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Julian Costas-Fernandez & Simon Lodato

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Centre for Research and Analysis of Migration

Department of Economics, University College London
Drayton House, 30 Gordon Street, London WC1H 0AX

cream@ucl.ac.uk

www.cream-migration.org

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Julián Costas-Fernández[†] Simón Lodato[‡]

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Abstract

We present evidence whereby immigration increases labour productivity while reducing the labour share, thus redistributing income from workers to employers. This result is unlikely in competitive markets with skill-neutral capital, where labour share is orthogonal to immigration shocks in the long run. Instead, our empirical evidence better matches predictions from imperfect labour market models where immigrant and native workers are heterogeneous in both skills and labour supply elasticities.

JEL codes: D33, J21, J24, J42, J61, O47
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1 Introduction

In canonical models of immigration, price-taking firms operating in perfect labour markets produce a homogeneous good by combining heterogeneous labour with skill-neutral capital under constant returns to scale. Within this framework, immigration shocks improve aggregate labour productivity when migrants induce a more efficient skill mix but do not alter the income shares of workers and employers in the long run.

In contrast, we document that shocks of immigration to Great Britain correlate positively with labour productivity and negatively with labour share, as Figure 1 shows. To provide evidence for the causality of these relations, we exploit the heterogeneous exposure of British regions to migration (Altonji and Card 1991; Card 2001). Our estimates

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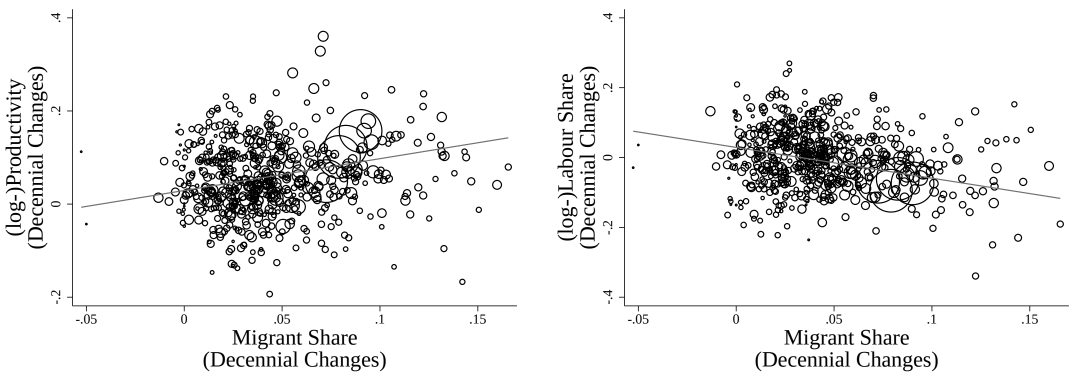
[†]CReAM, UCL, `j.costas-fernandez@ucl.ac.uk`.

[‡]Middlesex University London, `s.lodato@mdx.ac.uk`.

show that one standard deviation increase in the immigrant share[1] increases labour productivity by 4%. On average, three additional immigrants per 100 individuals increase output per worker by £1,874. Labour compensation, however, goes down with immigration. At the mean, one standard deviation increase in the migrant share contracts annual labour costs by £392 per worker. These effects together result in immigration shocks compressing the labour share. We provide evidence of the robustness of these results to a comprehensive set of specifications and different versions of the instrument.

Figure 1: Immigration and

(a) Labour Productivity **(b)** Labour Share



Note: Labour share and labour productivity: computed by the authors from ONS data. Labour productivity: output (Gross Value Added, GVA) per job. The latter includes employees, self-employed and civil servants. Labour share: wages plus a proportion of the self-employed income as per equation 3 in Appleton (2011) divided by GVA. Point size proportional to regions' contribution to national GVA in 2002. The grey line represents the best linear fit.

Two alternative models allow for a long-run increase in productivity with a simultaneous decrease in labour share: perfect markets with capital-skill complementarity and imperfect labour markets. Both rely on skill heterogeneity between natives and migrants, while the latter also requires immigrants to earn a smaller share of their marginal product than (comparable) natives. Although both models produce similar redistribution effects, i.e. migrants shift income (shares) from workers to employers, the mechanisms differ. In perfect labour markets with capital-skill complementarity, capital owners gain from new migrants whose skills complement capital because they boost the marginal product of capital. In imperfect labour markets with capital-skill neutrality, employers absorb a larger share of workers' marginal product because they have higher labour market power[2] over migrant workers.

Supporting the imperfect labour markets hypothesis, we document that immigration productivity and labour share effects vary with migrants' reservation wages[3]. We follow Dustmann, Ku, et al. (2021) by using home-host exchange rates as a proxy for reservation

[1]Roughly three percentage points.

[2]We do not explore the source of employers' labour market power.

[3]Throughout this article, differences in reservation wages and labour supply elasticities are sometimes considered equivalent concepts. Of course, this is not always the case since reservation wages are directly related to participation in the labour force but not necessarily to elasticities. A positive relationship between reservation wages and labour supply elasticities usually emerges at the aggregate level under restrictive assumptions.

wages. A unit of host country currency buys a larger basket of goods when the home-to-host exchange rate is low. Therefore, if immigrants spend part of their income in their home country, immigrants from low home-to-host exchange rates will be more willing to accept lower wages. We find that the positive and negative effects of immigration on productivity and labour share, respectively, accentuate when immigrants come from countries with lower reservation wages.

The evidence in this article contributes to recent work on the economics of immigration (e.g. Amior and Manning 2021; Amior and Stuhler 2022; Manning 2021; Naidu et al. 2016) claiming that imperfect labour markets, where firms have monopsony power, provide a better description of the mechanisms behind observed migration effects. This claim has implications for redistributive policies, since workers bear the welfare costs of immigration. In this way, our results highlight the importance of considering the effects of immigrants on both workers and employers when assessing the long-run welfare consequences of immigration (Borjas 1995).

The rest of the article proceeds as follows. The next section presents a canonical model with an arbitrary number of skills and capital-skill neutrality. In this setting, immigration shocks show positive productivity effects when migrants are, on average, more productive than natives or induce native upskilling. Nonetheless, the income distribution between labour and capital is constant because of capital-skill neutrality. Furthermore, the section contrasts the implications of the canonical model with the imperfect labour markets' that allow for heterogeneity between migrants and natives in both skills and labour supply elasticities. Section 3 contains all the empirical evidence. It shows immigration to Great Britain has had positive productivity effects and has shrunk the labour share. The section discusses why, within perfect competition, capital-skill complementarity is the only explanation consistent with our evidence. Subsection 3.1 provides additional empirical evidence for the case of imperfect markets. Section 4 concludes.

2 Canonical Model versus Imperfect Markets

An extensive literature (for example, Borjas 1995, 2013, 2014; Card 2001; Dustmann, Frattini, et al. 2013; Manacorda et al. 2012; Peri 2012) explores the effect of immigration on the receiving economy, often native wages, starting from perfectly competitive labour markets and constant returns to scale. This approach provides a rich framework for assessing different redistributive consequences of immigration. For instance, the various costs and benefits immigration imposes on and offers to native workers, consumers and taxpayers.

Similar to most immigration literature (e.g. Amior and Manning 2021; Card 2001; Dustmann, Frattini, et al. 2013), we consider a production function with constant returns to scale (CRS) and skill-neutral capital, $F(H(\vec{L}), K)$. H is a CRS skill aggregator and the skill vector, $\vec{L}$, has s^{th} element $L_s = \eta_s N + \mu_s M$. The densities η_s, μ_s ($s \in \{1, \ldots, S\}$) represent the distribution of skills for native labour, N, and migrant, M, respectively. Moreover, we focus on the long run when capital is fully elastic and can be purchased in the international market at an exogenous price, say r.

Unlike most literature, we are concerned with the aggregate productivity effects of immigration and its distributional impact on labour and employers. We start our analysis by deriving the implications of the canonical model for immigration on labour productivity

$$\begin{gathered}\frac{dF(H(\vec{l}),k)}{dm} = F_H \sum_s H_s(\mu_s - \eta_s) - r\frac{F_{KH}}{F_{KK}} \sum_s H_s(\mu_s - \eta_s) \\ \frac{dF(H(\vec{l}),k)}{dm} > 0 \iff \sum_s H_s\mu_s > \sum_s H_s\eta_s,\end{gathered} \tag{1}$$

where lower-case letters indicate per-worker quantities, and m is the migrant share.

Equation (1) shows that, within the canonical model, aggregate productivity increases with immigration if the average migrant is more productive than the average native.

A strand of literature has argued that heterogeneous elasticities of native labour supply may explain the disagreement between the canonical model and some empirical evidence (see Dustmann, Schönberg, et al. 2016). Yet, this claim does not necessarily affect our qualitative outcomes, as we are concerned with the overall effect of immigrants on aggregate quantities allowing for changes in composition. For example, a change in the immigrant share can also change the skills on which natives concentrate.[4] In such a case, the productivity effect of immigration takes the form[5]

$$\begin{gathered}\frac{dF(H(\vec{l}),k)}{dm} = \left(F_H - r\frac{F_{KH}}{F_{KK}}\right) \sum_s H_s \left(\mu_s - \eta_s(m) + \frac{\partial \eta_s(m)}{\partial m}(1-m)\right) \\ \frac{dF(H(\vec{l}),k)}{dm} > 0 \iff \sum_s H_s \left(\mu_s + \frac{\partial \eta_s(m)}{\partial m}(1-m)\right) > \sum_s H_s\eta_s\end{gathered} \tag{2}$$

Equation (2) shows that if natives respond to immigration by upskilling ($\sum_s H_s \frac{\partial \eta_s(m)}{\partial m} > 0$), as in Peri and Sparber (2009), this adds to the positive effects of immigration on productivity. More generally, equation (2) highlights that immigration affects productivity by shifting the distribution of skills.[6] When migrants and natives have the same skill distribution and natives' skills do not respond to immigration, productivity and immigration are orthogonal in the long run. In contrast, Figure 1 suggests productivity changes with immigrants in the long run, corroborated by our evidence in Section 3, which shows that immigrants shift the overall distribution of skills.

As for the distribution of income between labour and capital, capital-skill neutrality imposes a tight restriction in the long run, (Lewis 2013). By constant returns to scale and labour aggregation, we can express the labour share as follows,

$$\frac{\sum_s F_s l_s}{F(H(\vec{l}),k)} = 1 - \frac{rk}{F(H(\vec{l}),k)} = 1 - \frac{pF_k^{-1}(1,p)}{F(1,F_k^{-1}(1,p))} \tag{3}$$

[4] We could allow immigrant shocks to change the distribution of migrants' skills. The resulting effect is analogous to migrants changing the distribution of natives' skills.

