Examining the Link between Migration and Productivity*
[Working Paper]

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Abstract

During recent years we have seen increased interest in the effects of immigration in the UK economy. We contribute to the ongoing discussion by analysing the link between immigration and productivity. We use outcome data and labour figures to estimate the relative productivity of immigrants and natives in the UK. This informs us about the effect of changes on labour relative supply in labour productivity. We differentiate from previous literature in that our estimates do not rely on competitive pricing on the labour market. Overall, we find evidence for immigrant labour being at least as productive as native and gross substitution between them. When we allow for different occupations we find a positive and significant productivity differential, and this is robust to changes on specification, controls for underlying characteristics and different samples. Furthermore, we use our estimates to produce a counter-factual for the accession of eastern European countries in 2004 with which we evaluate its impact on labour productivity. We find a small non-significant effect from accession.

1 Introduction

Immigration into the UK has been steadily growing for the last 16 years, with immigrant employment in 1998 equal to 7% of native employment and rising to 17% in 2014. Accordingly, immigration into the UK has not only received interest from academia[1] –e.g. Dustmann, Fabbri et al. (2005), Dustmann, Frattini et al. (2013) and Manacorda et al. (2012)– but also from political actors and the general public. Within this context of increasing interest in the topic the 27 July 2017 the government commissioned the

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[1]With the main focus being on the effects of immigration on natives' outcomes

Migration Advisory Committee –MAC– to produce evidence on the composition and impact of immigration on the British economy[2]; with a focus on the industrial level, skill mix and training. Here we aim to enter the discussion by providing evidence on the link between immigration and labour productivity. In contrast with the effect of immigration on natives' labour market outcomes –for which the academic literature is rich albeit controversial and focused in the US; see Altonji and Card (1991), Borjas (2003), Card (2001), Dustmann, Frattini et al. (2013) and Manacorda et al. (2012)– the connection between immigration and productivity is a fairly unexplored field. With this question in mind we provide evidence for the relative productivity of immigrant labour with respect to its native counterpart during the last 15 years in the UK and the link between the EU accession of eastern European countries and labour productivity. These two pieces of evidence give us a broad picture of the link between immigration in the UK. Furthermore, we explore this using an economic framework that allows us to give a consistent and economically meaningful description of the matter. We see this as an interesting topic to treat as it not only helps enlarging the existing academic literature on a direction that is relatively unexplored but also addresses a matter that interests the general public[3].

In terms of the existing literature, our paper contributes to two different strings; that on the link between immigration and productivity and that on estimation of the elasticity of substitution between immigrant and native labour. With respect to the first, previous literature, –e.g. Peri (2012)– typically use growth accounting to decompose output growth into different quantities and then regress these on some measure of immigration. In terms of literature estimates, there is no consistent evidence on direction of the relation between productivity and immigration but it is typically estimated to be small. For the US, Peri (2012) and Ottaviano and Peri (2006) find a positive effect of immigration on labour productivity [4]. A positive effect is also found in Aleksynska and Tritah (2009) for a panel of 20 OECD countries. On the other hand, Paserman (2013) finds a negative non-significant or marginally significant effect of immigration on the productivity of Israeli firms. Finally, Kangasniemi et al. (2012) study the cases of Spain and the UK, finding a negative and positive effect –respectively– of immigration on total factor productivity. Using growth accounting techniques the authors find a negative impact on labour productivity in both countries, although negligible for the UK. On a historical perspective, Hornung (2014) studies the long run effects of high skilled immigration on productivity. Using a natural experiment the author finds a positive long-run effect of immigration on productivity, as far in time as 100 years after the arrival. Moreover, this positive effect is concentrated on textile manufacturing, where immigrants tended to specialize

We differentiate from most of previous literature on the link between immigration and labour productivity in that we directly estimate the parameters of the underlying production function. These informs us about the effect of changes on labour relative supply on labour productivity, allow us to simulate counter-factuals and avoids external validity concerns from using literature estimates that have been obtained from other samples. Moreover, at the cost of flexibility our estimates are robust to departure from perfectly competitive labour markets. This has been maintained in most of the previous literature,

[2]See commissioning letter available at https://www.gov.uk/government/publications/commissioning-letter-to-the-migration-advisory-committee

[3]This has been reflected –for example– in the 27 July 2017 MAC commission where the government asked: *What is the current impact of immigration, both EU, EEA and non-EEA, on the competitiveness of UK industry, including on productivity, innovation and labour market flexibility?*

[4]Ottaviano and Peri (2006) look at diversity rather than immigration per se

both on estimation of immigrant-native elasticity of substitution and the link between immigration and productivity –see Card (2009), Manacorda et al. (2012), Ottaviano and Peri (2006) and Peri (2012)–.

Throughout the paper, we note that establishing causality of immigration effects is in any case a difficult task, as it requires an identification strategy able to cope with immigrants self-selection into countries, regions, industries and even firms. Such concerns have been approached in the literature –mainly– through use of various Instrumental Variable (IV) strategies, often times using previous settlement of migrants to exploit independent variation between this and current economic conditions[5] –see seminal work in Altonji and Card (1991) and Card (2001)–. We contrast results that rely on immigrant exogeneity with those obtained from using Card's instrument. Overall, we find evidence for immigrant labour being at least as productive as native. And this is robust to use of Card's instrument, controls for underlying characteristics, production function specification and choice of sample. Out of a wide set of estimates, only in the two most restrictive specifications[6] we reject a null-hypothesis of equality of productivity against native labour being more productive than immigrant. Furthermore, when we allow for different occupations we find a positive and significant productivity differential. Finally, we use our estimates to simulate a counter-factual for eastern Europe accession, and find a negligible relation between immigration and productivity.

The rest of the paper is organized as follows: section 2 introduces the data, 3 sketches a simple framework for the analysis and reports estimates; 5 produces simulations using estimates from 3 and 6 concludes.

2 Data

Our main data source is the UK Labour Force Survey –LFS–[7]. From this, we compute employment figures for the period 1998-2014. We select all observations belonging to employed individuals -private or self-employed- that are not still in education[8], for whom industry, occupation, region of work and country of birth information was available. Then we partition the sample into region-industry –hereafter markets– groups, and compute employment by country of birth and qualification level. We use occupations to classify individuals' qualifications[9]. And differentiate between high and medium-low skilled –low skilled for sorter–. Using occupations instead of highest education attained or years of education, helps us on dealing with imperfect transferability of overseas qualifications, downgrading of immigrants and measurement error on educational levels –to which immigrants are more prone to, see Manacorda et al. (2012) for further discussion

[5]A notable –although hardly replicable– exception is the natural experiment provided by the Mariel Boatlift first explored in Card (1990) and then discussed and revised in –e.g.– Borjas (2015).

