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Research Article

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The Impact of Migration on Productivity: Evidence from the United Kingdom

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Abstract: The UK saw a sharp rise in work-related migration, particularly from the EU, in the 2000s and 2010s, with profound impacts on the labour market. We investigate the relationship between migration and productivity in Great Britain between 2002 and 2018, using an instrumental variable approach which follows the commonly used shift-share methodology. Our results, which are robust to a variety of tests, suggest that immigration has a positive and significant impact (in both the statistical sense and more broadly) on productivity, as measured by GVA per job at the Travel-to-Work-Area level. We indeed find that a 1 p.p. increase in the share of migrants is associated with a 0.84 % increase in productivity in 2SLS estimates. We discuss the implications for post-Brexit immigration policy.

Keywords: immigration; productivity; United Kingdom; Brexit

1 Introduction

There is now a considerable body of evidence on the direct labour market impacts of migration to the UK (see Wadsworth et al. 2017 for a summary). There is a clear consensus that, in aggregate, migration has little or no impact on employment or

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wages, but that it may have some, relatively small, impact on the distribution of wages, i.e. depressing wages for some, generally low-paid, sectors, while increasing it for others (Dustmann, Frattini, and Preston 2013).

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

However, beyond the direct labour market impacts, relatively little is known about the broader consequences of immigration on the UK economy and productivity in particular. This topic is clearly of great importance. The UK's low level of labour productivity, compared to many other advanced economies, has long been recognized as a key weakness, and this has been greatly exacerbated by its extremely poor productivity performance since the 2008–09 financial crisis (see, for example, Office for Budget Responsibility 2018). Moreover, to the extent that it is the impact of immigration on "prosperity", or GDP per capita, that is of most interest to policymakers (as opposed to the overall, undeniably positive, impact of immigration on GDP), productivity is likely the key. The impact of immigration, and in particular of changes in immigration policy, on productivity is therefore of immense policy relevance, particularly in the context of changes to migration policy after Brexit.

The objective of this paper (originally commissioned by the UK government's independent Migration Advisory Committee, and intended to inform the development of the post-Brexit immigration system) is to provide a more detailed and UK-specific evidence on the relationship between migration and productivity at the geographical level. In particular, we exploit the variation in both levels of migration and productivity over-time across Travel-To-Work-Areas[1] in Great Britain between 2002 and 2018.[2] We use publicly available data, provided by the UK Office of National Statistics, on local migration share and gross-value added per job and, in the attempt to gauge the causal impact of migration, we rely on an instrumental variable approach which uses a shift-share instrument similar to the one in Card (2001),

1 More details on the definition of TTWAs are provided in Section 3.

2 The United Kingdom is composed of four nations: England, Scotland, Wales and Northern Ireland. Although migration policy is formulated at UK level, our data covers only the first three, which are referred to collectively as Great Britain. Northern Ireland's population is less than 3 % of the UK total, and has relatively low migration levels, so this is unlikely to affect our results.

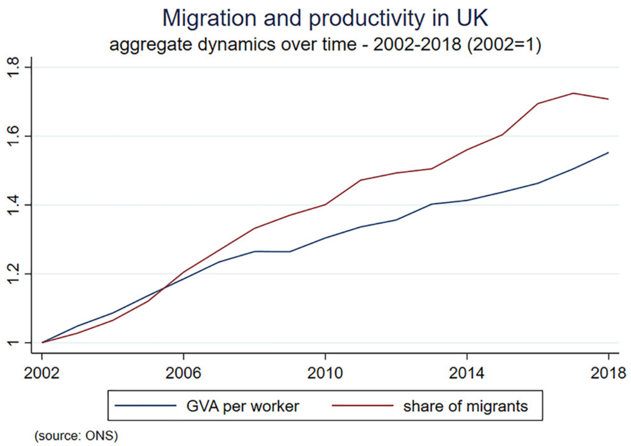

Figure 1: Migration and productivity in UK.

which we supplement with a range of tests to establish that our instruments are valid and appropriate.

Figure 1 shows the evolution of productivity (GVA per worker, current prices) and migration (share of foreign-born population) in the UK, indexed to 2002 levels.[3] While the migration share has grown by approximately 70 % (from 8.4 % in 2002 to 14.3 % in 2018), productivity growth was sluggish, in particular after 2008–09's financial crisis. At first glance, there is little indication of any positive impact. However, Figure 2 shows a geographical disaggregation of the same data, where we plot the differences between 2002 and 2018 in GVA per job and the foreign-born share of population, and reveals a positive association between migration and productivity.

For our econometric analysis, we use the same underlying variables as in Figure 2, employing a two-way fixed effect model with a shift-share instrumental variable. We find clear evidence of a positive association between migrants share in the workforce and productivity, with a 1 p.p. increase in the share of migrants associated with an increase in productivity of 0.84 % in 2SLS estimates with a standard shift-share instrumental variable (Card 2001).

This paper adds to the existing literature by examining the influence of immigration on overall economic performance in developed economies, with a specific

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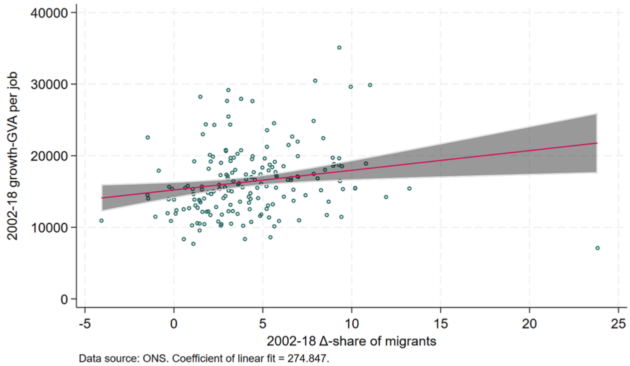
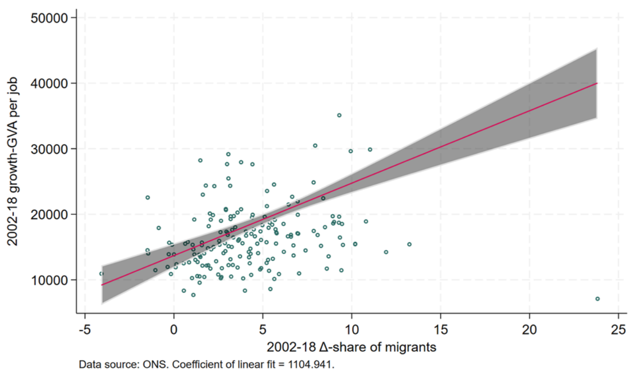
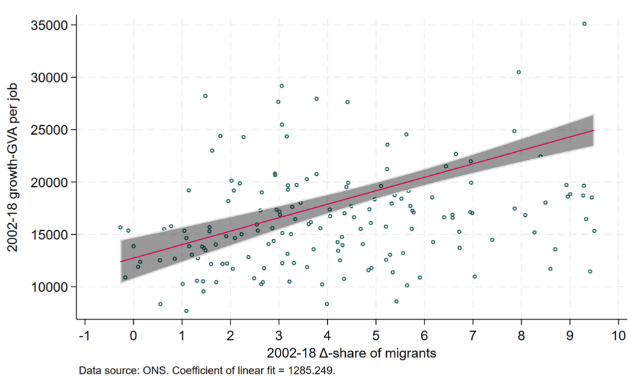
3 Figures on GVA per worker are computed by using data on UK aggregate GVA (current prices) and workforce, which are taken from ONS "UK National Accounts, The Blue Book: 2020" (available at the link: https://www.ons.gov.uk/economy/grossdomesticproductgdp/compendium/unitedkingdomnationalaccountsthebluebook/2020/supplementarytables). Note that this is slightly different from the definition of productivity, i.e. GVA per job, used in this paper for the analysis at the TTWA-level. Migration share is calculated from Annual Population Survey data produced by ONS.