[5] We have imposed no restrictions on $\vec{\eta}(m)$. Thus, immigrants may compress some native skill groups through unemployment, i.e. without positive compensation in some other skill group.

[6] One may wonder whether it could be the migrants working longer hours that drive the migration productivity effects. Figure B.5a shows that measuring productivity as GVA per hour only mildly reduces the migration productivity effect.

where we use that, in competitive labour markets, the price of labour equals its marginal productivity, $w_s = F_s \equiv F_H H_s$.

Equation (3) shows that the labour share is not a function of the skill aggregator. Therefore, in perfect labour markets with capital-skill neutrality, migration shocks do not alter the income distribution between labour and capital, which contradicts the correlations in Figure 1.

Two assumptions prevent migration from altering the labour share in the long run: capital-skill neutrality and perfect labour markets. We now relax the latter. We explore a monopsony model where immigrant and native labour are heterogeneous in both their skills and labour-wage elasticity. This new setting allows for the simultaneous effects of immigration observed in the data: negative on labour share and positive on productivity when immigrants induce higher average workforce skills (or even labour upskilling) and have lower labour-wage elasticity.

In a simple form of imperfect labour markets with monopsony employers wages take the form (see, for instance, Amior and Manning 2021; Card et al. 2018),[7]

$$\omega_s = \gamma(e_s) F_s \tag{4}$$

where ω_s is the wage of workers with skill s; $e_s = \frac{e_N \eta_s (1-m) + e_M \mu_s m}{\mu_s m + \eta_s (1-m)}$ is the (weighted) average elasticity of labour supply, with e_M and e_N being the elasticities of native and migrant labour supply (to firms); and $\gamma(e_s) \in (0, 1]$ is the wage wedge.[8,9]

The behaviour of average labour productivity is orthogonal to wage determination, given our assumptions about the capital supply. Then, (also) in imperfect markets, an inflow of migrants that induces higher average workforce skills can be the reason for a concurrently increasing average labour productivity. This feature naturally leads to a distributive expression of labour productivity where the labour and employer shares depend on the labour-supply elasticities,

$$\sum_s \left[\Big(1 - \gamma(e_s)\Big) + \gamma(e_s) \right] \frac{F_s l_s}{F} = 1 - \frac{r F_k^{-1}(1, r)}{F(1, F_k^{-1}(1, r))} \tag{5}$$

In the left-hand side of (5), the total average labour productivity is distributed between workers and monopsony employers, with the labour share increasing in the labour supply elasticity. Because the capital supply is infinitely elastic (can be purchased at a fixed price), capital-skill neutrality again implies that the RHS of (5) does not change with immigration. As a result, the differential of the labour share is the opposite of that of monopsony employers, $d(\sum_s \gamma(e_s) \frac{F_s l_s}{F}) = -d(\sum_s \Big(1 - \gamma(e_s)\Big) \frac{F_s l_s}{F})$. For the labour share to decrease with the migrant share, the proportional change in (per unit) labour com-

[7]Our monopsony wage specification in (4) is not fully general as we assume that migrants' and natives' labour elasticities are constant but possibly heterogeneous.

[8]The wage wedge $\gamma_s(\cdot)$ is the fraction of the marginal productivity of workers of type s, F_s, that goes to the worker. The wage wedge function is increasing in the labour supply elasticity e_s.

[9]The equation for wage-setting in 4 may also result from a bargaining model (see Barnichon and Zylberberg 2019) where elasticities, reservation wages, and workers' bargaining power are positively related.

pensation should be smaller than the proportional change in (per labour) production,[10]

$$dln\sum_s \omega_s l_s = dln\sum_s \gamma(e_s)F_s l_s < dlnF(H(\vec{l}),k) = dln\sum_s F_s l_s \tag{6}$$

The impact of productivity-enhancing immigrants with more inelastic labour supplies on the share of labour has two components with opposite signs. On the one hand, migrants push average wages up because they are more productive and/or induce a more productive skill mix. On the other hand, immigrants with more inelastic labour supplies reduce labour compensation. We can then express inequality (6) as

$$\frac{(e_M - e_N)}{\sum_s \omega_s l_s}\sum_s \gamma'(e_s)F_s l_s \Gamma_s + \frac{\sum_s \gamma(e_s)\frac{\partial F_s l_s}{\partial m}}{\sum_s \gamma(e_s)F_s l_s} < \frac{\sum_s \frac{\partial F_s l_s}{\partial m}}{\sum_s F_s l_s} \tag{7}$$

where $\Gamma_s = \frac{\mu_s \eta_s}{l_s^2} > 0$.

In (7), when the labour-supply elasticities of immigrants and natives are equal, i.e. $e_M = e_N = e$, the proportional increase of the labour compensation equals that of production, so the labour share does not change with immigration,

$$\frac{\gamma(e)\sum_s \frac{\partial F_s l_s}{\partial m}}{\gamma(e)\sum_s F_s l_s} = \frac{\sum_s \frac{\partial F_s l_s}{\partial m}}{\sum_s F_s l_s} \tag{8}$$

Equation (8) implies that imperfect markets alone do not suffice for migrants to compress the labour share. Instead, when the labour supply of migrants is inelastic with respect to natives', $e_M < e_N$, a sufficient condition for the labour share to be decreasing in the migrant share is as follows,

$$\frac{\sum_s \gamma(e_s)\frac{\partial F_s l_s}{\partial m}}{\sum_s \frac{\partial F_s l_s}{\partial m}} \leq \frac{\sum_s \gamma(e_s)F_s l_s}{\sum_s F_s l_s} \tag{9}$$

In imperfect labour markets, when migrants have more inelastic labour supplies than natives, we should expect the labour share to decrease with immigration. Under condition (9), this is compatible with a simultaneous increase in productivity. That is, the immigration of highly skilled workers with labour supply elasticities sufficiently low might raise the average labour productivity and decrease the labour share.

3 Empirical Evidence

Consider an empirical counterpart of the production function above

$$\tilde{F}(H(\vec{l_{rt}}),k_{rt}) \equiv e^{\epsilon_{rt}+\xi_r+\vartheta_t}F(1,k_{rt}/H(\vec{l_{rt}}))H(\vec{l_{rt}}) \tag{10}$$

where ϵ_{rt} are transitory shocks, ξ_r are region-specific permanent productivity differentials and ϑ_t are national-level productivity shocks. Assuming that capital fully adjusts, changes in labour productivity take the form

[10]Equation 6 uses that, under CRS, the proportional change in the production equals the proportional change in the factors.

$$d\log\left(\tilde{F}(H(\vec{l_{rt}}),k_{rt})\right)=\sum_s \frac{H_s(\vec{l_{rt}})}{H(\vec{l_{rt}})}\frac{\partial l_{srt}}{\partial m}dm+\frac{1}{F(1,F_k^{-1}(1,r))}\frac{\partial F(1,F_k^{-1}(1,r))}{\partial r}dr + d\vartheta_t + d\epsilon_{rt} \tag{11}$$

Because we assume capital is purchased in international markets, the second term in the RHS of (11) is common across regions. This feature leads to the following empirical counterpart to the proportional change of production in the theoretical section,

$$\Delta\log\left(\tilde{F}(H(\vec{l_{rt}}),k_{rt})\right)=\beta\Delta m+\theta_t+\Delta\epsilon_{rt} \tag{12}$$

where Δ are decennial changes and the year fixed effects (θ_t) capture both national-level productivity shocks and changes in the price of capital. The parameter of interest β identifies not a single structural parameter, but rather the reduced form of the marginal effect of immigration on labour productivity.

As for the labour share, equation (3) conveys that the canonical model predicts no immigration effects. We use an analogous equation to (12) to test whether this null effect holds empirically.

We estimate the effects of immigration on labour productivity and labour share using data from Great Britain. Most data comes from ONS publicly available sub-regional figures, disaggregated at level three of the Nomenclature of Territorial Units for Statistics (i.e. NUTS3).[11] With one exception: we have merged London sub-divisions into a single regional unit. Even though the data on productivity is available for all years since 2002, we restrict our analysis to 2002-2015. The idea is to avoid possible confounders from the 2016 EU membership referendum results.

Figure 1 in the introduction shows the main relations of interest. In Sub-figure 1a, we plot decennial changes in the migrant share against decennial changes in (log-)labour productivity, measured as gross value added (GVA) per job. It shows a clear positive correlation between immigration and labour productivity. With an estimated slope of 7% increase in labour productivity per every ten percentage point increase in the migrant share. This positive relation is statistically significant at the 99% confidence level.

In Sub-figure 1b, we represent the relationship between the labour share, i.e. total compensation of labour over total production,[12] and immigration. As with productivity, decennial changes in the labour share show a strong relationship between both magnitudes but with a negative sign. Indeed, the slope of the best-fit line is -9% per every ten percentage point increase in the migrant share. If the relations in Figure 1 were causal, we would conclude that data contradicts the predictions of the canonical model as migrants redistribute income away from workers in the long run.

However, a causal interpretation of the relations in Figure 1 is only valid under strong assumptions. As is common in immigration studies, we face an identification challenge posed by the endogeneity of immigrants' location choices. (e.g. Altonji and Card 1991; Card 1990, 2001; Ottaviano et al. 2018; Peri 2012). It is likely that economic shocks ($\Delta\epsilon_{rt}$) jointly determine production levels and demand for labour, thus generating an

[11] A detailed list of data sources is provided in Online Appendix A.

[12] We follow ONS productivity figures in measuring total production as GVA.

endogenous supply of both immigrant and native workers. For identification, we construct an instrument similar to the one pioneered by Altonji and Card (1991) and Card (2001). Thus, we exploit within-region variation by combining heterogeneous exposure to immigration inflows from various countries of origin across GB regions with changes in the country composition of inflows at the national level.[13]

We illustrate the source of identifying variation with an example that uses the distribution of exposure to immigration shocks from Poland and India, as these are the countries of birth driving our estimates.[14,15] Because of the initial settlements of WWII Polish refugees, Swindon presents a high exposition to immigration from Poland and little from India. The opposite holds for Blackburn with Darwen, where, following the Industrial Revolution, a large textile industry (Leunig 1998) attracted Indian immigrants until as late as the 1960/70s (Swift 2021). A comparative look at the evolution of immigrant flows from Poland and India, Figure D.2b, shows that immigration from Poland grew sharply from 2004 onwards following the enlargement of the EU towards Eastern Europe, with close to zero net inflows before 2004. Net inflows from India were already positive before 2002 and increased sharply after 2002. Thus, Swindon would have been exposed to immigration shocks later than Blackburn with Darwen if all migrants had come from either Poland or India. Similar comparisons hold for other British regions and countries of birth.