[6]Where we do not control for differences on capital stock and make parametric restrictions based upon assumption or out-of-sample estimates

[7]LFS data has been retrieved through the UK Data Archive http://www.data-archive.ac.uk/

[8]We perform a double check and drop all those for which either or both *edage* = still in education; and *enroll* = Yes.

[9]Specifically, we use MAC's mappings to translate occupations into four levels of national qualification framework –NQF, we thank the MAC for kindly providing the mappings–. The highest NQF –6– corresponds roughly to professional occupations while the lowest –NQF 2– to process, plant and machine operatives; and elementary occupations. Moreover, there are six occupations without NQF match that we drop from the analysis –see table C.15–. See appendix C.3 for a detailed description of the data preparation.

and references–[10]. Other than employment figures, we also obtain average weekly gross wages by occupational qualification and country of birth in each market and year[11]. Furthermore, to be able to compare LFS data through the period of study we homogenize it to account for changes on industry and occupation codes –see appendix C.3–. We define immigrants using country of birth and classify as immigrant anyone who was not born in the UK, with the exception of Irish that are treated as natives due to their cultural characteristics and close connection

We obtain our outcome of interest –market level production– from UK ONS regional accounts for years 1998-2014. We choose to use production side GVA data[12], as ONS produces a deflator for this series but not for the income side[13]. In figure 1, we display a broad representation of the state and evolution of immigrant employment and labour productivity in the UK. Overall, there has been a sustained increase on immigrant employment with both higher initial stock and growth for immigrants in low skilled occupations. At the same time, labour productivity has been increasing up to the beginning of the 2008 crisis when it drops to –roughly– 2002 levels[14]. The raw correlation between the two series is negative and larger for low skilled immigration.

[10] Furthermore, during our period of study there have been changes on the LFS coding scheme for highest qualification.

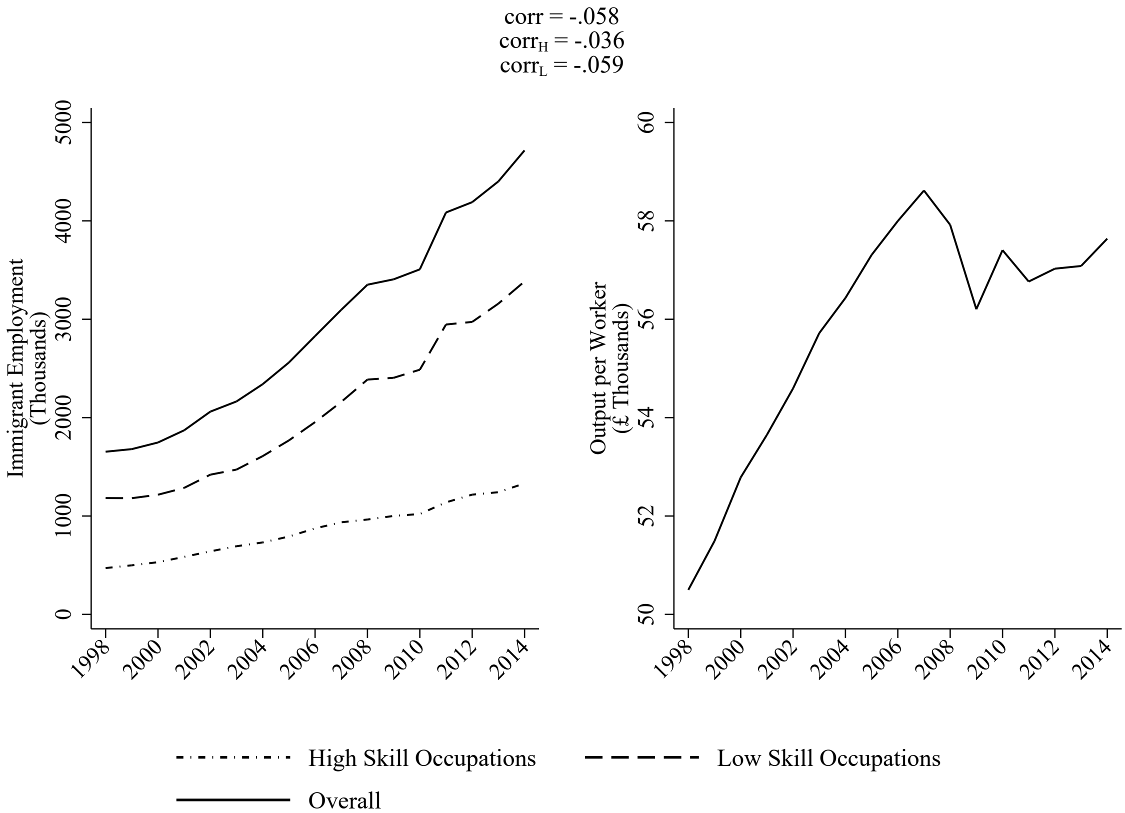
[11] We aggregate individual observations using LFS frequency weights *pwt*. When we use earnings information all figures are computed with LFS income weights *piwt*.

[12] Even though the time series for income side GVA are slightly lengthier, 1997-2015. Available at https://www.ons.gov.uk/economy/grossvalueaddedgva

[13] All figures are expressed in £2013.

[14] The post–crisis UK's productivity puzzle has been studied somewhere else –see Blundell et al. (2014) and Pessoa and Van Reenen (2014)–.

Figure 1: Immigrant Labour Supply (Left) and Output per Worker (Right)



Correlations are between immigrant labour and labour productivity computed at the market-year level

Moreover, there is substantial variation on employment and labour productivity across sectors. For example, in 2014 the occupational distribution of workers varies across sectors, but is similar for natives and immigrants, with the exception of the primary sector where the proportion of immigrants in high skilled occupations almost doubles the native figure –see table C.3–. Furthermore, we observe that the service sector accounts for 78% of both immigrant and native total employment. While the primary sector shows the larger labour productivity –predominantly driven by the energy sector–. Overall, –in our selected sample– total employment is 27,425 thousand workers with a labour productivity of £57,639 per worker and –roughly– 28-29% of immigrant and native employment corresponding to high skilled occupations. In terms of immigrant to native ratios, manufactures and services show the largest figures and all sectors display a monotonically increasing pattern over time –see table C.4–. At the aggregate level, the immigrant to native ratio has increased from .077 in 1998 to .208 in 2014. When we differentiate by high and low skilled we still appreciate the same increasing pattern. In the last panel of table C.4, we show the ratio of high to low skilled labour relative supplies. We find that immigrant over-representation in high skilled occupations has been decreasing since 1998. In fact, by the end of our sample immigrants are over-represented in low skilled occupations in all sectors but primary.