(a) Unweighted



(b) Weighted by 2001 Employment



(c) Weighted, without Δ-share outliers

Figure 2: Migration and productivity in UK travel-to-work areas.

emphasis on productivity – an aspect less explored compared to wages and other labour market outcomes. Our focus is on the unique context of the UK in the years leading up to Brexit. The results we present have therefore important policy implications for the post-Brexit migration system and, potentially, for other European economies.

The rest of the paper is organized as follows. Section 2 shortly summarizes the literature regarding the impact of migration on productivity and on the potential mechanisms. Section 3 describes the research design and the identification strategy. Section 4 presents the data and descriptive statistics. Section 5 collects the battery of validity tests for shift-share instruments suggested by Goldsmith-Pinkham, Sorkin, and Swift (2020). Section 6 shows our empirical findings. Section 7 offers some concluding remarks.

2 Literature

The theoretical impact of immigration on productivity is *a priori* ambiguous, because there are a number of conceptually different mechanisms that are potentially at work. First, the simple “batting average” effect. If individual immigrants are more or less productive on average than natives, they will directly raise or lower productivity for the whole economy, even if they do not affect the productivity of natives. In the context of the UK, it is worth noting the aggregate figures on the human capital of foreign-born residents and UK natives from Census 2021 (Tolland et al. 2023). This data, referring to shortly after the end of our time frame, serves as good indicator of the human capital accumulated by migrants until then. The share of UK natives with Higher Education stands at 31 %. In contrast, it amounts to almost 35 % among Eastern European migrants from countries who entered EU after 2004, and to 46 % among the rest of migrants. There is a sizeable gap between natives and both group of migrants. These figures suggest that migration may have positively influenced the UK skill mix, and imply that the positive contribution to overall human capital might underlie the observed positive migration-productivity link.

Secondly, migrants may supply skills which are complementary to those of native workers (Ottaviano and Peri 2012). For example, lower language proficiency may push migrants to specialize, and increase the labour supply, in manual occupations which, in turn, may raise demand for complementary communication-intensive, and higher value-added, occupations, in which native workers might have a comparative advantage for specialization (Foged and Peri 2016; Peri and Sparber 2009). At the same time, the presence of low-skilled immigrant workers may increase the availability and affordability of home and children-care services, and help native women, especially high-skilled, to access or participate more into labour force (Barone and Mocetti 2011; Forlani, Lodigiani, and Mendolicchio 2021). Conversely, migration might harm productivity if there are increased frictions within the firm, perhaps because of language differences.

Finally, migration may affect the incentives to invest in capital, both human and physical. One the one hand, migration may indeed increase or decrease the incentive for native workers to acquire human capital depending on the type of immigration and how it impacted wages and labour demand (Chiswick 1989; Hunt 2012). On the other hand, although some investments might be complementary to the skills of immigrants, migration may reduce the incentive to invest in productivity-enhancing physical capital – perhaps because the availability of low-skilled labour is partly a substitute for automation (Lewis 2011).

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

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

Only a small body of research performs a within-country analysis of this relationship. The paper with the closest relation to ours is Peri (2012), which looks at Total Factor Productivity, analysing US state-level data, and finds positive impacts.

In the UK, Ottaviano, Peri, and Wright (2018) focus on the services sector, while Rolfe et al. (2013) look at productivity by region and sector, although they do not attempt to establish causality. In Germany, Trax, Brunow, and Suedekum (2015) find a positive impact of diversity by nationality on productivity at both firm and regional level. Overall, the message from these papers is that the impact of immigration on productivity is generally positive, but the size (and the implicit causal mechanisms assumed to be at work) vary and results are generally not conclusive. In particular, the use of instrumental variables – usually a shift-share instrument – to deal with the endogenous selection of migrants into sectors or geographical areas is often contested. We therefore apply a battery of diagnostic tests to ensure our use of this instrument is robust.

As noted above, an earlier version of this paper was commissioned by the Migration Advisory Committee (Migration Advisory Committee 2018) to inform the development of the post-Brexit migration system; two other papers were also commissioned on this topic. Costas-Fernández (2018) assumes a CES production function, and incorporates new estimates of the capital stock at a regional and sector level. The study finds that both migrants in high- and low-skilled occupations are, at the margin, more productive than their UK-born counterparts, with the central estimates suggesting that the marginal migrant is around 2.5 times as productive as a UK-born worker. Smith (2018) analyses the relationship between migration and total factor productivity at the region-by-sector level. The paper employs firm-level data and imposes less structure on the production function. The main estimate suggest that a one percentage point increase in the migrant share results in a 1.6 % increase in TFP. These results are consistent with, albeit somewhat larger than, the estimates we report below.

An example of the policy relevance of such analysis on the links between migration and productivity is also provided by Portes and Forte (2017), who produce scenario analyses of potential reductions in net migration resulting from Brexit (which, so far, appear to have been reasonably accurate (Portes 2021)). They then apply the coefficients estimated by Boubtane, Dumont, and Rault (2016) and Jaumotte, Koloskova, and Saxena (2016) to estimate the potential impact on productivity and GDP per capita and find potentially macroeconomically significant – that is, large and negative – impacts. This illustrates that migration policy post-Brexit could potentially have substantial impacts on UK productivity (and hence overall prosperity); however, they caution that the applicability of quantitative estimates based on historical cross-country data to scenarios for the impact on the UK economy going forward is inevitably speculative. However, our results here provide considerable reinforcement for the concerns expressed in Portes and Forte (2017) – and more broadly by a wide array of economic and business commentators – by providing UK-specific evidence of the potential negative impact of a sharp reduction in migration flows.

3 Research Design

We examine the relationship between immigration and productivity by leveraging the within-labour markets variation over time. In particular, we specify a linear two-way fixed effects reduced-form model as follows:

$$y_{lt} = \alpha + \beta m_{lt} + \gamma_l + \delta_t + \varepsilon_{lt} \quad \text{with} \quad t = 2002, , 2018, \tag{1}$$

where the outcome variable, y_{lt}, is the natural logarithm of productivity, measured as per capita gross value added, in labour market l in year t. The explanatory variable of interest is the immigrants' local share, m_{lt}, which indicates the percentage fraction, out of total residents,[4] of population born outside United Kingdom. The parameter γ_l accounts for labour market fixed effects and absorbs any unobserved time-invariant characteristic at the local level, while δ_t captures time fixed effects and adjusts for shocks that are common to all British labour markets in a given year. Finally, ε_{lt} is an idiosyncratic error component.