For identification, we exploit this geographical heterogeneity in exposure to immigration inflows from different countries in combination with national-level migration supply shocks. We measure the latter using region-specific leave-one-out national stocks from the countries of birth. To illustrate how we compute this leave-one-out, consider the case of Swindon again and the national stock of Polish workers: we subtract the Polish population living in the NUTS-1 region *South West of England*, that contains Swindon, from the national total. We use this broader geographic delimitation for two reasons. First, ONS yearly data on migrant location and country of birth is noisy at the NUTS-3 level, with many instances of data censoring because of disclosure concerns. Second, we seek to attenuate possible confounding effects driven by spatial correlation.

Formally, our instrument is defined in equation (13) where we allocate leave-one-out (LOO) national stocks ($Pop_{ct}^{-R(r)} := \sum_{k \notin R(r)} Pop_{ctk}$) from country-of-birth c to a given NUTS-3 region r, contained in NUTS-1 region $R(r)$, using the exposure measure $Pop_{cr}^{91}/Pop_{c}^{91}$ and then normalised by the region's population in 1991.

$$z_{rt} = \sum_{c=1}^{C} \overbrace{\underbrace{\frac{1}{Pop_r^{91}}}_{\text{Normalization}} * \underbrace{\frac{Pop_{cr}^{91}}{Pop_c^{91}}}_{\text{Allocation}}}^{\text{Exposure}} * \underbrace{Pop_{ct}^{-R(r)}}_{\text{LOO-Stock}} \tag{13}$$

We use this instrument[16] to identify the reduced form effect of immigration on pro-

[13]This approach follows a well-established tradition in migration economics. For a survey on this topic, see Jaeger et al. (2018).

[14]See Online Appendix B.4.

[15]Figure D.2a, in Online Appendix B.4, represents the spatial distribution of exposure to immigration shocks from Poland (left panel) and India (right panel).

[16]Figure D.1 shows a strong correlation between the instrument on the x-axis and the endogenous variable on the y-axis (first stage). We provide a formal weak-instrument statistic in Table 1.

ductivity, β, in equation (12). Table 1 reports OLS and IV estimates of the effect of immigration on productivity, labour costs, and labour share. Both sets of estimates convey the same qualitative effect: immigration increases labour productivity, yet this does not translate into labour compensation. These two effects produce a sharp contraction in the labour share.

Table 1: Main Estimates

	(1) Productivity	(2) Labour Cost†	(3) Labour Share
		A. OLS	
Immigrant Share	0.671***	-0.209	-0.881***
	(0.199)	(0.137)	(0.233)
		B. IV	
Immigrant Share	1.198***	-0.424**	-1.621***
	(0.241)	(0.165)	(0.296)
F-Stats		46.513	
Obs.		592	
Regions		148	

Note: †We compute labour costs and labour shares following ONS methodology (see Appleton 2011), where a fraction of mixed-income is added to the compensation of employees. We compute labour cost (share) per job by dividing the resulting measure of income by the number of jobs (GVA). Jobs include employees, self-employed, government-supported trainees and members of His Majesty's Forces. We control for the time-varying national level. We weigh estimates by the region's contribution to national GVA in 2002. Every estimate comes from its regression all of them estimated in decennial changes as per equation (12). Standard errors (clustered by region) between parenthesis. * $p < 0.10$ ** $p < 0.05$, *** $p < 0.01$

When evaluating IV estimates at the means (see Table C.1), we find that a one within-region standard deviation rise in the immigrant share increases productivity by 4%, or equivalently a rise of 3 immigrants per every 100 working-age increases productivity by £1,874 per worker. Moreover, labour compensation contracts by £392 for one standard deviation increase in the immigrant share. Finally, a one standard deviation increase in the immigrant share contracts the labour share by 5%.

These estimates are robust to a comprehensive set of specifications and changes in the instrument. In Online Appendix B, we first provide evidence that measurement error may be the predominant driver of the differences between OLS and IV. We then show, in Online Appendix B.3, that a saturated specification results in similar estimates, supporting the causal interpretation of Table 1 (see Blandhol et al. 2022). Furthermore, in Online Appendix B.4, we characterise the countries of birth that drive our estimates using the methodology introduced by Goldsmith-Pinkham et al. (2020). We show that the country-of-birth-specific estimates (for the most relevant countries) are close to the baseline and that they heel the evolution of immigrant stocks. Last, in Online Appendix B.5, we show our estimates are robust to several changes in the specification. To mention a few, exploiting the 2004 EU expansion towards Eastern Europe, constructing an instrument with inflows to countries other than the UK, or using lagged immigration shares all produce similar estimates.[17]

In the canonical model, the effect of immigrants on the distribution of skills is the primary mechanism behind migration productivity effects. To estimate whether immigration shocks shift the skill distribution, we use occupational shares.[18] Table 2 reports the effects of immigration shocks on the weights of nine occupational groups in the total of workers. Estimates in Table 2 show that a higher immigrant share decreases the share of workers in intermediate occupations[19] while increasing those in both high-skilled professional occupations and low-skilled process and elementary occupations.[20] Thus, empirical evidence supports the skill-based mechanism for migration productivity effects emphasized by the canonical theory.[21]

3.1 Imperfect Labour Markets

Our imperfect market mechanism relies on the heterogeneity of immigrants in terms of reservation wage or labour supply elasticity to explain the negative response of the labour share to immigration. Our evidence of this mechanism, which follows Dustmann, Ku, et al. (2021), exploits the fact that when immigrants realise part of their consumption in their home country, reservation wages are a function of relative exchange rates. When the exchange rate at home (country of origin) is low, a pound buys a larger basket of goods at home, inducing immigrants to accept lower wages (for a detailed discussion see Dustmann, Ku, et al. 2021; see also Albert and Monras 2018). We then use exchange rates in the home country relative to the UK as a proxy for immigrants' reservation wages.

To estimate heterogeneous effects along migrants' reservation wages, we use data on immigrant inflows by country of birth and year from ONS. Call these I_{tc}. We complement this data with migrants' return rates by experience in the UK (τ) computed from the Labour Force Survey (LFS). Call these R_τ.[22] Finally, we add the exposure to immigration

[17]Although this will not affect the main point of this paper, one may wonder whether the (one-to-one) substitution of more productive immigrants for natives explains the positive effect of immigration on labour productivity. In Online Appendix B.1, we provide evidence of this not being the case.

[18]We use occupations instead of education because, when education is not fully transferable across international borders, immigrants may experience downgrading. Thus, immigrants may have jobs for which they would seem over-qualified, considering their observed educational attainment. In such cases, occupations may be a better proxy for the skills migrants bring to the receiving economy.

[19]"Intermediate occupations" comprises associate professional, administrative or secretarial, skilled trade, caring, leisure and other services, sales and customer service occupations. According to ONS, these occupations require a level of education above compulsory education but below degree or equivalent qualification.

[20]Such changes in the occupational structure are in line with the extreme-skill complementarity productivity mechanism proposed for city wage premiums (Eeckhout et al. 2014).

[21]As noted in the theory section, we are interested in changes in the overall distribution of skills. Hence, whether these changes are induced directly by immigrants entering these occupations or indirectly by immigrants shifting natives' occupations is immaterial.

[22]We restrict migrants' return rates to be fixed across calendar time and country of birth because of the LFS's limited sample size and to exploit variation in the exchange rates rather than in return rates.

Table 2: Immigration Induced Changes in Occupation Shares
IV estimates, Decennial Changes

	(1)	(2)	(3)	(4)	(5)
	Managers	Professional	Associate	Administrative	Skilled
Immigrant Share	-0.009	0.312***	-0.118**	-0.425***	0.023
	(0.055)	(0.036)	(0.058)	(0.085)	(0.051)
Avg.Occ.Share	11	18	14	12	11
	Caring	Sales	Process	Elementary	
Immigrant Share	-0.170***	-0.019	0.232***	0.175***	
	(0.037)	(0.024)	(0.033)	(0.056)	
Avg.Occ.Share	8	8	7	11	
F-Stats			46.513		
Obs.			592		
Regions			148		

Note: We compute occupational shares from the Annual Population Survey (APS). Because the APS covers 2004-onwards, we interpolate occupation shares between the 2001 Census and the (2004) APS data. We control for time-varying national-level shocks. Estimates are weighted by the region's contribution to national GVA in 2002. Standard errors (clustered by region) between parenthesis. * $p < .10$ ** $p < 0.05$, *** $p < 0.01$

measures in (13) to compute the expected exchange rates for a region-year as

$$\bar{E}_{tr} = \frac{\sum_{c=1}^{C} \frac{1}{Pop_r^{91}} \frac{Pop_{cr}^{91}}{Pop_c^{91}} \sum_{\tau=t-10}^{t} I_{\tau c} R_{t-\tau} E_{\tau c}}{\sum_{c=1}^{C} \frac{1}{Pop_r^{91}} \frac{Pop_{cr}^{91}}{Pop_c^{91}} \sum_{\tau=t-10}^{t} I_{\tau c} R_{t-\tau}} \tag{14}$$

where E_{tc} is the exchange rate for country of birth c and entry year t (relative to the Pound Sterling).

We use the expected exchange rate defined above as a proxy for expected reservation wages of the immigrant stock in the region r at year t and estimate the following regression

$$\Delta y_{rt} = \beta \Delta m_{rt} + \omega \Delta e_{rt} + \tau_t + \Delta \epsilon_{rt} \tag{15}$$

where $e_{rt} \equiv \bar{E}_{tr} m_{rt}$.