If we look at the market level, there is still heterogeneity in terms of outcome and inputs. For example, in our most disaggregated sample –with 12 regions and 32 industries, see table C.5 and C.6– we see that the largest immigrant shares are in industries T –

activities of households–, I –accommodation and food service– and CA –manufacture of food products, beverages and tobacco–. But this picture moves over regions. While above 70% of workers in industries I and T in London are immigrants; in all other regions the same figure is below 30%. Indeed, London has the highest share of immigrants overall –38%–, followed by the South East –16%–. A the other end, the North East and Wales have the lowest shares –8.8%–. Labour productivity also moves across these dimensions. For example, –within manufactures– industry CM –other manufacturing and repair– has a labour productivity of £36,353 per worker well below the national at £57,639. Opposite to this, manufacturing of basic pharmaceutical products and preparations –industry CF– shows a figure of £97,177. As mentioned earlier, the larger productivity observed in the primary sector in table C.3 is given by industry D –Electricity, gas, steam and air-conditioning supply–. There is also variation across regions, with London at the head –£83,740– and Northern Ireland at the tail –£44,391–. At the top of all other industries is real state –L– with an overall labour productivity £607,700 –£952,804 in London–. Some of this differences in productivity are given by idiosyncratic characteristics of the industry, that –for example– make it capital intensive –this is clearly the case for real state–. In order to control for this, we need to incorporate capital data to our analysis. To the best of our knowledge, there are no public figures on capital stocks for our definition of market. Thus, to compute capital stocks for each market, we obtained gross fixed capital formation from ONS for twelve regions and eleven aggregated industries[15] for the period 2000-2014[16]. This gives us investment figures from which we can apply –given some initial level of capital stock– a perpetual inventory model to compute current capital stock. As the base capital stock is unknown to us, we use industry level capital stock from UK ONS [17] and impute it to each market in 1999 proportionally to the employment contribution of the market to national employment in its industry, i.e. keeping the capital to labour ratio constant within industry[18]. Then we use consumption of capital from the same source to compute depreciation rates for each market-year, where depreciation rates are assumed constant across regions within the same industry and year. Given an initial capital stock, investment and depreciation rates; we compute current capital stock as capital stock yesterday minus depreciation plus investment today[19]. The use of the market level gross fix capital formation data restricts our sample of capital stocks –and any analysis that includes it– to years 2000-2014 and 11 aggregate industries instead of 32. In table 3, we display the capital stocks for year 2014 using the 11 industry sample[20]. We see that those industries with larger labour productivity tend to have larger capital to labour ratios –note the case of industries L and D, the later now included in industry BDE–.

[15] See table C.13.

[16] Available at https://www.ons.gov.uk/economy/grossvalueaddedgva/adhocs/006749regionalgrossfixedcapitalformation2000to2014

[17] Available at https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/datasets/capitalstocksconsumptionoffixedcapital

[18] To compute the capital stock we used employment figures from the 1999 Workforce Jobs Dataset.

[19] This is, we assume that capital depreciates at the end of the period and investment is produced at the beginning. As a check of quality, we have plotted the actual capital stock for each industry against our computed capital stock sample aggregated across regions, with the expectation that points should lie around the 45° line. Results are displayed in figure C.1.

[20] Immigrant shares and labour productivity with this sample are displayed in tables 1 and C.8.

Table 1: Immigrant Share: Regions and Industries (11)

Industry	Immigrant Share												
	N. East	N. West	Yorksh/Humber	E. Midlands	W. Midlands	E. England	London	S. East	S. West	Wales	Scotland	N. Ireland	Total
A	0.000	0.099	0.132	0.218	0.145	0.195	0.586	0.239	0.109	0.047	0.138	0.018	0.151
BDE	0.051	0.131	0.167	0.080	0.185	0.169	0.351	0.219	0.130	0.023	0.119	0.000	0.152
C	0.118	0.161	0.203	0.242	0.192	0.256	0.434	0.228	0.215	0.100	0.130	0.206	0.210
F	0.085	0.061	0.069	0.069	0.079	0.074	0.419	0.099	0.059	0.048	0.084	0.058	0.124
GHI	0.110	0.154	0.125	0.173	0.190	0.170	0.483	0.202	0.151	0.105	0.119	0.108	0.202
J	0.066	0.139	0.162	0.147	0.155	0.178	0.344	0.214	0.140	0.145	0.170	0.208	0.220
K	0.095	0.066	0.081	0.123	0.140	0.079	0.308	0.147	0.113	0.070	0.079	0.098	0.171
L	0.115	0.148	0.071	0.156	0.150	0.181	0.322	0.129	0.105	0.000	0.054	0.000	0.152
MN	0.093	0.098	0.136	0.154	0.136	0.158	0.362	0.170	0.107	0.120	0.130	0.081	0.188
OPQ	0.070	0.092	0.089	0.113	0.104	0.146	0.330	0.150	0.102	0.085	0.084	0.061	0.137
RST	0.061	0.124	0.101	0.124	0.119	0.121	0.383	0.171	0.167	0.058	0.068	0.075	0.171
Total	0.088	0.117	0.122	0.153	0.145	0.160	0.380	0.175	0.129	0.088	0.105	0.093	0.172

Source: Labour Force Survey 2014

Table 2: Labour Productivity: Regions and Industries (11)

Industry	Labour Productivity (£ thousands per worker)												
	N. East	N. West	Yorksh/Humber	E. Midlands	W. Midlands	E. England	London	S. East	S. West	Wales	Scotland	N. Ireland	Total
A	42.993	37.313	47.607	49.261	48.980	53.327	2.660	26.558	48.994	25.263	40.336	28.864	39.798
BDE	91.822	65.397	78.495	110.749	85.521	69.202	81.970	115.911	105.814	69.108	90.200	78.962	88.402
C	50.333	68.755	46.677	51.513	47.821	57.825	42.910	52.697	45.337	62.542	59.975	52.791	53.314
F	35.651	39.211	35.710	44.585	39.463	64.644	62.244	58.390	36.559	31.120	41.932	35.088	46.847
GHI	34.251	42.070	34.722	41.426	42.208	44.630	70.495	59.121	41.765	31.564	45.242	48.026	47.483
J	84.181	67.317	50.051	49.853	65.347	73.924	115.255	101.860	51.899	50.787	73.181	55.426	85.291
K	96.522	108.411	83.552	81.721	109.166	95.783	106.530	126.027	100.923	98.587	92.538	71.523	103.012
L	404.682	374.188	492.940	645.221	605.220	653.557	952.804	657.951	526.685	418.434	447.034	806.550	607.700
MN	41.084	56.345	45.024	43.625	46.605	51.873	88.477	65.492	47.647	38.020	58.266	37.497	60.733
OPQ	32.523	33.797	36.600	35.441	34.110	33.666	48.412	35.446	34.789	36.194	37.929	30.468	36.764
RST	35.187	48.765	32.871	41.237	52.716	43.265	58.662	55.062	34.028	34.072	43.360	36.005	46.510
Total	45.258	52.634	45.420	49.397	50.461	55.809	83.740	65.473	50.103	45.900	54.216	44.611	57.645