We pick Travel-to-Work-Areas (TTWAs henceforth) as the geographical unit of analysis. TTWAs are non-overlapping and contiguous areas which are identified using Census commuting flow data.[5] They are built upon Census LSOAs, in England and Wales, and Data Zones, in Scotland. The basic criteria for their definition are that at least 75 % of an area's resident workforce work in the area and at least 75 % of the people who work in the area also live in the area (Office for National Statistics 2007).[6] TTWAs hence represent the most appropriate geographical approximation of labour markets as they are self-contained clusters of both resident and working populations. In Appendix Table A5, we provide alternative estimates using local authorities as the geographical unit, with very similar results. Our findings therefore appear robust to adopting a different and more granular specification.

4 We use the immigrant share of total residents as data on the share of the labour force is not available. One reason to focus on Travel-To-Work Areas, which are meant to more closely capture local labour markets than local authorities, is that we think the difference between population and labour force immigrant share is likely to vary less over these labour markets than over local government areas.

5 We make use of TTWAs boundaries which were determined according to 2001 Census commuting flows.

6 More information about the methodology used for the definition of TTWAs, as well as about the exceptions to the general criteria for their identification, are available at: https://webarchive.nationalarchives.gov.uk/20160106004211/http://www.ons.gov.uk/ons/guide-method/geography/beginner-s-guide/other/travel-to-work-areas/index.html.

Our baseline estimates rely on yearly values of productivity and migrants' share for each year between 2002 and 2018. The coefficient β in (1) therefore provides an estimate of the short-term association between migration and productivity.

In order to account for within-TTWA serial correlation of residuals, in all regressions we cluster standard errors at the TTWA level. Moreover, since both our dependent and explanatory variables express labour market averages, we weight regression results by employment size in 2001 (Card 2001; Peri and Sparber 2009).

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

Relatedly, the choice of gross value added (GVA) per worker (as opposed to, for example, total factor productivity – TFP) is guided by the multiple effects immigration may have on production.[7] As (production approach) GVA is defined as the difference between the real value of output and the real cost of intermediate inputs, immigration can affect it through (i) input prices, (ii) input quantities, and (iii) input productivity. Conversely, analysing TFP only allows for the effect of immigration on (iii). Furthermore, this latter effect is unlikely to realise at the frequency analysed in this paper, and it is more likely to realise (and be quantifiable) at the firm level (Azoulay et al. 2022) than at the labour market level.

3.1 Identification Strategy: Shift-Share IV

The key issue in establishing the causal impact of migration is addressing the potentially non-random distribution of immigrants across labour markets. If immigrant flows are in part driven by productivity, or other labour market variables that are related to productivity (most obviously wages), then a simple regression of productivity on immigration may be biased. Note, however, that in contrast to employment or wage impacts, the direction of the bias is not obvious. That is, immigration flows might be higher to low productivity areas or sectors, which need more workers to expand or maintain output; or they might be higher to high productivity areas which are more likely to be growing and therefore see rising demand for more workers.

7 GVA per worker is also used by Ottaviano, Peri, and Wright (2018): see Table 2 in their paper.

Empirically, we will attempt to tackle the endogeneity related to the non-random distribution of immigrants across areas by employing a shift-share instrumental variable based on that developed in Card (2001), which has been largely adopted by the migration literature. The rationale of this type of instrument is to isolate an exogenous component in the migration flows by country of origin, driven by supply-push factors, such as economic and political crisis or natural calamities, and therefore not related to area-specific pull-demand factors. These migration flows are then allocated across labour markets on the base of the historical concentration of immigrants by area of origin, exploiting the fact that new immigrants are more likely to settle in regions where same-origin immigrants' presence is higher, and benefit from the resulting network effects. This procedure creates counterfactual inflows that are expected to be correlated with the real-world inflow, but credibly uncorrelated with local economic developments (including labour market-specific trends in productivity) that also, on the demand side, may influence actual immigration flows. If this is the case, the requirements for a valid instrument will be satisfied and 2SLS regression yields unbiased estimates of the causal impact of immigration on the dependent variables of interest.

We build the shift-share instrumental variable, z_{lt}, for the endogenous migration share, m_{lt}, as follows:

$$z_{lt} = 100 \times \sum_{c}^{C} \widehat{M_{clt}} / P_{l,2001} \tag{2}$$

with:

$$\widehat{M_{clt}} = M_{\mathrm{cl},2001} + s_{\mathrm{cl},2001} \times \Delta M_{ct,-r} \tag{3}$$

$\widehat{M_{clt}}$ is the predicted stock of migrants born in country/area of origin c and living in TTWA l in year t. This is computed as the sum of the local stock of migrants from c in baseline year 2001, $M_{cl,2001}$, with the predicted inflow between 2001 and t. The latter is obtained from the product of (i) $s_{cl,2001} = M_{cl,2001} / \sum_{l}^{L} M_{cl,2001}$, i.e. the share of all migrants from c in Great Britain in 2001 living in TTWA l, and (ii) the shift-component, $\Delta M_{ct,-r}$, which indicates the change in the number of migrants between 2001 and t in all Great Britain except the NUTS1 region r where TTWA l is located.[8] This excludes from nation-wide migration inflows the component that is directly affected by pull-factors originating from a specific TTWA and the surrounding ones within the same NUTS1 region. In order to get the final instrument z_{lt}, the

8 Great Britain is divided into 10 NUTS1 regions: North East, North West Yorkshire and The Humber, East Midlands, West Midlands, East of England, London, South East, South West, Wales, Scotland.

predicted migrants stocks are then aggregated by TTWA and year, and normalized by TTWA resident population in 2001.

We construct two versions of the shift-share instrument. A baseline version considers migration from all countries, while an additional instrument only takes into account inflows from post-2004 European Union Accession countries (EUA04 henceforth), i.e. those, mostly Eastern European,[9] which gained access to EU after 2004 and whose nationals were entitled freedom to move, for both leisure and work, to UK without restrictions. The vast majority of pre-2004 EU countries imposed restrictions, which lasted until 2011, on workers from new member states. The UK, together with Ireland and Sweden, instead allowed immediate access to their labour markets for workers migrating from EUA04 countries. As a consequence, combined with the relative strength and flexibility of the labour market, the UK experienced very large inflows from EUA04 countries. The population share of EUA04 migrants rose from 0.34 % in 2002 to 2.85 % in 2018, while total migrants' share rose from 8.4 % to 14.3 %. More than a third of net inflows were EUA04 migrants. We exploit the clear temporal discontinuity induced by this change in migration policy to study the impact of migration in a framework more resembling a quasi-experimental setting.

4 Data

We employ publicly available data on productivity and migration provided by UK Office for National Statistics. Data on productivity (Campos and Patel 2020) report the yearly gross value added per filled job for each local authority (NUTS3) in Great Britain between 2002 and 2018.[10] ONS also releases statistics at the local authority level on the number of foreign-born residents by country of birth from 2001 onward (James 2021). These estimates are produced using micro-data from Annual Population Survey and Labour Force Survey, and are used to compute local migrants' share as well as aggregate migration inflows by country of birth for the shift-share

9 Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia and Slovenia entered EU in 2004; Bulgaria and Romania in 2007; Croatia in 2013. Due to data limitations, we consider the following aggregates for EUA04 countries of origin: Baltic States, Cyprus, Czech Republic, Poland, Romania, and the residual category "Other Eastern Europe".