As in our baseline regression, we still may face endogeneity concerns, for shocks $\Delta\epsilon_{rt}$ that determine productivity levels may also affect the demand for immigrant labour. All endogeneity in (15) is introduced by the immigrant share, m. We exploit this by using the shift-share instrument introduced earlier within a control function estimator. We then impose an additional structure on the error term in (15) and assume that $\epsilon_{rt} = \rho\eta_{rt} + \varepsilon_{rt}$. Thus equation (15) takes the form

$$\Delta y_{rt} = \beta \Delta m_{rt} + \omega \Delta e_{rt} + \tau_t + \rho \Delta \eta_{rt} + \Delta \varepsilon_{rt} \tag{16}$$

We further assume that changes in the immigrant share comprise an exogenous term, time-varying national shocks, and an endogenous term. The exogenous term is our shift-share instrument,

$$\Delta m_{rt} = \gamma \underbrace{\Delta z_{rt}}_{\text{Instrument}} + \underbrace{\varkappa_t}_{\text{National Shocks}} + \Delta \underbrace{\eta_{rt}}_{\text{Endogenous Shock}} \tag{17}$$

Under this additional set of assumptions, we estimate $\Delta\eta_{rt}$ with the residuals of a regression of immigrants shares decennial changes on the instrument and year-fixed effects. We then plug this estimate, $\widehat{\Delta\eta}_{rt}$, into our structural equation in (15) and estimate the following equation

$$\Delta y_{rt} = \beta\Delta m_{rt} + \omega\Delta e_{rt} + \Delta\tau_t + \rho\widehat{\Delta\eta}_{rt} + \Delta\varepsilon_{rt} \tag{18}$$

Table 3: Heterogeneous Effects
Decennial Changes

	(1) Productivity	(2) Labour Cost†	(3) Labour Share
		A. OLS	
Immigrant Share	1.417***	-0.351	-1.767***
	(0.465)	(0.313)	(0.267)
Imm. Share x Exch. Rate	-1.802*	0.341	2.143***
	(1.021)	(0.789)	(0.557)
		B. Control Function	
Immigrant Share	1.516***	-0.410	-1.926***
	(0.434)	(0.310)	(0.248)
Imm. Share x Exch. Rate	-1.149	-0.050	1.099*
	(1.061)	(0.944)	(0.582)
Obs.		592	
Regions		148	

Note: †We compute labour costs and labour shares following ONS (see Appleton 2011) methodology: a fraction of mixed-income is added to the compensation of employees. We compute labour cost (share) per job by dividing the resulting measure of income by the number of jobs (GVA). ‡Includes employee jobs, self-employed jobs, government-supported trainees and members of His Majesty's Forces. We control for time-varying national-level shocks. Estimates are weighted by the region's contribution to national GVA in 2002. Standard errors (clustered by region) between parenthesis. * $p < .10$ ** $p < 0.05$, *** $p < 0.01$

Table 3 presents OLS and control function estimates of immigration shocks along with migrants' relative exchange rates. The baseline effects are like those in Table 1: immigration shocks increase productivity and reduce the labour share. However, a relevant new pattern stands out: immigration shocks with higher reservation wages (i.e. higher exchange rate) show a weaker impact on both productivity and labour share.

The evidence in this section matches the predictions of the imperfect market hypothesis. Immigrants are, on average, more skilled than natives and produce positive effects on labour productivity. These productivity effects, however, do not translate into wages because immigrants register lower reservation wages or bargaining ability. Firms can then absorb migrants' positive productivity effects.

4 Final remarks

Using sub-regional data from Great Britain, we show that immigration shocks have a positive productivity effect while reducing the labour share. This finding is robust to several specifications with different estimators, weights, and instruments.

In the canonical model, immigration shocks with skill composition changes result in productivity and wage changes in the same direction. Instead, our results coincide with the predictions of imperfect labour markets where immigrants are productivity-enhancing and willing to work for lower wages, bringing together the positive effect of immigration on productivity with a decline in the labour share.

Once in imperfect markets, migrants will accept lower wages, the weaker their bargaining power or lower their reservation wages. We use the home-destination relative exchange rate at entry as a proxy for migrants' reservation wages (see Dustmann, Ku, et al. 2021) to show that migrants from countries with higher exchange rates earn higher wages once in Great Britain. Similarly, we provide evidence whereby regions that received immigrants from lower exchange rate countries experience a stronger negative effect of immigration on the labour share.

Our results thus offer further supporting evidence to a recent sub-field of the literature within migration economics studying immigration effects in imperfect labour market (e.g. Amior and Manning 2021; Amior and Stuhler 2022; Manning 2021; Naidu et al. 2016).

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ONLINE APPENDIX

A Data Sources

A.1 Data

- Annual population survey workplace analysis data provided in *~/Data/Orig/APS/Emp_OccupationMajGrp.csv* is available from NOMIS
- 1991 Census data provided in *~/Data/Orig/Census_1991/Migrants1991.csv* and *~/Data/Orig/Census_1991/Migrants1991SC.csv* is available from NOMIS
- 2001 Census data provided in *~/Data/Orig/Census_2001/Occupation_groups.csv* is available from NOMIS. Similar data for Scotland provided in *~/Data/Orig/Census_2001/KS12a.csv* is available from Scotland's Census.
- ITL / NUTS regional accounts provided in *~/Data/Orig/ITL_Accounts/gvabalanced.xlsx*, *~/Data/Orig/ITL_Accounts/itlproductivity.xls* and *~/Data/Orig/NUTS_Accounts/gvaincome.xls* are available from ONS Regional Accounts.
- Migrant counts by local authority provided inside folder *~/Data/Orig/LAD_Migrants* are available from ONS. Scottish data comes from National Records of Scotland (NRS).
- Migrant counts by individual country of birth provided inside folder *~/Data/Orig/LAD_Migrants_Detail* are available from ONS.
- LFS microdata needs to be obtained from the UK Data Service and placed inside folder *~/Data/Orig/LFS*. We cannot provide direct access to these data. Data needs to be organised as follows *~/Data/Orig/LFS/SEYY/SEYY.dta* where S (E) is the initial of the month on which the LFS wave start (ends) and YY is the two last digits of the LFS year. For example, for the 2002 January - March wave the relevant file should be stored as *~/Data/Orig/LFS/JM02/JM02.dta*.
- Geographic lookups in *~/Data/Orig/Lookup* are available from National Records of Scotland (NRS) and from Office for National Statistics licensed under the Open Government Licence v.3.0.
- Migrant flows data contained in folder *~/Data/Orig/Migrant_Flows* comes from ONS.
- Population estimates in *~/Data/Orig/Population_Estimates/PopByAge02_20.csv* and *~/Data/Orig/Population_Estimates/Pop1664.csv* are available from NOMIS.

- UN migrant bilateral stocks provided in *~/Data/Orig/UN/UN_MigrantStockByOriginAndDestination_2019.xlsx* are available from United Nations Population Division.

- Exchange rates provided in *~/Data/Orig/WBExchange_Rates/Data.csv* are available from the World Bank.

A.2 Maps

- ILT-3 Map provided in *~/Maps/ITL3.geojson* comes from Office for National Statistics licensed under the Open Government Licence v.3.0. It contains OS data ©Crown copyright and database right 2021. Originals can be obtained from Open Geography Portal

B Robustness

B.1 Displacement Effects on Native Employment

Here we provide evidence against (strong) displacement of natives by migrant workers. We start by showing, in Table B.1, that the positive effect of immigration on labour productivity takes place despite immigration shocks increasing the number of jobs, see Columns (1) and (2).

The magnitude of the impact of immigrants on job growth is easier to interpret if we redefine the endogenous variable as the contribution of immigration to workforce growth, i.e. working-age population growth. Then, we estimate

$$\frac{Jobs_{rt} - Jobs_{rt-10}}{M_{rt-10} + N_{rt-10}} = \vartheta_t + \gamma \frac{M_{rt} - M_{rt-10}}{M_{rt-10} + N_{rt-10}} + \omega(l_{rt} - l_{rt-10}) + \varepsilon_{rt}, \tag{19}$$

where M and N are migrant and native working-age populations, respectively. Table B.1 reports the estimates of γ in (19). Column (3) shows that an increase of 10 migrants per every 100 working-age population increases the number of jobs by roughly eight jobs per 100 working-age population. Assuming no effect of immigration on native employment and the working-age population, this would translate into 88% of incoming immigrants securing a job.

Of course, immigration shocks may displace natives out of employment or out of the region. This issue has concerned the migration literature that estimates effects on natives' wages (Borjas 2003, 2006; Borjas and Edo 2021; Dustmann, Schönberg, et al. 2016). While we do not have data to test for outmigration, we can still identify net displacement at the regional level. In the lower panel of Table B.1, Column (3), we report estimates for the effect of working-age population growth on job growth. Instrumenting working-age population growth with the immigrant shift-share, we find that an immigration-induced 10-percentage points increase in workforce growth translates into eight jobs created per 100 working-age population. Furthermore, as the top panel Column (4) in Table B.1 reports, a 10-percentage point increase in the migrant contribution to the workforce[23] growth translates into a 0.7 percentage point increase in natives' contribution to workforce

[23]We define the workforce as the working-age population.

growth. These results suggest immigrants do not cause net native outmigration and that most of the immigration-induced workforce growth translates into jobs. In the same direction, the resulting negative effect on jobs per working-age individual is statistically insignificant (see Column (2) in the top panel of Table B.1).

Table B.1: The Effect of Immigration on Jobs Growth
IV Estimates

	(1)	(2)	(3)	(4)
Left-hand-side:	$\Delta_{10}\log(Jobs_{rt})$	$\Delta_{10}\log\left(\frac{Jobs_{rt}}{L_{rt}}\right)$	$\frac{Jobs_{rt}-Jobs_{rt-10}}{L_{rt-10}}$	$\frac{N_{rt}-N_{rt-10}}{L_{rt-10}}$
Right-hand-side:				
Immigrant Share	1.914***	-0.156		
	(0.501)	(0.308)		
F-stat	46.513			
$\frac{M_{rt}-M_{rt-10}}{L_{rt-10}}$	0.824***	-0.067	0.881***	0.071**
	(0.135)	(0.139)	(0.120)	(0.032)
F-stat	435.336			
$\frac{L_{rt}-L_{rt-\tau}}{L_{rt-\tau}}$			0.823***	
			(0.117)	
F-Stat	300.202			
Obs.	592			
Regions	148			

Note: Left hand-side in the column header. M_{rt}, N_{rt} and L_{rt} are, respectively, the foreign-born, native and total working-age populations in the region-year (rt). Our measure of jobs includes employee jobs, self-employed jobs, government-supported trainees and members of His Majesty's Forces. We control for time-varying national-level shocks. Estimates are weighted by the region's contribution to national GVA in 2002. Every estimate comes from its regression. Standard errors (clustered by region) are in parentheses. * $p < .10$ ** $p < 0.05$, *** $p < 0.01$

B.2 Measurement Error

Table B.2: Main Table in Deviations from Means
NUTS-3 Fixed Effects

	(1) Productivity	(2) Labour Cost†	(3) Labour Share
		A. OLS	
Immigrant Share	0.457***	-0.127	-0.583***
	(0.149)	(0.093)	(0.165)
		B. IV	
Immigrant Share	1.223***	-0.377**	-1.601***
	(0.232)	(0.147)	(0.261)
F-Stats		50.292	
Obs.		2072	
Regions		148	

Note: †We compute labour costs and labour shares following ONS (see Appleton 2011) methodology, where a fraction of mixed-income is added to the compensation of employees. We compute labour cost (share) per job by dividing the resulting income by the number of jobs (GVA). Jobs include employee jobs, self-employed jobs, government-supported trainees and members of His Majesty's Forces. We control for time national-level shocks. Estimates are weighted by the region's contribution to national GVA in the year 2002. Standard errors (clustered by region) are in parentheses. * $p < .10$ ** $p < 0.05$, *** $p < 0.01$

IV estimates in Table B.2 are, in general, larger than OLS. Such differences could be driven by measurement errors. Aydemir and Borjas (2011) provide evidence of attenuation bias due to measurement error when estimating the effects of immigrants on natives. They show that with measurement error, the OLS estimator of the effect of immigration on productivity converges in probability to

$$p \lim \hat{\beta} = \beta \left(1 - (1-\gamma) \frac{\bar{\pi}(1-\bar{\pi})/\bar{n}}{(1-R^2)\sigma_\pi^2} \right) \tag{20}$$

Where $\bar{\pi}$ is the average immigrant share, $\bar{n}$ is the average region-year cell sample size, σ_π^2 is the variance of the immigrant share, R^2 is the R-squared from regressing the immigrant share on year and region fixed effects. δ is the sampling rate.