Source: Labour Force Survey 2014 and UK ONS Regional Accounts

Table 3: Capital per Worker: (12) Regions and (11) Industries

Industry	Captial Stocks (£ thousands per worker)												
	N. East	N. West	Yorksh/Humber	E. Midlands	W. Midlands	E. England	London	S. East	S. West	Wales	Scotland	N. Ireland	Total
A	292.925	263.251	255.086	337.897	340.063	302.524	85.194	192.826	314.453	296.066	229.517	395.020	276.938
BDE	826.688	620.077	876.671	766.709	739.770	643.861	806.092	816.262	841.013	737.754	897.612	747.662	786.612
C	166.933	190.262	135.174	155.176	167.125	168.206	131.673	166.030	156.529	176.478	162.836	163.129	161.919
F	231.781	259.105	259.744	305.164	272.305	313.384	272.969	288.315	230.147	238.619	305.520	340.484	275.487
GHI	106.188	117.490	106.700	101.339	109.891	109.650	184.043	146.188	117.286	103.074	117.632	105.533	125.657
J	350.068	249.307	241.566	197.592	246.230	338.650	238.550	245.651	204.580	197.202	287.440	182.854	247.548
K	150.280	148.720	161.727	148.362	168.727	173.908	137.269	173.777	155.385	112.542	149.063	144.373	150.373
L	5591.241	5966.269	8333.194	10743.225	8806.096	7782.563	8152.192	8097.607	7909.089	6429.266	8941.681	22782.117	8028.894
MN	135.334	179.550	139.266	159.377	143.890	205.947	147.221	210.043	138.948	122.989	148.510	105.803	161.722
OPQ	76.610	76.319	79.120	84.978	73.979	83.221	89.355	88.068	81.794	79.932	97.713	70.311	83.212
RST	60.964	76.777	65.492	69.062	71.531	65.283	80.940	87.421	64.321	65.221	78.618	65.480	73.913
Total	207.377	228.661	216.300	231.751	226.923	247.494	260.115	271.957	244.492	215.937	264.618	254.405	243.807

Source: Labour Force Survey 2014 and Own Capital Stock

One of the caveats with computing aggregate employment for narrowly defined markets using LFS, is that underlying sample sizes can become rather sparse and sampling error can induce substantial artificial variation[21]. There are other sources from which we can obtain more accurate employment figures but at the cost of detail. For example, the Workforce Jobs dataset[22]. However, this only give us information about year, region and industry. As a robustness check, we have compared employment from Workforce Jobs with the correspondent figures computed for LFS. When we plot both employment figures together –figure C.2– we see that LFS tends to underestimate employment as compared to the figure provided by Workforce Jobs. We also compute counterparts for tables 3 and 2 using Workforce Jobs –tables C.7 and C.8–. Even though there are changes on the

[21]As an extreme example, note that there are no observations for industry CE in Northern Ireland year 2014 –see table C.6–.

[22]Available at NOMIS https://www.nomisweb.co.uk/

levels –with capital to labour ratios and labour productivity computed with Workforce Jobs employment being typically lower– the pattern of variation across regions and industries is broadly the same. Furthermore, in the analysis we present estimates using a sample with employment imputed from Workforce Jobs. Where we have imputed figures into market-year-country of birth-occupational level cells using employment proportions computed from LFS[23].

Finally, a possible way to measure –marginal– labour productivity and estimate underlying production functions is to use wage information jointly with an assumption of perfectly competitive labour markets –see Manacorda et al. (2012) for the UK and Card (2009) and Ottaviano and Peri (2006) for the US–. In the LFS we have self-reported earnings from which we can compare wages of immigrants and natives and also compute wage bills for each market-year-country of birth-occupational level cell. We estimate immigrant-native wage differentials using aggregate data for 1998-2014 and 32 industries; and also pooling together the underlying micro data. Results are displayed in table C.9. We show estimates using the whole sample and only the last four years where we do not need to use crosswalks for industries and occupations[24]. For those in high skilled occupations we obtain positive point estimates that are always non-significant. While for low skilled there is a wage-penalty that is only significant in the microdata. Point estimates obtained from the aggregate data are always larger in size and noisier. If workers are paid their marginal product, these estimates suggest that immigrants and natives in high skilled occupations are equally productive, while immigrants in low skilled occupations are less productive than their native counterparts. If there is no competitive pricing we cannot infer productivity differentials from wages. In such case, wage differentials might reflect other factors such as discrimination –see Carlsson and Rooth (2007)– or immigrants' lack of knowledge of the labour market to find jobs –see Colussi (2015)–. Throughout the rest of the paper we will not rely on wage information, with the exception of a robustness check where we use wage bills to let free some production function parameters[25]. Not relying on wages comes at the cost of increased complexity on our estimating functions, and the number of estimators available. This will become clearer in section 3.

2.1 Dealing with Endogeneity

One of the main concerns when exploring the effect of immigration and its channels is endogeneity. If immigrants are driven by economic motives it seems reasonable to think that they will self-select into the most buoyant industries and regions thus –possibly– biasing up our estimates of productivity. However, it is also reasonable to think that immigrants may have lower reservation wages, information or connections within the labour market that make them more likely to find less productive jobs than a comparable native, therefore biasing down our productivity estimates. We aim to tackle endogeneity through use of an instrumental variables strategy. Specifically a past settlement based instrument that is a variant of the well known Card's instrument –Card (2001)–. The

[23]That is why we do not display immigrant shares computed from Workforce Jobs, as they are only determined by the underlying LFS figures.

[24]For the aggregate data we use proportional crosswalks while for the microdata we use one-to-one matching the industry/occupation with the largest proportion.