10 These are available at: ONS – GVA data. Data are nominal, i.e. they are not adjusted for inflation, and smoothed using a weighted 5-year moving average. However, the inclusion of TTWA fixed effects in (1) already accounts for systematic differences in prices across TTWAs. At the same time, year fixed effects adjust for shocks to prices which hit all TTWAs in the same year.

instruments.[11] We use ONS local authority data from the 2001 Census to compute the initial concentration of foreign-born residents by country of birth, $s_{cl,2001}$, that enters the definition of the instrument in (3). We finally quantify employment size through data on the number of employees by local authority from Annual Business Inquiry (ABI), between 1998 and 2008, and, from 2009 onward, from the Business Register Employment Survey (BRES).[12]

Aggregating data from local authority level to TTWAs is not a straightforward operation. Most of local authorities' territory indeed fall into more than one TTWA and a direct association is not possible. We therefore calculate for each local authority the share of its area lying in a TTWA. We then assign the local authority to the TTWA including the larger share of its area. This procedure yields a balanced panel of 178 TTWAs spanning over 17 years. Table 1 presents descriptive statistics for GVA per job and the share of migrants, both at the aggregate and TTWA level.

5 Tests for Shift-Share Instruments Validity

The identification strategy in this paper, as well as in any analysis leveraging on instrumental variables, hinges on the crucial assumption that the instrument itself is orthogonal to the error term. In the case of Bartik-style (Bartik 1991) shift-share predicted migration rate (Card 2001), on the one hand the shift component can be fairly considered independent from region-specific innovations, especially in the leave-out version adopted here.[13] On the other hand, we cannot *a priori* exclude that initial country shares, $s_{cl,2001}$, which measure the cross-sectional variation in pre-existing migrants' settlements, correlate with local characteristics in 2001. More in detail, the heterogeneity across TTWAs in migrants' shares may be determined by unobserved differences at the baseline in productivity, economic development or a broader set of regional factors. If this is the case and these factors also influence future innovations of productivity,[14] which are not absorbed by TTWA fixed effects in (1), the exclusion restrictions are likely to be violated as the instrument may also affects the outcome through channels that are not directly related to immigration.

11 Available at: ONS – Migration data. A total of 58 countries/areas of origin have been consider to build the shift-share instrument. Table A1 in Appendix reports the list of countries/areas with the corresponding share over GB population.

12 Local authority level statistics from 2001 Census, ABI and BRES are publicly available on NOMIS website (link: https://www.nomisweb.co.uk/).

13 For the definition of the shift-component, $\Delta M_{ct,-r}$ in (3), we indeed exclude from the nation-wide change in country-specific inflows the component related to the NUTS1 region in which TWWAs are located.

14 This is the case if there is serial correlation in the error term ε_{lt}.

Table 1: Descriptive statistics on productivity and migration.

year	GVA per job			Share of migrants		
		TTWA stat.			TTWA stat.	
	UK	Mean	SD	UK	Mean	SD
2002	35.2	32.6	5.3	8.4	4.7	3.1
2003	36.9	34.1	5.5	8.6	4.9	3.2
2004	38.2	35.3	5.8	8.9	5.1	3.3
2005	40.0	36.8	6.2	9.4	5.3	3.5
2006	41.7	38.3	6.6	10.1	5.9	3.7
2007	43.4	39.6	7.0	10.6	6.2	3.9
2008	44.5	40.3	7.1	11.1	6.6	4.2
2009	44.4	40.2	7.2	11.5	6.7	4.1
2010	45.9	41.0	7.3	11.7	6.8	4.1
2011	47.0	41.8	7.4	12.3	7.1	4.4
2012	47.7	42.9	7.5	12.5	7.2	4.4
2013	49.3	44.1	7.8	12.6	7.4	4.6
2014	49.7	45.0	8.0	13.0	7.8	4.5
2015	50.5	45.7	8.1	13.4	8.1	4.9
2016	51.4	46.8	8.3	14.2	8.6	5.1
2017	52.9	48.1	8.6	14.4	9.0	5.1
2018	54.6	49.0	8.8	14.3	8.9	5.1
2002–18	45.5	41.3	8.6	11.6	6.8	4.4

Notes: This table displays descriptive statistics on productivity and migration for the period 2002–2018 with the data sources employed in this paper. Column 1 shows the yearly value of GVA per worker (£ 1000s, current prices) for the whole UK. Column 2 and 3 respectively report the yearly average and standard deviation, across TTWAs, for GVA per job (£ 1000s, nominal values). Columns 4–6 exhibit the same statistics for the share of foreign-born population.

In what follows, we perform a battery of diagnostic tests aimed at disentangling the sources of variation induced by the shift-share IVs employed in this paper. We proceed with the methodology suggested by Goldsmith-Pinkham, Sorkin, and Swift (2020), which is useful to identify which countries contribute the most to the explanatory power of the instruments. Considering, as in our setting, a total number of C countries of origin, this procedure yields the Rotemberg-decomposition (Rotemberg 1983) of the Bartik IV into a weighted sum of C just-identified instrumental variable estimators that use each initial share as a separate instrument. The Rotemberg weights sum to 1 and depend on the covariance between the cth instrument's fitted value and the endogenous variable.[15]

15 The cth instrument's fitted value is equal to the shift-share predicted change in local immigrant stocks, i.e. $s_{cl,2001} \times \Delta M_{ct,-r}$ from (3).

Table 2: Shift-share IVs – Rotemberg weights.

Panel A: negative and positive weights

	SSIV – all countries			SSIV – EUA countries		
	Sum	**Mean**	**Share**	**Sum**	**Mean**	**Share**
Negative	−0.026	−0.004	0.025			
Positive	1.026	0.020	0.975	1.000	0.167	1

Panel B: correlations of country aggregates

SSIV – all countries				SSIV – EUA countries			
	α_c	g_c	Var(z_c)		α_c	g_c	Var(z_c)
α_c	1			α_c	1		
g_c	0.896	1		g_c	0.983	1	
Var(z_c)	0.081	−0.051	1	Var(z_c)	−0.424	−0.492	1

Panel C: top 5 Rotemberg weight countries

SSIV – all countries			SSIV – EUA countries		
Country	$\hat{\alpha}_k$	g_k/1000	**Country**	$\hat{\alpha}_k$	g_k/1000
Poland	0.217	791.516	Poland	0.554	791.516
India	0.103	357.268	Other Eastern Europe	0.140	212.628
Nigeria	0.056	117.354	Romania	0.136	314.189
Other Eastern Europe	0.055	212.628	Baltic States	0.135	256.708
Romania	0.054	314.189	Czech Republic	0.025	38.632

This table reports the set of diagnostic statistics, suggested by Goldsmith-Pinkham, Sorkin, and Swift (2020), for both shift-share IVs in this paper (All-SSIV and EUA-SSIV). Panel A reports the share and sum of both positive and negative Rotemberg weights. Panel B reports the correlation matrix, across countries, between the Rotemberg weight (α_c), the nation-wide change in immigrants stock ($g_c = \Delta M_{ct,-r}$) and the standard deviation in the 2001 countries shares across TTWA (Var($s_{cl,2001}$)). Panel C reports the top five countries according to Rotemberg weights together with the corresponding values of average nation-wide change in immigrants stock, g_c.