Using (20), we can compute a worst-case scenario, $\delta \approx 0$, measurement error downward bias. The ONS data we used to construct immigrant shares comes from the Annual Population Survey. This survey has a sample size of about 320K individuals (ONS 2012), which, with 148 regions, makes $\bar{n} \approx 2162$. The average immigration share and its variance reported in table C.1 are $\bar{\pi} = 0.161$ and $\sigma_\pi^2 = 0.018$. Finally, the R-squared from regressing immigrant shares on year and region fixed effects, is $R^2 = 0.987$. Combining these numbers, we get an attenuation of 27% downward bias in the fixed effects estimate. Comparing OLS and IV estimates in table 1 panel *B* columns (1) and (6), we find OLS are about 56% lower than IV, suggesting that the measurement error alone explains most of the difference between OLS and IV.

B.3 2SLS as LATE

Blandhol et al. (2022) show that, with covariates and a valid instrument, two-stage least squares (2SLS) have a local average treatment effect interpretation if and only if the specification is saturated. Since the specifications behind estimates in Table 1 are not saturated, they may not reflect a causally interpretable estimate. To address this concern, in Table B.3 column (1), we first report 2SLS where we do not include any control. In this exercise, the story repeats: immigration increases productivity and reduces labour share. We then report the estimates from the non-parametric saturated 2SLS. In column (2), we instrument the endogenous variables with a quintile discretization of the original instrument, which produces similar estimates to those in column (1) and Table 1. Column (3) of Table B.3 reports estimates from a specification where, in the first stage, we interact the instrument dummies with year dummies. In the second stage, we control for year dummies and exclude the instrument-year interactions, thus using the latter to identify the effect of interest.

Table B.3: Rich IV specification
Decennial Changes

	(1)	(2)	(3)
		Instrument:	
	Continuous	Discretised†	Discretised† with Interactions
		A. Labour Productivity	
Immigrant Share	1.154***	0.877***	0.966***
	(0.232)	(0.296)	(0.293)
		B. Labour Share	
Immigrant Share	-1.653***	-1.338***	-1.307***
	(0.296)	(0.310)	(0.306)
RK-Statistic	44.553	35.604	12.466
Obs.		592	
Regions		148	
		Fixed Effects	
Year	No	No	Yes

Note: †We discretize the immigrant instrument into quintile bins. RK-Statistic is the Kleibergen and Paap (2006) rank statistic for under-identification. In column (3), we use interactions of the binned instrument and the fixed effects as instruments. We weighted estimates by region's contribution to national GVA in 2002. Standard errors clustered by region between parenthesis. * $p < .10$ ** $p < 0.05$, *** $p < 0.01$

B.4 Goldsmith-Pinkham et al. (2020)

Our discussion of the instrument in Section 3 suggests an identification argument similar to that of Difference-in-Differences. This analogy follows Goldsmith-Pinkham et al. (2020), who provide a decomposition of the IV estimator as a weighted combination of possibly heterogeneous country-of-birth specific treatment effects.

In Table B.4, we describe country-of-birth weights and estimates (see Goldsmith-Pinkham et al. (2020)). Similar to their re-analysis of Card (2009), we find a strong correlation between Rotemberg weights (α_k, where k is country-of-birth) and immigration inflows g_k (Panel B of table B.4). However, unlike Card (2009), some countries of birth receive negative weight (see Panel A of Table B.4). Still, both sub-samples (positively and negatively weighted) produce similar estimates (third column of Panel E. Goldsmith-Pinkham et al. (2020)). When country-specific estimates are similar, IV weights are unlikely to be negative. As a result, 2SLS has a LATE interpretation, which is in line with our evidence in Online Appendix B.3, and further supports the causal interpretation of our estimates.

In Table B.4, Panel D.2, we provide the top five countries of birth in terms of their Rotemberg weights. Accounting for 15% of the total positive weight, Poland is the country of birth receiving the largest weight. India follows by a narrow margin, while Pakistan, Nigeria and Romania are more distant. Unsurprisingly, the average decennial changes (g_k) are increasing in weight for all the top five countries of birth.

Panel D.2 shows country-of-birth-specific estimates for the top five countries: productivity and labour share estimates are, both qualitatively and quantitatively, similar to our main results in Table 1. Except for Pakistan, all the estimates are statistically significant at the 95% confidence level. These results suggest that those countries producing larger positive productivity effects are also leading the negative impact on labour share.

Finally, we produce pre-trend tests for the top countries of birth that drive our estimates. In Figures B.1 and B.3, we display the estimates from a regression of the outcomes of interest on standardised exposure, as defined in equation (13), interacted with year dummies controlling for year and location fixed effects. As we have a clear pre-and post-period around the 2004 and 2007 EU enlargements only for Poland and Romania, we focus our discussion on these two countries. Still, estimated effects for the rest of countries closely resemble the changes in their immigrant stock.

In figure B.1, we find those regions more exposed to Polish immigration shocks experienced a large positive productivity shock following 2004. We also found some positive effects in 2004 and 2003, when the net migration from Poland was close to zero (see Figure D.2b). Nonetheless, if we introduce controls for time-varying shocks at the NUTS-1 level, Figure B.2, these pre-trends disappear while the post-effects remain. Overall estimates are also robust to controlling for NUTS-1 time-varying shocks (see Online Appendix B.5). For the labour share, we find similar patterns, though with a negative sign (see Figures B.3 and B.4).

Another case to highlight is that of Romanian shocks, with a considerable positive effect after 2004, when immigration levels from this country were still stable. One plausible explanation is the strong correlation, 0.394, between exposure to Romanian and Polish immigration shocks. In fact, we find no statistically significant effects from exposure to Romanian immigration shocks after controlling for NUTS-1 time-varying shocks (see

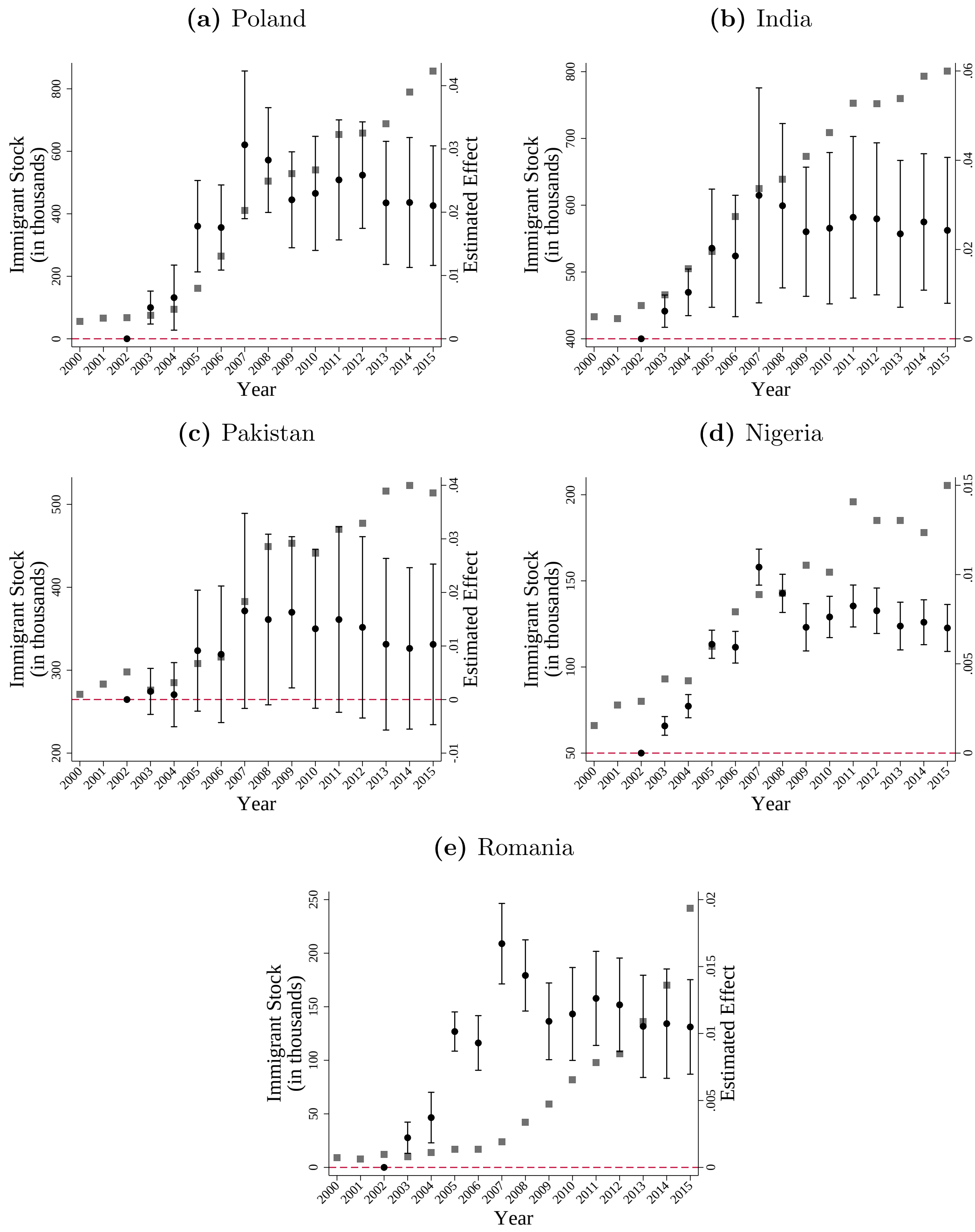
Figures B.2 and B.4).