[25]In figure C.3 we compare LFS wage bill with the wage bill from the UK ONS regional accounts income side. Even though not reported, we note that wage bills are widely underestimated from LFS if we do not use LFS income weights instead of the standard weights.

rationality behind this instrument comes through the effect of networks, where workers that are already settled in the receiving country provide with connections to new comers. This gives us variation on the factors that induce immigrants choice of a particular market. Furthermore, by computing this figure at a time that pre-dates our period of analysis we aim to obtain variation that is independent from current economic conditions. Nonetheless, long-lasting serial correlation on any unobserved factor that jointly determines economic conditions and immigrant employment will render the instrument invalid with no means to test for validity in the absence of other instrument known to be valid. For example, long lasting adjustments back to equilibrium from economic shocks will pose a threat to the exogeneity requirement. Indeed the validity of past-settlement instruments has generated debate in the academic literature –see discussion in Borjas (2014)–. However, our identification strategy lives from variation within any combination of industry, region and time. Thus long-lasting economic shocks at the region, industry or time level do no violate the exclusion restriction and violations would only be produced if shocks are long-lasting within any pairwise –or higher– combination of these three levels. We construct our instrument by computing employment figures for each market and qualification level for eight different country groups of birth in a base year. We set this base year to be the period 1985-1990 and obtain employment figures from the correspondent LFS datasets. Then using LFS base –1985-1990– and 1998-2014 we compute growth rates at national level for each country of origin[26]. In constructing this growth rate for a given market we do not take into account employment changes in this same market. With this we –at least partially– address validity threats derived from computing projections using national level growth rates. For example, it could be argued that immigration from some country may be driven by demand forces in a particular market[27] and this will challenge the exogeneity requirement of the instrument –even if the base employment is independent from current economic conditions, see Goldsmith-Pinkham et al. (2017)– [28]. Using the national level growth rates we project base employments into each year from 1998 to 2015, and use this projections to form the immigrant employment instrument. To be more specific, let S_{gqir90} be employment of individuals from country group g –with $g = 0$ for the UK–, with occupational qualification q, working at industry i, region r at base year 1985-1990. Then we form projected employments as

$$\tilde{S}_{gqirt} = \frac{\sum_{i'=1}^{11}\sum_{r'=1}^{12} \mathbb{1}[i \neq i', r \neq r'] S_{gqi'r't}}{\sum_{i'=1}^{11}\sum_{r'=1}^{12} \mathbb{1}[i \neq i', r \neq r'] S_{gqi'r'90}} S_{gqir90}$$

Where $\mathbb{1}[.]$ is the indicator function that takes value one if the inner condition is true and zero otherwise. In the following sections we provide with a wide set of estimates under various specifications that rely on either no correlation between economic shocks and immigrant employment or the instrument.[29]

[26]We use nine countries of origin: UK, Ireland, EU pre-2004 without Ireland, EU countries with accession in 2004 or later, other EEA, Asia, North America and the Caribbean; Africa, and Other.

[27]For example, during the 60s-70s Pakistani workers where driven into particular areas of UK by the textile sector –see chapter 3 in Finney and Simpson (2009)–.

[28]Note that we do not claim that by using this leave out version of the instrument we address all possible validity concerns.

[29]We searched for possible policies that may have had created natural experiments in the UK. For

3 Analysis

To help conceptualize our analysis we impose a data generation process for output. To start with, let the production function of each of the markets be defined by a constant elasticity of substitution –CES– function that combines native and immigrant labour; and capital[30]. More specifically

$$Y = AK^{1-\nu}[\delta N^{\rho} + (1-\delta)I^{\rho}]^{\frac{\nu}{\rho}} \tag{1}$$

Where A is total factor productivity –TFP–, K is the capital stock, I is immigrant employment and N is native employment. The ρ parameter tells us about the immigrant to native elasticity of substitution $-\sigma_I \equiv 1/(1-\rho)$–, such that natives and immigrants are gross substitutes if $\rho \neq 1$. The CES function is a Cobb-Douglas for $\rho = 0$ and Leontieff when $\rho \to -\infty$. On the other hand, the δ and ρ parameter jointly with the native to immigrant relative labour supply tells us about relative productivity of immigrants to natives at the margin. Note that the relative marginal product from (1) is

$$MRTS \equiv \frac{MP_N}{MP_I} = \frac{\delta}{1-\delta}\left(\frac{N}{I}\right)^{\rho-1} \tag{2}$$

When native and immigrant labour are perfect substitutes the MRTS[31] is independent of employment levels, and fixed at $\delta/(1-\delta)$. In such case if $\delta > .5$ immigrants are more productive than natives and the opposite if $\delta < .5$. For any other case, the marginal relative productivity is jointly determined by the native-efficiency parameter –δ–, the elasticity of substitution and relative labour supply. This specification is similar to Peri (2012) in the sense that we impose a constant elasticity of substitution –CES– that combines two types of labour and an upper Cobb-Douglas nest that combines the labour composite with capital. However, Peri (2012) differentiates between low and high skill with no explicit inclusion of immigrants in his production function. Furthermore, our estimation procedure differs from his in that we aim to estimate the parameters of the production function. Moreover, we also differentiate from the main body of previous literature in that we produce estimates without turning to wage information. This gives us robustness to non–perfectly competitive labour markets –an assumption maintained in most of the literature– at the cost of less flexibility. Note that –if perfect competition does not hold– workers are not paid their marginal product and estimates from relative wages do not readily –or not at all– reflect the deep –structural– parameters of the underlying production function. We note that there is evidence that points towards caution on that direction –as already pointed out in the previous section–. Specifically, the empirical regularity of immigrant wage downgrading/penalty (see Dustmann, Frattini et al. 2013) can be conceptualise within a perfectly competitive labour market with imperfect human capital transferability across countries. But an equally appealing conceptualization is that labour markets are frictional and immigrants have –for example– a worse search technology or lower bargaining power. Thus we produce estimates that are

example, during 1946-1951 the European Volunteer Workers scheme centrally allocated Easter European refugees into UK region-industries with tight rules for job and residential mobility. This could have been used for historic analysis or to create a past settlement instrument. However, the allocation of workers was hardly orthogonal to the performance of industries (see Kay and Miles 1988).

[30] Similar functional forms have been widely used in the migration literature since Borjas (2003) –see Manacorda et al. (2012) for an example with UK data–.

[31] With some abuse we will use MRTS to refer to MRTS of native to immigrant labour.

robust to departures from perfectly competitive labour markets, although still sensitive to production function misspecification and endogeneity.