Table 2 collects for each of the shift-share IVs (All-SSIV and EUA-SSIV), the set of statistics advised by Goldsmith-Pinkham, Sorkin, and Swift (2020). We compute country-specific Rotemberg weights by making use of the replication code provided by authors.[16] Panel A displays the share and sum of both positive and

16 Code available at: https://github.com/paulgp/bartik-weight. More in detail, we adopt the same procedure as for the estimates of the inverse elasticity of labour supply (Section 6) as it resembles our baseline panel specification with two-way fixed effects. In this case, we include the country

negative Rotemberg weights. Panel B reports the correlation matrix, across countries/areas of origin, between the Rotemberg weight (α_c), the nation-wide change in immigrants stock ($g_c = \Delta M_{ct,-r}$) and the standard deviation in 2001 country shares across TTWAs (Var($s_{cl,2001}$)). Panel C finally lists the top five countries according to Rotemberg weights together with the corresponding average values of nation-wide change in immigrants stock (in thousands), $g_c/1000$.

Panel C reveals that top 5 Rotemberg weights countries for the All-SSIV account for almost half of positive weights ($0.48/1.03 = 0.46$). Poland, with about 21 % of weights, contributes the most to the instrument overall explanatory power.[17] India ranks second with approximately 10 % of weights, followed by Nigeria, Other Eastern European countries and Romania, with respectively slightly more than 5 % of weights. Panel B indicates that Rotemberg weights are weakly correlated with the variation across TTWAs in the initial ethnicities shares (corr(α_c, Var($s_{cl,2001}$)) = 0.081), and strongly correlated with the nation-wide changes in immigrants stock (corr(α_c, g_c) = 0.896). This results suggest that the explanatory power of the instrument (expressed by Rotemberg weights α_c) is strongly associated with the variation in the shift component, while the association is much weaker with the dispersion in initial concentration of migrants – it is the latter component of the IV which, as noted above, is more likely to be endogenous and hence threat the validity of our identification strategy, so this provides some further evidence validating our approach.

The results for the EUA-SSIV show that Poland is the top Rotemberg weights country, with more than half of weights, followed by Other Eastern European countries and Romania. Since we just consider six country aggregates, it is straightforward to observe Rotemberg weights on average much higher than the All-SSIV. The correlation matrix in Panel B again exhibits a sizeable association between Rotemberg weights and the aggregate inflows, g_c, (corr(α_c, g_c) = 0.983).

Next, as a further diagnostic test on the shift-share IVs, we first perform the balance tests of top 5 Rotemberg weights countries initial shares, $s_{cl,2001}$, on TTWA level and pre-trends of productivity at the baseline. In Panel A of Table 3 we regress 2001 countries shares on 2001 level of TTWA (log) GVA per job, while in Panel B on the difference in (log) GVA per job between 1998 and 2001.[18] This empirical

shares interacted with year fixed effects as underlying instruments, and then aggregate Rotemberg weights at the country of origin level.

17 To ensure that our findings are not solely influenced by the country of origin with the most significant impact on the variation of the shift-share instruments, we create alternative versions that exclude migration flows from Poland. Results are significant and quantitatively similar to our baseline results and are available on request.

18 ONS provides data for GVA per filled job from 2002 onward, while data for total GVA from 1998 onward. We therefore manually compute GVA per job for the years 1998–2001 by dividing total GVA

Table 3: Balance test: 2001 country shares and labour market outcomes.

	Dependent variable: $s_{cl,2001}$ – 2001 country share						
	Baltic States	**Czech Republic**	**India**	**Nigeria**	**Other East. Europe**	**Poland**	**Romania**
	Panel A: correlation with TTWA 2001 (log) GVA per job						
	0.0599	0.0778	0.0626	0.129	0.0805	0.0652	0.0776
	(0.0543)	(0.0571)	(0.0591)	(0.121)	(0.0646)	(0.0572)	(0.0635)
	Panel B: pre-trends in (log) GVA per job – 1998–2001						
	0.0251	0.0185	0.0220	0.0368	0.0249	0.0232	0.0242
	(0.0177)	(0.0184)	(0.0191)	(0.0360)	(0.0206)	(0.0182)	(0.0201)
	Panel C: correlation with TTWA 2001 (log) workforce size						
	0.0120	0.0126	0.0137	0.0212	0.0138	0.0127	0.0133
	(0.00780)	(0.00832)	(0.00843)	(0.0178)	(0.00942)	(0.00823)	(0.00925)
	Panel D: correlation with TTWA 2001 unemployment rate						
	0.119	0.0861	0.148	0.193	0.112	0.111	0.0974
	(0.0851)	(0.0902)	(0.0946)	(0.186)	(0.101)	(0.0896)	(0.0993)
	Panel E: correlation with TTWA 2001 inactivity rate						
	0.390	0.343	0.463	0.642	0.402	0.380	0.358
	(0.275)	(0.293)	(0.301)	(0.610)	(0.329)	(0.291)	(0.324)
	Panel F: correlation with TTWA 2001 (log) mean hour-pay						
	0.0465	0.0546	0.0512	0.0901	0.0579	0.0499	0.0548
	(0.0394)	(0.0426)	(0.0429)	(0.0868)	(0.0476)	(0.0419)	(0.0466)
Observations	178	178	178	178	178	178	178

We here consider the group of top-5 Rotemberg weights for both shift-share IVs (All-SSIV and EUA-SSIV). Each entry a_{pc} reports the coefficient from a regression of 2001 country c's share ($s_{cl,2001}$) on the variable in panel p. White-robust standard errors in parenthesis ($^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$).

exercise reveals that, despite point estimates being positive, there is no significant association between initial countries shares and either the level or pre-trends in productivity. Panels C–F test for the correlation between initial countries shares and 2001 (i) (log) number of employees (from Annual Business Inquiry data), (ii) unemployment rate (from 2011 Census data), (ii) inactivity rate (from 2011 Census data), (iv) (log) mean gross hourly pay (from Annual Survey of Hours and Earnings data). None of these correlations appear to be significant.

on the number of employees in TTWA from Annual Business Inquiry (ABI) data (publicly available at the link: https://www.nomisweb.co.uk/).

Finally, in Tables A2 and A3 we check whether 2001 countries shares are significantly associated with, respectively, TTWA NACE industries and SOC occupations shares. None of these estimates exhibit significant correlations between initial countries shares and TTWA labour market composition in 2001.

Overall, therefore, we conclude that there is no evidence suggesting that the validity of our instrument is undermined by the potential endogeneity arising from the initial characteristics of the TTWAs. The shift-share approach appears to yield a valid instrument.

6 Results

In this section we present our empirical findings. First, we show first stage results of the endogenous migration local share on the shift-share instruments. We then introduce OLS and 2SLS baseline estimates of the short-term impact of migration on productivity growth.