Table B.4: Goldsmith-Pinkham et al. (2020) Rotemberg Weight Summary
Decennial Changes

Panel A: Negative and positive weights				
	Sum	Mean	Share	
Negative	-0.108	-0.008	0.089	
Positive	1.108	0.006	0.911	
Panel B: Correlations of country-of-birth aggregates				
	α_k	g_k	$\beta_k^{Prod.}$	$\beta_k^{Lab.Share}$
α_k	1.000			
g_k	0.952	1.000		
$\beta_k^{Prod.}$	-0.035	-0.124	1.000	
$\beta_k^{Lab.Share}$	0.053	0.144	-0.402	1.000
Panel C: Variation across years in α_k				
	Sum	Mean		
2012	0.303	0.002		
2013	0.275	0.001		
2014	0.221	0.001		
2015	0.201	0.001		
Panel D: Top 5 Rotemberg weight countries				
Panel D.1: Weights and Inflows				
	$\hat{\alpha}_k$	g_k		
Poland	0.162	634.942		
India	0.116	285.882		
Pakistan	0.058	216.048		
Nigeria	0.059	93.116		
Romania	0.048	153.708		
Panel D.2: Estimates				
	$\hat{\beta}_k^{Prod.}$	95 % CI	$\hat{\beta}_k^{Lab.Share}$	95 % CI
Poland	1.169	(0.50, 1.70)	-1.570	(-2.20, -0.90)
India	1.087	(0.00, 1.80)	-1.447	(-1.90, -0.30)
Pakistan	0.824	(-10.00, 10.00)	-1.218	(-10.00, 10.00)
Nigeria	1.488	(1.20, 1.80)	-1.987	(-2.40, -1.70)
Romania	1.022	(-0.20, 1.50)	-1.703	(-2.40, -0.40)
Panel E: Estimates of β_k^y for positive and negative weights				
	α-weighted Sum	Share of overall β	Mean	
			Productivity	
Negative	-0.145	-0.113	1.611	
Positive	1.423	1.113	1.328	
			Labour Share	
Negative	0.196	-0.114	-1.848	
Positive	-1.913	1.114	-1.770	

Note: Here, we report Rotemberg weights statistics. Panel A reports descriptive statistics for negative and positive weights. Panel B reports correlations between the weights (α_k), migrant inflows (g_k) and country-of-birth specific estimates (β_k). Panel C reports variation in Rotemberg weights across years included in the estimation sample. Panel D reports the top five origin countries according to the Rotemberg weights and country-of-birth specific effects along with weak instrument robust 95 percent confidence intervals constructed using the method from Chernozhukov and Hansen (2008). Panel E reports statistics for estimates within the negative and positive weighted sub-samples.

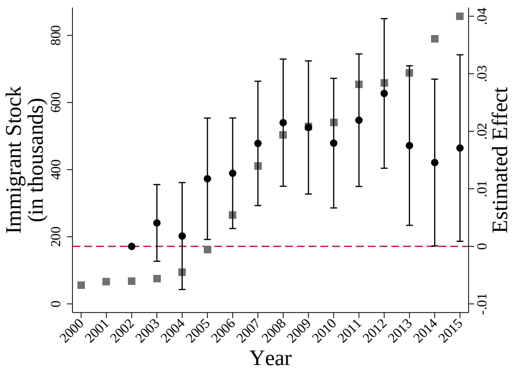
Figure B.1: Productivity Effect for top 5 countries



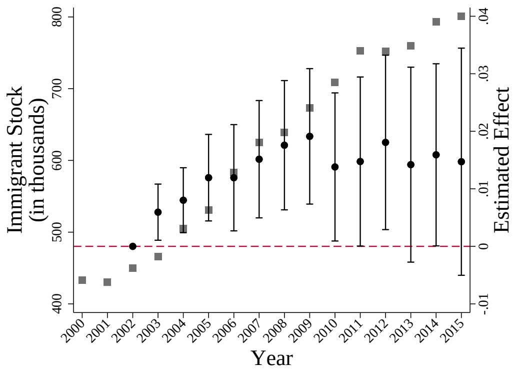
Note: We present the evolution of the stocks (grey squares left-hand vertical axis) of the five most relevant countries of birth (as ranked by their Rotemberg weights). Also, we estimate the effect of being one additional standard deviation exposed to a particular country of birth. We do this with a regression where we interact exposure to the country of birth with year dummies setting 2002 as the baseline. We have year and location fixed effects and weight the data by region contribution to national GVA in 2002. Vertical lines are 95% confidence intervals from location clustered standard errors.

Figure B.2: Productivity Effect for top 5 countries
Controlling for NUTS1-Time Varying Shocks

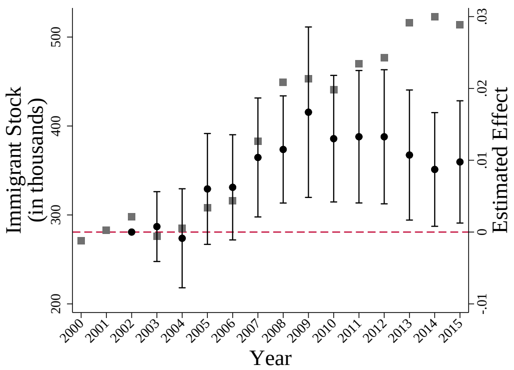
(a) Poland



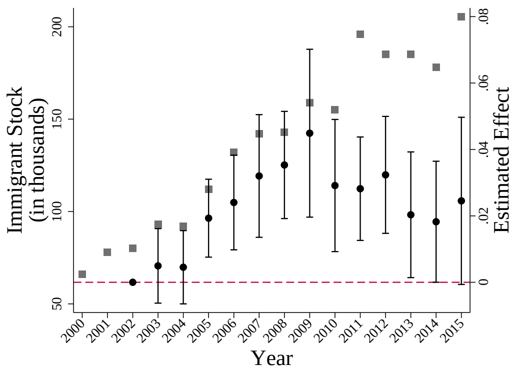
(b) India



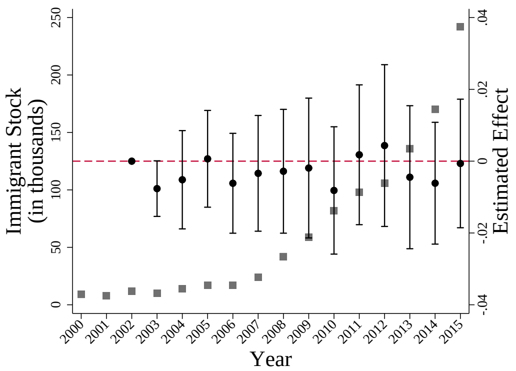
(c) Pakistan



(d) Nigeria



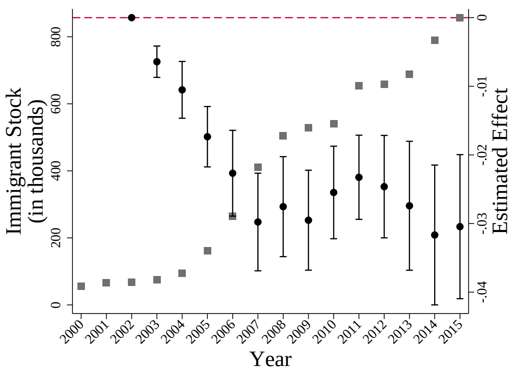
(e) Romania



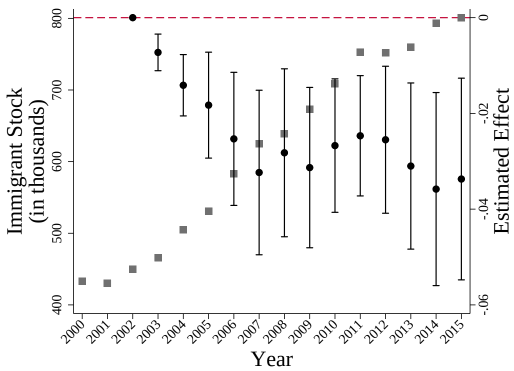
Note: We present the evolution of the stocks (grey squares left-hand vertical axis) of the five most relevant countries of birth (as ranked by their Rotemberg weights). Also, we estimate the effect of being one additional standard deviation exposed to a particular country of birth. We do this with a regression where we interact exposure to the country of birth with year dummies setting 2002 as the baseline. We have year and location fixed effects and weight the data by region contribution to national GVA in 2002. Vertical lines are 95% confidence intervals from location clustered standard errors.