3.1 The Relative Productivity of Immigrants

To learn about the relative productivity of immigrants and natives, we estimate (2). As a first step, we obtain estimates of the production function that governs the MRTS. From this we form some measure of it. This inform us not only about the relative productivity of immigrants and natives but also about labour induced changes on labour productivity. Caeteris paribus –given constant returns to scale–, increasing labour decreases labour productivity. However, if the MRTS differs from one, the effect's scale depends on which labour input we increase. If immigrants are more productive than natives $-MRTS < 1-$, an increase on immigrant supply decreases labour productivity. But less than if the same increase were on native employment; and the opposite if natives are relatively more productive $-MRTS > 1-$. In what follows we produce a comprehensive set of estimates for the parameters governing the production function. The main challenge on estimation is that the CES function is inherently non-linear and there is no exact linearization. Thus we produce estimates under two different approaches. Linear approximations that can be estimated by OLS and exact specification estimated by non-linear least squares –NLS–. Specifically we produce estimates from fitting a log-approximation, Kmenta (1967) approximation and the exact CES function in (1). To make the log-approximation linear we need to fix the elasticity of substitution parameter. We provide estimates under perfect substitution –i.e. $\rho = 1$–, with an immigrant-native elasticity of substitution equal to 7.8 as reported in Manacorda et al. (2012) –implying $\rho \approx .87$– and with the NLS elasticity estimate. On the other hand, Kmenta (1967) specification is a first-order Taylor approximation around $\rho = 0$ that happens to be linear on parameters and can be estimated by OLS. In our case this approximation takes the form

$$\ln Y_{irt} \approx \ln A_{irt}+(1-\nu)\ln K_{irt}+\nu\delta\ln(N_{irt})+(1-\delta)\nu\ln(I_{irt})+\frac{\nu\delta(1-\delta)\rho}{2}\left(\ln\frac{N_{irt}}{I_{irt}}\right)^2 \quad (3)$$

While the log-approximation takes into account that the immigrant to native relative labour supply is typically smaller than one to write

$$\ln Y_{irt} \approx \ln A_{irt} + (1-\nu)\ln K_{irt} + \frac{\nu}{\rho}\ln\delta + \nu\ln N_{irt} + \frac{\nu}{\rho}\frac{(1-\delta)}{\delta}\left(\frac{I_{irt}}{N_{irt}}\right)^{\rho} \quad (4)$$

From reduced form estimates based on equations (3) and (4), it is straight forward to recover estimates of the production function parameters –hereafter primitives, see appendix B.1–. We start by estimating the primitives without controlling for the capital stock. In this case we have a time series from 1998-2014 with 32 industries and 12 regions[32] Furthermore, we restrict the primitives to force constant returns to scale, i.e. $\nu = 1$. Note that under this restriction we have an implicit test for the Kmenta approximation fulfilling the constraints implied by the underlying CES function, namely a significance test of the slope of log-native employment minus the slope of log-immigrant employment

[32] If one computes the number of markets this is typically larger than the number of observations used for estimation. Note, that we need to drop those markets with either zero immigrant or native employment as in such cases there are some quantities that we need for estimation that are not well defined.

being equal to one[33]. In table 4 we report the full set of primitive estimates. Reduced form parameters from equations (3) and (4) are reported in table C.1. Let D_i and D_r be controls for industry and region, β a time trend and ϵ transitory economic shocks. Then in all specifications –unless otherwise stated– we model TFP as

$$A_{irt} = exp(D_i + D_r + \beta(t - \bar{t}) + \epsilon_{irt}) \tag{5}$$

Table 4: Production Function: Deep Parameters

	Log-approx	Log-approx	Log-approx	Kmenta	NLS
ρ	1.000	0.872	0.744	0.190***	0.744***
	(.)	(.)	(.)	(0.051)	(0.177)
δ	0.717***	0.706***	0.700***	0.771***	0.361***
	(0.047)	(0.043)	(0.038)	(0.059)	(0.078)
$\overline{MRTS}$	2.536	1.829	1.383	0.788	0.335
	(0.589)	(0.377)	(0.250)	(0.313)	(0.046)
95% CI‡	$[1.608, 3.999]$	$[1.221, 2.739]$	$[0.970, 1.971]$	$[0.361, 1.718]$	$[0.257, 0.437]$
Spe.Test (P-val)	.	.	.	0.964	
Observations	5878	5878	5878	5878	5878

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors other than for NLS are delta method from market clustered variance-covariance matrix estimate. All regressions but NLS include additive dummies for industry, region and a linear time trend. NLS includes controls for industry, London and a time trend. ‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2)

Column 1 of table 4 reports estimates from the log-approximation with perfect substitutes, column 2 are obtained using Manacorda et al. (2012) elasticity, column 3 uses the ρ from column 5, column 4 are estimates from Kmenta approximation and column 5 are NLS using the specification in (1). MRTS are weighted means, i.e. we compute the MRTS for every market-year and then take the average weighting by GVA. For each column we report the estimated MRTS –$\overline{MRTS}$–, standard errors and confidence intervals. Confidence intervals constrained in the economically meaningful segment $[0, \infty)$ –see appendix B.2–. Moreover, note that with $\rho = 1$ the reduced form estimate presented in column one and five of table C.1 gives us the correlation between output per native worker and the proportion of immigrant employment. The OLS estimate points towards a one percentage point increase on the immigrant to native ratio relating to –roughly– .4% increase on output per native worker. The IV estimate shows a larger size –1.3%– but also more noise, although still significant. The instrument passes the typical rules of thumb for weak instruments and the endogeneity test rejects the null of non-endogeneity. In terms of the deep parameter estimates, the native efficiency parameters δ are tightly estimated around .7 in all the approximations, but it drops to .36 when using NLS with the exact specification. Elasticity parameters are only estimated in the last two columns and they vary depending on the specification. The NLS estimate using the exact specification gives an estimate of ρ equal to .744 with an implied elasticity of substitution between immigrants and natives of around 3.9. On the other extreme, the Kmenta approximation ρ estimate is equal to .190 with an implied elasticity of substitution equal to 1.23. A plausible cause for this difference is that the Kmenta approximation is an expansion around $\rho = 0$, and for values that are not in a neighbourhood approximation error might be an issue. The hypothesis of equal marginal productivity is rejected for the

[33]P-values for specification test are reported under the name Spe.Test.

non sample-driven fixed ρ in the first two columns and for the NLS estimates using the exact specification. In the two first columns the MRTS point towards migrants being less productive than natives, specifically natives are twice and a half and almost twice more productive than migrants –respectively–. On the other hand, the NLS estimates in the last column point towards migrants being almost three times as productive as natives.