6.1 First Stage Estimates

Table 4 collects the first-stage results from the regression of the endogenous migrants' share, m_{lt}, on the shift-share instrumental variables introduced in Section 3.1. The estimate in Column 1 refers to the shift-share IV that considers all countries of origin (All-SSIV), while the one in Column 2 to the instrument that only includes EUA04 countries (EUA-SSIV). Both instruments are positively and significantly correlated with the migration share. A 1 p.p. increase in the predicted migration share is associated with a 0.3 p.p. for the All-SSIV and a 0.86 p.p. increase for the EUA-SSIV. The F-statistics are well above 10, i.e. the threshold which is commonly set as a rule of thumb for the identification of a weak instrument (Stock and Yogo 2005). It is worth noting that some of the assumptions underlying the validity of the first stage F test as specified in Stock and Yogo (2005) may fail in our setup. In particular, given the nature of our data, there is no reason to assume that the error term is homoscedastic and serially uncorrelated. The violation of these conditions would invalidate the asymptotic results on which the results in Stock and Yogo (2005) are based. As a result, in accordance with recommendations in Andrews, Stock, and Sun (2019) and the results in Young (2022), we also compute the Montiel Olea and Pflueger (2013) effective F-statistic to check for instrument weakness. This statistic is shown in the last line of Table 4. Though the effective F statistic is lower than the non-robust F statistic, it is still well-above the $\tau = 5\ \%$ worst case bias critical value of 37.418. This further reinforces confidence in the strength of the first stage.

Table 4: First stage results – shift-share IVs – 2002–2018.

	Dependent variable: share of migrants	
	(1)	**(2)**
	Shift-share IV	
All countries	0.303***	
	(0.0275)	
EUA countries		0.865***
		(0.0686)
Observations	3026	3026
TTWA FE	Yes	Yes
Year FE	Yes	Yes
SY F-stat	120.8	159.3
MOP F-stat	113.7	149.9
MOP CV 5 %	37.40	37.40

Notes: The outcome of first stage estimates is the migrants' share, m_{lt}, i.e. the fraction, out of resident population in TTWA l in year t, of non UK-born residents. All regressions consider yearly data for each year between 2002 and 2018, and include TTWA and year fixed effects. The shift-share instrumental variable is the predicted migrants' share defined according to a methodology similar to Card (2001) and described in detail in Section 3.1. Regression in Column 1 uses a shift-share IV which considers the whole set of countries/areas of origin, while in Column 2 we select the group of countries which gained access to EU after 2004. The last three rows report Stock and Yogo (2005) (SY F-stat) and Montiel Olea and Pflueger (2013) (MOP F-stat) F-statistics for weak instrument test, as well as the MOP threshold for $\tau = 5$ % worst case bias. Regressions results are weighted by employment size in 2001. Standard errors clustered at the TTWA level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6.2 Baseline Estimates

Table 5 displays our baseline estimates of the impact of immigration on productivity growth according to the specification in (1) with yearly data for the period 2002–2018. Column 1 shows OLS results, while Columns 2 and 3 collect 2SLS estimates by using, respectively, the All-SSIV and the EUA-SSIV.

All specifications yield a positive and significant correlation between migration and productivity. The 2SLS result in Column 2 indicates that a one p.p. increase in the migrants' share, which is roughly a quarter of a standard deviation in the sample,[19] is associated with a 0.84 % increase in GVA per job. At the sample mean, which is equal to £ 41,273.75, this is equivalent to an increase of £ 346.7 in GVA per job in a year. When we only select EUA04 countries for the definition of the shift-share instrument, as in Column 3, point estimates are still positive and significant, although slightly lower in magnitude (the difference is not significant).

19 The sample mean for migrants' share 6.8 %, standard deviation is 4.4 %.

Table 5: Immigration and productivity – baseline estimates – 2002–2018.

	Dependent variable: (log) GVA per filled job		
	OLS	2SLS: shift-share IV	
		All countries	EUA countries
	(1)	(2)	(3)
Share of migrants	0.00358**	0.00842***	0.00781***
	(0.00161)	(0.00228)	(0.00272)
Observations	3026	3026	3026
R^2	0.986		
TTWA FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
MOP F-stat		113.7	149.9
MOP CV 5 %		37.40	37.40

Notes: the outcome and explanatory variable of interest in all estimates are, respectively, the natural logarithm of gross value added per filled job, and the migrants' share, m_{lt}, i.e. the fraction, out of resident population in TTWA l in year t, of non UK-born residents. All regressions consider yearly data for each year between 2002 and 2018, and include TTWA and year fixed effects. Column 1 shows OLS estimates, while Columns 2 and 3 2SLS results with shift-share instrumental variable which are defined according to a methodology similar to Card (2001) and described in detail in Section 3.1. 2SLS regression in Column 2 uses a shift-share IV which considers the whole set of countries/areas of origin, while in Column 3 we select the group of countries which gained access to EU after 2004. The last two rows report Montiel Olea and Pflueger (2013) (MOP F-stat) F-statistic for weak instrument test and the MOP threshold for $\tau = 5$ % worst case bias. Regressions results are weighted by employment size in 2001. Standard errors clustered at the TTWA level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

One p.p. higher migration share is now associated with a 0.78 % increase in productivity. Appendix Table A5 shows that the results do not differ significantly when the analysis is performed at the local authority level rather than the TTWA level.

The impact estimated through OLS, despite being positive and significant, is less than half of 2SLS point estimates. As documented in Aydemir and Borjas (2011), part of this difference may be explained by the attenuation bias caused by sampling error in the measurement of migrants' share in the population; in this case, the 2SLS results would provide a better estimate of the causal impact. However, an alternative interpretation is that migrants are selecting into low productivity TTWAs; so that in contrast to the usual endogeneity concern in the analysis of labour market impacts of migration (where migrant selection into high employment or wage areas masks a negative causal impact of migration on employment or wages in these areas) selection would partially mask the positive impact of migration on productivity in these areas.

This would be consistent with the known stylised facts about recent migration, especially from the EU, to the UK: new migrants tend to be significantly lower paid than natives and to be concentrated in relatively low productivity sectors (Wadsworth et al. 2017); however, they also tend to be better qualified than natives in similar jobs, and employers in these sectors often cite the flexibility of migrant labour as facilitating productivity increases (Rolfe 2017).

Adao, Kolesár, and Morales (2019) suggest that estimates based on shift-share designs may lead to the over-rejection of the null hypothesis because of the correlation of regression residuals across regions with similar countries or sectoral shares, independently of their geographic location. We employ their novel methodology for the computation of standard errors that are robust to presence of cross-regional correlation in regression residuals.[20] Appendix Table A4 presents Adao, Kolesár, and Morales (2019) standard errors for first and second stage of both All countries and EUA04 countries shift-share instruments. We also reports *p*-values and 95 % upper and lower confidence intervals. Importantly, the significance of our results remains robust, unaffected by cross-TTWA correlation in initial countries' shares.

