	(23) IV	(24) IV
Migrant share at the TTWA level.								
Migrant share	1.761***	0.942***	0.768***	0.00488	1.731***	0.510*	-0.0597	-1.416
	(0.0276)	(0.137)	(0.199)	(0.668)	(0.0476)	(0.207)	(0.287)	(0.964)
Labour	0.0756***	0.0840***	-0.392***	-0.393***	0.0720***	0.0753***	-0.392***	-0.393***
	(0.00142)	(0.00147)	(0.00787)	(0.00788)	(0.00147)	(0.00154)	(0.00813)	(0.00815)
Capital per worker	0.222***	0.237***	0.133***	0.133***	0.199***	0.203***	0.121***	0.120***
	(0.00281)	(0.00447)	(0.00551)	(0.00550)	(0.00271)	(0.00438)	(0.00558)	(0.00557)
N	692,728	692,726	331,560	331,560	579278	579276	281142	281142
r2	0.0760	0.0424	0.0887	0.0893	0.0594	0.0333	0.0865	0.0852
Fixed Effects								
TTWA trend				✓				✓
Firm			✓	✓			✓	✓
TTWA		✓	✓	✓		✓	✓	✓
3dig Industry		✓	✓	✓		✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
With London?	Yes	Yes	Yes	Yes	No	No	No	No

Cluster robust standard errors in parentheses, clustered at the firm level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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