As we noted earlier consistency of the estimators used to obtain estimates in table 4 relies upon exogeneity of employment. We now use an IV strategy to address endogeneity concerns about immigrant employment. Note that we do not attempt to correct for native endogeneity nor we know of any previous attempt in the literature. A way to rationalize this is through natives being stickier to their currents jobs than immigrants. Natives might be more attached to a particular region due to habit or family/friendship ties, such ties are likely not to be present for –at least recent– migrants that have already broken with their homeland. Furthermore, natives might have job specific human capital that immigrants have not yet accumulated. Moreover, the immigrant population is already selected, they are the most mobile within their population of origin. As pointed out in section 2 we use a variant of Card's instrument to address immigrant endogeneity. In table 5, we report estimates using this instrument under various specifications. We neither provide IV estimates for the Kmenta nor the NLS with the exact specification. Reduced form estimates for Kmenta are available in table C.1 but the first stage turns to be extremely weak and the derived primitives noisy and outside any economically meaningful parameter space. On the other hand, the optimal moments implied by specification (1) induce that all conditioning variables are functions of parameters –they are the elements of the Jacobian–. And this complicates IV estimation[34].

Table 5: Production Function: Deep Parameters (IV)†

	Log-approx	Log-approx	Log-approx
ρ	1.000	0.872	0.744
	(.)	(.)	(.)
δ	0.435***	0.451***	0.448***
	(0.075)	(0.060)	(0.065)
$\overline{MRTS}$	0.769	0.627	0.481
	(0.236)	(0.151)	(0.126)
95% CI‡	$[0.422, 1.402]$	$[0.391, 1.005]$	$[0.288, 0.805]$
F-Stat	19.678	21.256	25.776
Endog Stat	9.425	8.973	8.247
Endog P-val	0.002	0.003	0.004
Observations	5878	5878	5878

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are delta method from market clustered variance-covariance matrix estimate. All regressions include additive dummies for industry, region and a linear time trend. ‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2)

IV point estimates of the native efficiency parameters are smaller than their OLS counterparts[35], translating into an estimated MRTS smaller than one and with the confidence

[34]We tried IV estimation projecting the Jacobian on the column space of a set of instruments but we were not able to achieve convergence.

[35]IV estimation has been performed with Stata's ivreg2, reported F-statistics are from Kleibergen-

interval of the last column bounded below one, i.e. immigrants being more productive than natives. The first stage power –as measured by the robust F-Statistic– is above the typical rules of thumb and the endogeneity test rejects the null of non-endogenous regressors.

3.1.1 Including Capital

We now perform the same exercise controlling for the capital stock in every market. If labour is exogenous to capital then including capital will only induce efficiency gains, on the other hand if capital is endogenous to labour controlling for it will correct for that source of endogeneity[36]. We have data on capital for the period 2000-2014 and a total of 11 industries that group the 32 industries we have used until now. In table 6, we re-estimate the above specifications using a sample that aggregates employment and GVA figures into these 11 industries and that includes our capital stock data computed from industry level capital stocks and market level gross fixed capital formation from ONS. Moreover, including capital gives us an specification test for whether the log- and Kmenta approximation meet the restrictions imposed by the underlying production function in (1). From (3) and (4) note that we can obtain two different estimates of ν and then use an equality test for which we should not be able to reject the null of equality. P-values for this test are reported under the name Spe. Test.

Table 6: Production Function With Capital: Deep Parameters

	Log-approx	Log-approx	Log-approx	Kmenta	NLS
ρ	1.000	0.872	0.555	0.121***	0.555
	(.)	(.)	(.)	(0.035)	(0.361)
δ	0.700***	0.670***	0.701***	0.870***	0.399*
	(0.110)	(0.085)	(0.067)	(0.062)	(0.158)
ν	0.408***	0.415***	0.426***	0.413***	0.502***
	(0.067)	(0.067)	(0.068)	(0.068)	(0.094)
$\overline{MRTS}$	2.335	1.566	1.004	1.429	0.284
	(1.226)	(0.604)	(0.323)	(0.768)	(0.068)
95% CI‡	$[0.834, 6.536]$	$[0.735, 3.336]$	$[0.534, 1.888]$	$[0.499, 4.098]$	$[0.178, 0.455]$
Spe.Test (P-val)	0.061	0.058	0.054	0.057	
Observations	1908	1908	1908	1908	1908

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors other than for NLS are delta method from market clustered variance-covariance matrix estimate. All regressions but NLS include additive dummies for industry, region and a linear time trend. NLS includes controls for industry, London and a time trend. ‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2)

Table 6 is analogous to 4 but including capital and allowing ν to be estimated from the data. The native-efficiency technology parameter point estimates are broadly the same as before, with the largest change being on that estimated using Kmenta approximation. The elasticity parameters –ρ– estimates are smaller than their respective counterparts in table 4. The MRTS point estimates are now larger with confidence intervals neither bounded below nor above one. The NLS estimate is the exception, with a point estimate smaller than one and confidence intervals bounded below one. The estimated average

Paap rk Wald statistic and endogeneity tests are from differences on Sargan-Hansen statistics.

[36]Note that in the case of the IV if the instrument fulfils the validity condition controlling for capital should not induce changes on the point estimates even if capital is endogenous to labour.

MRTS is equal to .284 implying that the marginal immigrant is almost four times as productive as its native counterpart. As in the previous section we also produce IV estimates for the log-approximations. Again the Kmenta approximation fitted through 2SLS shows a weak instrument problem and the estimated primitives are noisy and nowhere within a meaningful space, thus we only report its reduced form parameters –see table C.2–.

Table 7: Production Function With Capital: Deep Parameters (IV)†

	Log-approx	Log-approx	Log-approx
ρ	1.000	0.872	0.555
	(.)	(.)	(.)
δ	0.290*	0.335**	0.647*
	(0.112)	(0.125)	(0.304)
ν	0.523***	0.517***	0.437***
	(0.126)	(0.130)	(0.116)
$\overline{MRTS}$	0.408	0.388	0.784
	(0.223)	(0.217)	(1.045)
95% CI‡	[0.140, 1.190]	[0.129, 1.164]	[0.058, 10.679]
F-Stat	14.536	16.224	24.979
Endog Stat	2.197	1.599	0.027
Endog P-val	0.138	0.206	0.869
Spe.Test (P-val)	0.066	0.065	0.063
Observations	1908	1908	1908

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are delta method from market clustered variance-covariance matrix estimate. All regressions include additive dummies for industry, region and a linear time trend. ‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2)

The first thing we notice from table 7 is that the estimated MRTS are now lower than one and not statistically different. Compared with their OLS counterparts, native efficiency parameters point estimates are smaller and ν larger. Note that we fail to reject the null of no endogeneity and that the specification test –for both OLS and IV– marginally fails to reject –at 95%– the null of approximations fulfilling the underlying constraints.