7 Conclusions and Policy Implications

Our results suggest that immigration to the UK has a positive and significant impact (in both the statistical sense and more broadly) on productivity, as measured at a geographical level, with a 1 percentage point increase in the migrant share being associated with an increase in GVA per job ranging between 0.36 % (OLS) and 0.84 % (2SLS). We use two versions of a shift-share instrumental variable to control for the potential endogeneity of migration flows and productivity growth, and apply a variety of tests to check that our instruments are valid and appropriate; our conclusions appear robust. While both OLS and IV estimates of the impact of migration on productivity are positive, the IV estimates are substantially large, suggesting that the endogeneity resulting from migrants' selection biases OLS downwards, implying that the key impact of migration is to raise productivity in areas or sectors that began with lower productivity.

These results are of considerable policy significance, both in the UK and potentially more widely. During the period under consideration, immigration to UK rose sharply as the government liberalised policy towards work-related migration from outside the EEA, and rose further after the expansion of the EU in 2004 to new Member States. Measured net migration peaked at approximately 330,000 in the year leading up to the Brexit referendum in June 2016, of which a substantial majority was from within the EU. Since then, as a consequence of the fall in the exchange

20 This computation is performed using the *STATA* package `ivreg_ss`, which was developed by the same authors.

rate (which makes the wage differential between the UK and poorer countries less sharp), the weakening of the UK economy relative to the eurozone, and the psychological and political impact of the Brexit vote, migration from the EU to the UK has fallen sharply. This has in turn had some impact on the policy debate, with increasing concern among firms about the availability of workers in both high and low-skilled occupations.

During the covid-19 pandemic, immigration unsurprisingly largely ceased, and in addition there appears to have been a significant exodus of migrant workers from the UK. Given the nature of the pandemic and its economic and social impacts, this is not surprising. Migrants, especially from Europe, are disproportionately likely to be employed in the hospitality sector, and other service sectors that require face-to-face contact, so are more likely to have been furloughed or lose their jobs (Portes 2021). The extent to which this will be reversed during the recovery remains uncertain, particularly given the introduction of a new migration system at the end of the Brexit transition period on January 1, 2021. Under the new system, free movement between the UK and EU member states has ended; migrants coming to work in lower-skilled and paid occupations will in principle no longer be able to gain entry (Portes 2021). Indeed, significant labour shortages have already arisen in some sectors, particularly those that were most dependent on relatively low-paid EU migrants before Brexit and the pandemic (see, for example, Partington 2021).

The topic of this paper therefore remains highly relevant. A number of studies have attempted to estimate the impact of the new system on UK GDP and GDP per capita (these are reviewed in Portes 2021). These estimates of the mechanical impact of migration on the labour force, ignoring wider productivity impacts, suggest that the new system will reduce migration flows, but with little impact on GDP per capita. However, as the Migration Advisory Committee puts it: "If there is an impact on productivity this effect is very important and likely to out-weigh many or most other impacts" (Migration Advisory Committee 2020). Our estimates suggest that this is indeed the case. Reductions (or increases) in migration flows could have large and economically significant impacts on the UK economy. In particular, our results suggest that the interaction of covid-induced emigration with post-Brexit migration policy change could potentially reduce productivity and inhibit the post-pandemic recovery in a number of sectors that have been most adversely affected by the pandemic.

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Conflict of interest: The authors have no relevant financial or non-financial interests to disclose.

Data availability: The datasets generated and analysed for the realization of this paper are publicly available on UK's Office for National Statistics and NOMIS websites (links to these data are provided in the main text). Codes used to implement the empirical analysis in this paper are available upon request to the authors.

Appendix A

Table A1: Descriptive statistics on population by country/area of birth – 2002–2018.

Country/area of birth	Share of GB pop.		Country/area of birth	Share of GB pop.	
	2002	2018		2002	2018
All non UK-born	8.36	14.28	North Africa	0.11	0.17
Afghanistan	0.00	0.11	Caribbean-West Indies	0.08	0.13
Albania	0.02	0.05	Central-Western Africa	0.11	0.27
Australia	0.19	0.21	Eastern Europe	0.04	0.39
Austria	0.03	0.03	European USSR	0.05	0.16
Baltic States	0.02	0.44	Far East	0.18	0.47
Bangladesh	0.33	0.37	Middle East	0.04	0.25
Belgium	0.03	0.05	North America	0.01	0.02
Canada	0.12	0.13	Oceania	0.00	0.01
China	0.22	0.32	South Asia	0.00	0.09
Cyprus	0.13	0.09	South-Eastern Africa	0.32	0.43
Czech Republic	0.03	0.07	Western Europe	0.13	0.12
Democratic Rep. of Congo	0.01	0.03	Pakistan	0.51	0.81
Denmark	0.03	0.04	Poland	0.12	1.27
Finland	0.02	0.03	Portugal	0.10	0.22
Former Yugoslavia	0.01	0.06	Republic of Ireland	0.82	0.56
France	0.16	0.26	Romania	0.02	0.60
Germany	0.44	0.47	Sierra Leone	0.03	0.03
Greece	0.04	0.12	Singapore	0.07	0.08
India	0.77	1.27	Somalia	0.13	0.16
Iran	0.09	0.11	South Africa	0.27	0.37
Iraq	0.06	0.11	South America	0.11	0.31
Italy	0.17	0.38	Spain	0.09	0.23
Jamaica	0.26	0.20	Sri Lanka	0.14	0.20
Japan	0.05	0.07	Sweden	0.03	0.06
Kenya	0.22	0.20	Turkey	0.10	0.15
Luxembourg	0.00	0.00	United Kingdom	91.64	85.72
Malaysia	0.09	0.11	USA	0.23	0.26
Netherlands	0.07	0.12	Western-Central Asia	0.00	0.02
New Zealand	0.09	0.10	Zimbabwe	0.12	0.19

This table shows the share of population by country/area of birth in 2002 and 2018. Source: Annual population survey data.

Table A2: Balance test of 2001 countries shares on TTWA industries shares.

	Dependent variable: $s_{cl,2001}$ – 2001 country share						
	Baltic States	**Czech Republic**	**India**	**Nigeria**	**Other East. Europe**	**Poland**	**Romania**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
2001 share of workers in							
Agriculture, hunting, forestry	0.00100	0.0209	−0.0131	0.0997	0.0109	0.000420	0.0158
	(0.0610)	(0.0643)	(0.0692)	(0.136)	(0.0730)	(0.0653)	(0.0715)
Fishing	−0.265	0.0339	−0.321	0.150	−0.118	−0.323	0.0292
	(1.023)	(1.233)	(1.068)	(2.473)	(1.344)	(1.137)	(1.332)
Mining and quarrying	0.244	0.287	0.118	0.764	0.354	0.273	0.368
	(0.399)	(0.428)	(0.432)	(0.898)	(0.487)	(0.432)	(0.474)
Manufacturing	−0.0185	−0.0327	0.000684	−0.0438	−0.0320	−0.0205	−0.0342
	(0.0232)	(0.0247)	(0.0263)	(0.0508)	(0.0277)	(0.0245)	(0.0273)
Electricity, gas and water supply	−0.267	−0.377	−0.217	−0.669	−0.397	−0.265	−0.406
	(0.351)	(0.374)	(0.382)	(0.775)	(0.420)	(0.366)	(0.412)
Construction	−0.350	−0.292	−0.396	−0.614	−0.336	−0.367	−0.319
	(0.267)	(0.274)	(0.293)	(0.583)	(0.312)	(0.277)	(0.307)
Wholesale, retail and repair of motor vehicles	−0.0672	−0.151	−0.0831	−0.261	−0.142	−0.0946	−0.135
	(0.119)	(0.124)	(0.131)	(0.263)	(0.141)	(0.125)	(0.138)
Hotels and restaurants	0.0678	0.0746	0.114	0.170	0.0877	0.0968	0.0770
	(0.0953)	(0.102)	(0.105)	(0.209)	(0.113)	(0.0999)	(0.110)
Transport storage and communications	0.0561	0.116	0.0812	0.149	0.0927	0.0770	0.0750
	(0.0836)	(0.0914)	(0.0937)	(0.190)	(0.102)	(0.0915)	(0.100)
Financial Intermediation	0.146	0.134	0.144	0.290	0.130	0.139	0.139
	(0.145)	(0.146)	(0.157)	(0.317)	(0.168)	(0.150)	(0.166)