Figure B.3: Labour Share Effect for top 5 countries

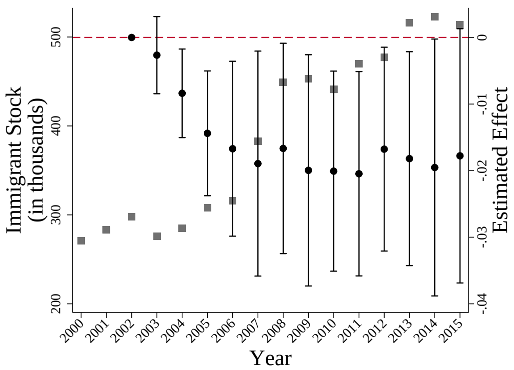
(a) Poland



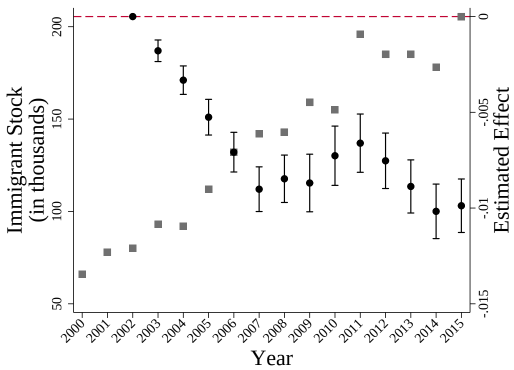
(b) India



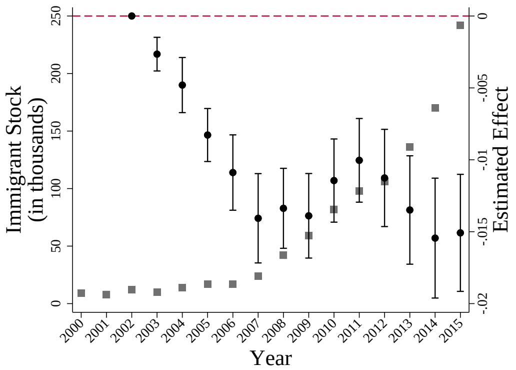
(c) Pakistan



(d) Nigeria

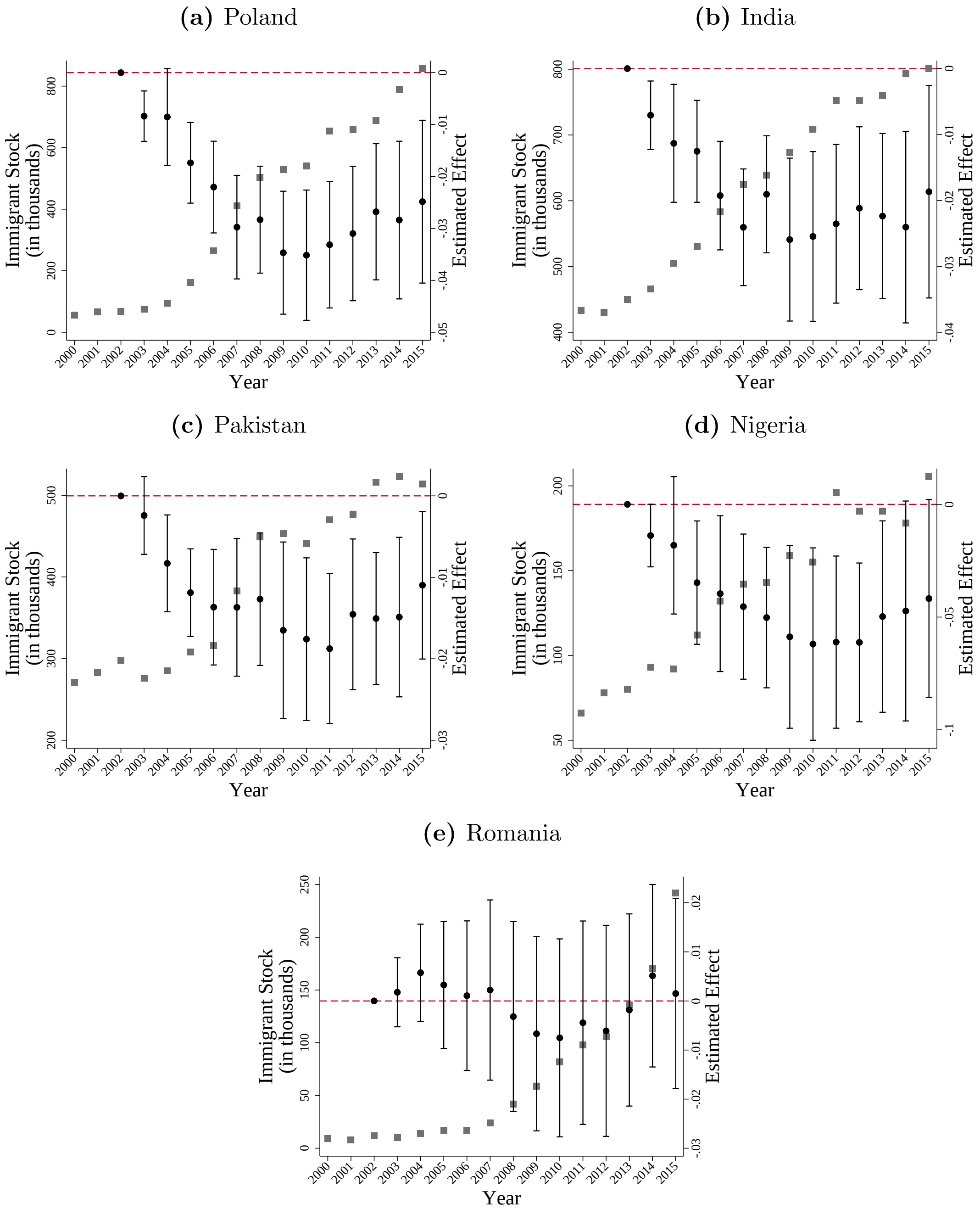


(e) Romania



Note: We present the evolution of the stocks (grey squares left-hand vertical axis) of the five most relevant countries of birth (as ranked by their Rotemberg weights). Also, we estimate the effect of being one additional standard deviation exposed to a particular country of birth. We do this with a regression where we interact exposure to the country of birth with year dummies setting 2002 as the baseline. We have year and location fixed effects and weight the data by region contribution to national GVA in 2002. Vertical lines are 95% confidence intervals from location clustered standard errors.

Figure B.4: Labour Share Effect for top 5 countries
Controlling for NUTS1-Time Varying Shocks



Note: We present the evolution of the stocks (grey squares left-hand vertical axis) of the five most relevant countries of birth (as ranked by their Rotemberg weights). Also, we estimate the effect of being one additional standard deviation exposed to a particular country of birth. We do this with a regression where we interact exposure to the country of birth with year dummies setting 2002 as the baseline. We have year and location fixed effects and weight the data by region contribution to national GVA in 2002. Vertical lines are 95% confidence intervals from location clustered standard errors.

B.5 Changes in Specification

Figure B.5 displays baseline productivity point estimates in Table 1, along with 95% confidence intervals. It compares these estimates with those obtained from more restrictive specifications, other measures of productivity, and the exclusion of some geographical areas. Measuring productivity as GVA per hour[24] also produces similar estimates to the baseline. Moreover, baseline results are robust to including NUTS-1 times year fixed effects and sequential exclusion of London, Scotland and Wales from the sample.

Figure B.6 explores different (versions of) the instrument. *Proj. Stock* is an estimate we have produced using a *leave-the-UK-out* immigration instrument built with migrant stocks in countries other than the UK. The data source is from UN international migration stocks which reports population numbers by country of origin and destination. Using data from 1990 for every country of origin, we compute the ratio of their emigrant population living in the UK over the rest of the countries, excluding their home country. For 2002-2015, we compute the immigrant stock for every given country of origin in countries other than the UK. These help us predict the stock of immigrants in the UK by scaling the leave-the-UK-out immigrant stock with the proportion of the 1990 population living in the UK vis-à-vis any other country of destination. The idea is to create an estimate of the UK national-level migrant supply driven only by push factors. Cutting out the UK, we exclude possible endogenous pull factors driving the UK's demand for international workers. We then allocate this national-level stock estimate to locations using (13). This instrument produces outcomes that are close to the baseline.

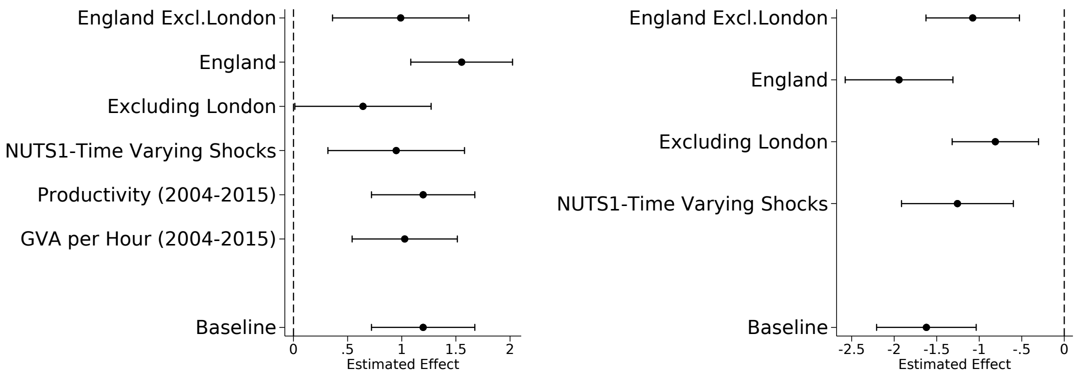
Our results are also robust to using decennial lags of the observed immigrant share as instruments, *10yr Lag* in Figure B.6. We get similar estimates when we instrument decennial changes with the 1991 immigrant share. In addition, at the top of Figure B.6, we provide estimates that exploit the enlargement of the European Union towards Eastern Europe in 2004. For this, we instrument migrant share changes with the share of A8 born in 1991. Using this instrumentation strategy, we, again, find similar results to those in table 1.

Figure B.7 shows that for definitions of the immigrant shock other than changes in the immigrant share, we also find a positive immigration effect on productivity and a negative one on the labour share. Figure B.8 shows that estimates do not vary (qualitatively) when we change how we weigh regions.

[24] This is only available from 2004 onwards

Figure B.5: Immigration Productivity Effect: Robustness

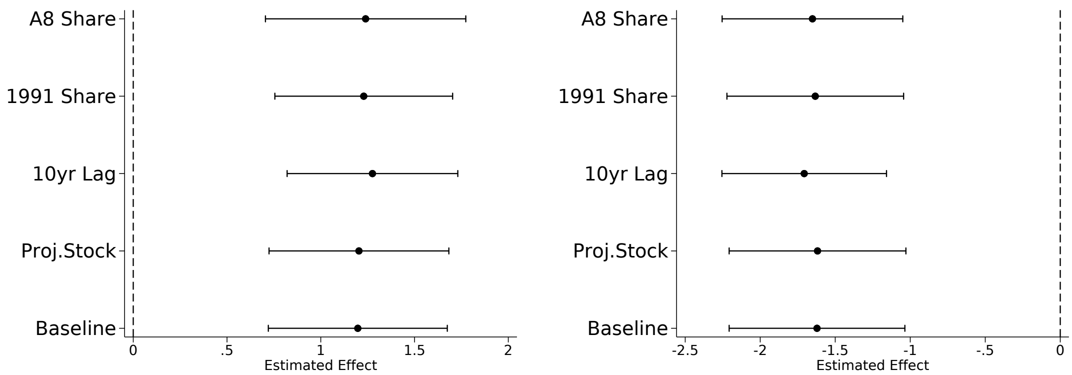
(a) Decennial Changes **(b)** Region Fixed Effects



Note: NUTS1-Time Varying Shocks includes NUTS1 times year fixed effects. Productivity estimates for the sub-period 2004-2015 were reported for comparison with productivity measured as GVA per hour, as the latter is available only from 2004 onwards. We do not provide the estimates for Scotland and Wales because they show weak first stages. 95% Confidence intervals from region clustered standard errors represented as horizontal lines.