Table A2: (continued)

	Dependent variable: $s_{cl,2001}$ – 2001 country share						
	Baltic States	**Czech Republic**	**India**	**Nigeria**	**Other East. Europe**	**Poland**	**Romania**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Real estate, renting and business activities	0.247	0.332	0.265	0.550	0.353	0.281	0.332
	(0.233)	(0.242)	(0.253)	(0.519)	(0.275)	(0.244)	(0.271)
Public administration and defence	−0.0515	−0.0534	−0.0624	−0.0847	−0.0588	−0.0584	−0.0595
	(0.0429)	(0.0431)	(0.0507)	(0.0896)	(0.0495)	(0.0458)	(0.0484)
Education	−0.159	−0.256	−0.160	−0.543	−0.268	−0.203	−0.248
	(0.248)	(0.258)	(0.275)	(0.552)	(0.293)	(0.260)	(0.288)
Health and social work	0.201	0.265	0.186	0.540	0.282	0.227	0.273
	(0.231)	(0.241)	(0.254)	(0.515)	(0.274)	(0.243)	(0.270)

We here consider the group of top-5 Rotemberg weights for both shift-share IVs (All-SSIV and EUA-SSIV). Each column reports the regression of 2001 country c's share ($s_{cl,2001}$) on 2001 TTWA NACE industries share. Source: 2001 census data. Excluded category: “other industries”. White-robust standard errors in parenthesis ($^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$).

Table A3: Balance test of 2001 countries shares on TTWA occupations shares.

	Dependent variable: $s_{cl,2001}$ – 2001 country share						
	Baltic States	**Czech Republic**	**India**	**Nigeria**	**Other East. Europe**	**Poland**	**Romania**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
2001 share of workers in							
Professional occupations	0.0399	0.0329	0.0351	−0.00314	0.0446	0.0454	0.0459
	(0.0610)	(0.0706)	(0.0707)	(0.143)	(0.0787)	(0.0671)	(0.0732)
Associate professional and technical occupations	0.161	0.220	0.155	0.460	0.244	0.186	0.230
	(0.231)	(0.255)	(0.244)	(0.532)	(0.286)	(0.245)	(0.279)
Administrative and secretarial occupations	0.163	0.173	0.238^{*}	0.209	0.154	0.152	0.139
	(0.108)	(0.115)	(0.124)	(0.235)	(0.130)	(0.114)	(0.125)
Skilled trades occupations	−0.137	−0.131	−0.113	−0.208	−0.146	−0.135	−0.138
	(0.0889)	(0.0934)	(0.0971)	(0.194)	(0.105)	(0.0937)	(0.103)
Personal service occupations	−0.140	−0.113	−0.172	−0.246	−0.153	−0.163	−0.146
	(0.129)	(0.139)	(0.140)	(0.282)	(0.153)	(0.134)	(0.151)
Sales and customer	−0.147	−0.152	−0.167	−0.289	−0.152	−0.119	−0.147
Service occupations	(0.141)	(0.150)	(0.155)	(0.310)	(0.168)	(0.148)	(0.165)
Process, plant and machine operatives	0.0236	−0.00807	0.100^{**}	0.00549	0.00885	0.0255	−0.00325
	(0.0331)	(0.0356)	(0.0473)	(0.0608)	(0.0372)	(0.0330)	(0.0363)
Elementary occupations	−0.0137	−0.0726	−0.123	−0.0818	−0.0587	−0.0431	−0.0458
	(0.0669)	(0.0721)	(0.0782)	(0.135)	(0.0772)	(0.0686)	(0.0760)

We here consider the group of top-5 Rotemberg weights for both shift-share IVs (All-SSIV and EUA-SSIV). Each column reports the regression of 2001 country c's share ($s_{cl,2001}$) on 2001 TTWA SOC occupations share. Source: 2001 census data. Excluded category: "manager and senior officials". White-robust standard errors in parenthesis ($^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$).

Table A4: Adao, Kolesár, and Morales (2019) standard errors.

	Coefficient	Std. error	*p*-value	Lower CI	Upper CI
	(A) All countries shift-share IV				
1st stage	0.3026	0.0000	0.0000	0.3026	0.3026
2nd stage	0.0084	0.0000	0.0000	0.0084	0.0084
	(B) EUA countries shift-share IV				
1st stage	0.8655	0.0000	0.0000	0.8655	0.8655
2nd stage	0.0078	0.0000	0.0000	0.0078	0.0078

Notes: This table reports the output from the *STATA* package `ivreg_ss` which computes the standard errors according to the methodology, developed by Adao, Kolesár, and Morales (2019), which account for correlation in regression residuals across TTWA with similar initial countries shares used for the construction of the shift-share instrumental variable.

Table A5: Immigration and productivity – local authority estimates – 2002–2018.

	Dependent variable: (log) GVA per filled job		
	OLS	2SLS: shift-share IV	
		All countries	EUA countries
	(1)	(2)	(3)
Share of migrants	0.00335^{***}	0.00799^{***}	0.00810^{***}
	(0.000999)	(0.00252)	(0.00288)
Observations	5746	5746	5746
R^2	0.976		
Local authority FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
MOP F-stat		27.97	37.41

Notes: the outcome and explanatory variable of interest in all estimates are, respectively, the natural logarithm of gross value added per filled job, and the migrants' share, m_{lt}, i.e. the fraction, out of resident population in local authority l in year t, of non UK-born residents. All regressions consider yearly data for each year between 2002 and 2018, and include local authority and year fixed effects. Column 1 shows OLS estimates, while Columns 2 and 3 2SLS results with shift-share instrumental variable which are defined according to a methodology similar to Card (2001) and described in detail in Section 3.1. 2SLS regression in Column 2 uses a shift-share IV which considers the whole set of countries/areas of origin, while in Column 3 we select the group of countries which gained access to EU after 2004. Bottom row reports Montiel Olea and Pflueger (2013) F-statistic for weak instrument test of corresponding first stage. Regressions results are weighted by employment size in 2001. Standard errors clustered at the local authority level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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