Figure B.6: Robustness: Instrument

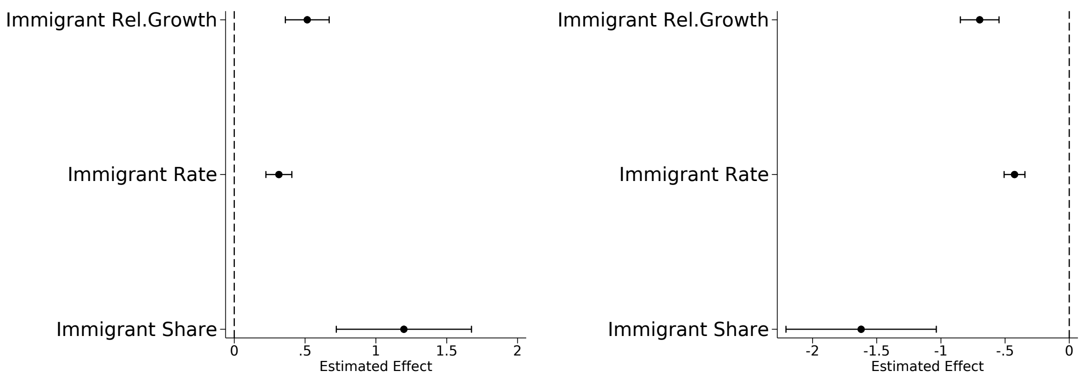
(a) Productivity **(b)** Labour Share



Note: Here, we show estimates from specifications where we change the definition of the instrument.

Figure B.7: Robustness: Endogenous Variable Definition

(a) Productivity **(b)** Labour Share



Note: Here, we present estimates from specifications where we change the definition of the endogenous variable. The *Immigrant Share* definition is the same used throughout the paper, i.e. the number of immigrants over the total population. *Immigrant Rate* defines the endogenous as Dustmann, Frattini, et al. (2013); i.e. the ratio of immigrants to natives. *Immigrant Rel. Growth* defines the endogenous as in Jaeger et al. (2018); i.e. migrant stock changes over lagged population.

Figure B.8: Robustness: Weights

(a) Productivity **(b)** Labour Share

Note: Here, we display estimates from specifications where we change observation weights. Throughout the paper, we weight locations by their GVA contribution to the total national in 2002, *2002 GVA Weight*. *2002 Jobs Weight* weights with jobs instead of GVA. *Weights a la Lewis (2003)* use weights constructed with $(x_{rt}^{-1} + x_{rt-\tau}^{-1})^{-1/2}$ where x is either GVA, *GVA Weights a la Lewis (2003)*, or number of jobs, *Job Weights a la Lewis (2003)*. Dustmann and Glitz (2015) use similar weights.

C Descriptive Statistics

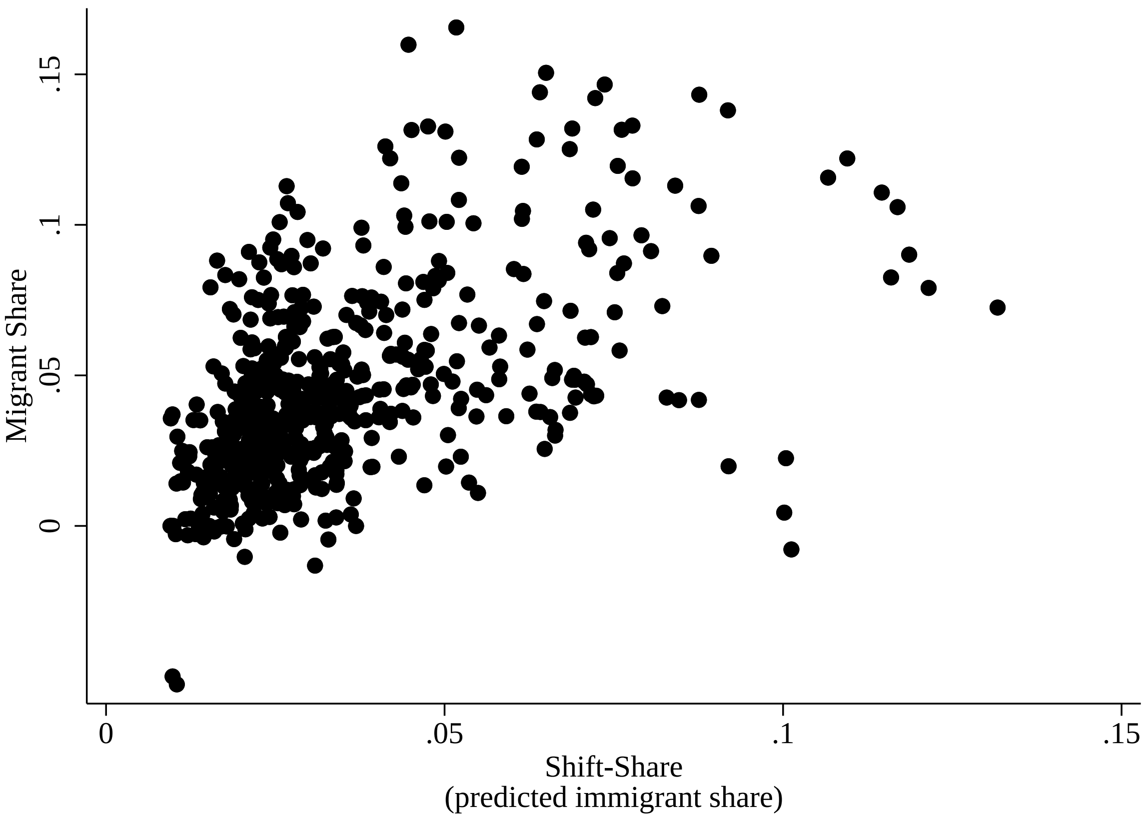
Table C.1: Descriptive Statistics

	Mean	Std.dev.	Min	Max
	2002-2015 Averages			
Labour Productivity	52.171	12.059	29.947	75.415
Jobs (in 100K)	11.442	18.094	0.102	53.545
Labour Cost	30.805	5.963	9.617	42.267
Labour Share	0.598	0.062	0.237	0.883
Immigrant Share	0.162	0.134	0.000	0.447
	Decennial Changes			
(log-)Labour Productivity	0.067	0.072	-0.193	0.360
(log-)Jobs	0.075	0.064	-0.174	0.266
(log-)Labour Share	-0.019	0.075	-0.339	0.270
(log-)Labour Cost	0.047	0.067	-0.178	0.385
Immigrant Share	0.055	0.031	-0.053	0.166
Years	14			
Regions	148			

Note: Authors' computation from ONS data. Labour productivity is measured as GVA per *productivity job*, the latter include employee jobs, self-employed jobs, government-supported trainees and members of His Majesty's Forces, see ONS (2021). Labour share is computed by adding a proportion of the self-employed income to the wage bill as per equation 3 in Appleton (2011), and the resulting figure is divided by GVA to obtain the labour share. Labour productivity and labour costs in 2015-constant thousands of pounds. Data covers 2002-2015, with regions defined as NUTS3 locations except for London, aggregated into a single unit.

D Additional Figures

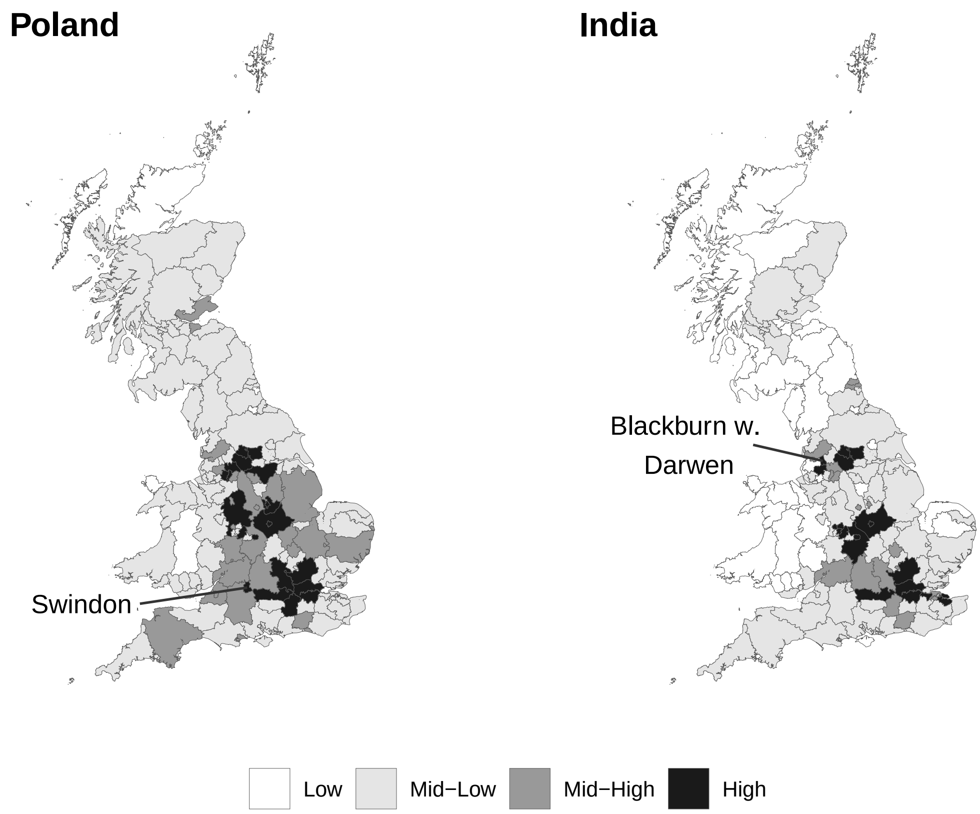
Figure D.1: First Stage:
Decennial Changes



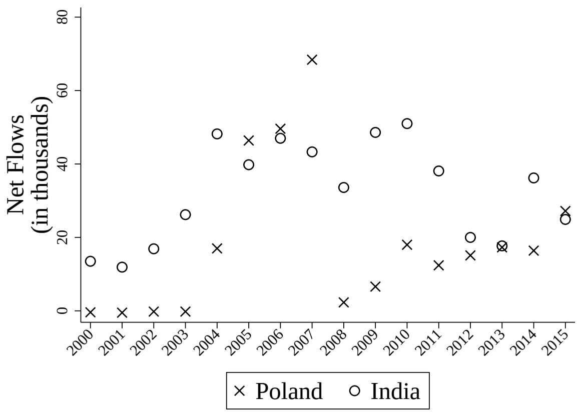
Note: Authors' computation from ONS and 1991 Census data. The shift-share instrument is computed as per equation (13). Actual migration shares on the y-axis. Predicted shift-share instrument on the x-axis. All in decennial changes.

Figure D.2: Immigration from Poland and India

(a) Exposure to inflows from:



(b) Net immigrant flows from Poland and India



Note: Sub-figure D.2a shows the spatial distribution of exposure, see equation (13), to immigration shocks from Poland (left) and Romania (right). Exposure was computed using data from the 1991 census. *Low* exposure regions contain less than 0.1% of the total immigrant population from a given country of origin. *Mid-low*, *Mid-high* and *High* regions have 0.1-0.5%, 0.5-1% and above 1%, respectively, of the relevant migrant population living in them. Sub-figure D.2b has been computed from ONS data and illustrates the evolution of net immigrant inflows from both Poland and India.