3.1.2 Allowing for Different Occupations

Up to now our production function specification is rather sparse, labour is treated all the same given migrant/native status. The heterogeneity and trends observed in table C.4 in terms of occupation skill, gives us suggestive evidence for the raw comparison between immigrants and natives being perhaps not accurate. It can be the case that the typical native tends to find less productive occupations than the typical immigrant –or the reverse–. In such case differences on productivity are not only given by differences on the workers productive characteristics but also on the types of jobs they perform. We –at least partially– control for this by allowing our production function to take four different labour inputs, i.e. immigrants and natives in low and high skilled occupations. Let

$$
\begin{aligned}
Y &= AK^{1-\nu}[\delta H^{\rho} + (1-\delta)L^{\rho}]^{\nu/\rho} \\
H &\equiv [\delta_H N_H^{\rho_H} + (1-\delta_H) I_H^{\rho_H}]^{1/\rho_H} \\
L &\equiv [\delta_L N_L^{\rho_L} + (1-\delta_L) I_L^{\rho_L}]^{1/\rho_L}
\end{aligned} \tag{6}
$$

Where N_H and I_H are native and immigrant employment in high qualified occupations, and similar for N_L and I_L[37]. With this specification we trade-off complexity for flexibility[38]. With this broader specification we cannot use the log-approximation and the Kmenta approximation is rather convoluted when there is a nested structure. Thus from now on we report estimates from fitting the exact function only, with consistency of estimates relying on the assumption of predetermined inputs.

Table 8: Production Function With Capital and Two Nests

	Baseline	Changes on TFP Specification		Changes on Parametric Restrictions (w quadratic time trend)		
		Quadratic Trend	Industry Trends	Free ρ	Free ρ, δ_H, δ_L	Unrestricted
ν	0.498 ***	0.502 ***	0.378 ***	0.497 ***	0.482 ***	0.487 ***
	(0.081)	(0.082)	(0.076)	(0.086)	(0.097)	(0.106)
ρ	1.000	1.000	1.000	1.164 **	1.000 *	1.057 *
	.	.	.	(0.442)	(0.482)	(0.515)
δ	0.797 ***	0.790 ***	0.829 ***	0.809 ***	0.802 ***	0.790 ***
	(0.081)	(0.083)	(0.082)	(0.098)	(0.090)	(0.101)
ρ_H	.	.	.	.	.	0.538
	.	.	.	.	.	(0.459)
δ_H	.	.	.	.	0.357 *	0.396
	.	.	.	.	(0.137)	(0.247)
ρ_L	.	.	.	.	.	0.777
	.	.	.	.	.	(0.680)
δ_L	.	.	.	.	0.439 *	0.389
	.	.	.	.	(0.199)	(0.288)
δ_2	0.440 **	0.423 **	0.564 **	0.416 **	.	.
	(0.139)	(0.136)	(0.193)	(0.149)	.	.
ρ_2	0.601 *	0.636 *	0.370	0.630 *	0.655 *	.
	(0.304)	(0.303)	(0.354)	(0.316)	(0.308)	.
$\overline{MRTS_H}$	0.359	0.358	0.398	0.344	0.281	0.268
	(0.107)	(0.107)	(0.147)	(0.106)	(0.137)	(0.123)
95% CI‡	$[0.200, 0.644]$	$[0.200, 0.642]$	$[0.193, 0.821]$	$[0.188, 0.630]$	$[0.108, 0.730]$	$[0.109, 0.659]$
$\overline{MRTS_L}$	0.362	0.361	0.407	0.347	0.399	0.407
	(0.107)	(0.106)	(0.155)	(0.107)	(0.199)	(0.197)
95% CI‡	$[0.203, 0.647]$	$[0.202, 0.643]$	$[0.193, 0.857]$	$[0.190, 0.633]$	$[0.150, 1.059]$	$[0.157, 1.051]$
Observations	1800	1800	1800	1800	1800	1800

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$. All columns include industry dummies, a London dummy and a linear trend. Market clustered standard errors in parenthesis. Estimator's limiting distribution with degrees of freedom correction.‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2).

In table 8 we depict estimates for the two occupation production function specification. All columns use the same sample and differences across columns are only in terms of

[37]At a minimum risk of confusion we keep the same symbolic description for the parameters on the upper nest, but note that now δ is a skill–efficiency technology parameter and ρ determines the –partial– elasticity of substitution between labour in high and low skilled occupations, and these are composites of native and immigrant labour.

[38]Note that, even though we could classify occupations into a larger number of levels, this would have made estimation more challenging. Furthermore, allowing for further differences will result into a larger number of markets with some of the inputs equal to zero and –as we noted earlier– we cannot use these because some of the figures we need for estimation are not well defined in such case.

parametric restrictions. The baseline specification constraints $\rho = 1$, $\rho_H = \rho_L = \rho_2$ and $\delta_L = \delta_H = \delta_2$. And uses a TFP specification with industry dummies, a London dummy and a linear time trend. The estimates from the baseline specification show a skill biased technology –$\delta = .8 > .5$–, native efficiency parameter below .5 –although not significantly different– and an elasticity estimate of 2.5 –i.e. $1/(1 - .601)$–. Estimates are stable across specifications with the largest changes experienced when we allow for industry specific time trends in the TFP specification. When we free all parameters the estimates become noisier and non statistically different from zero. In terms of the estimated MRTS, this is consistently estimated below one with confidence intervals always bounded below one for high skilled and only crossing one for low skilled in the last two columns. There are no major differences between high and low skilled.

To explore changes over time, in figure C.6 we plot the evolution of the MRTS for high and low skilled –respectively– under the baseline estimates with quadratic time trend from table 8. Note that all changes across time are given by changes on the relative supply of immigrant workers. Our interest here is –therefore– on seeing how responsive is the MRTS and whether it is statistically different from one for the whole period of study. The lines we display are GVA weighted average MRTS for each year.In figure C.6, we observe that for the whole period of study both high and low skilled migrant labour is significantly more productive than their native counterpart. Differences on productivity are roughly the same for low and high skilled labour, with upper-bounds of the 95% confidence interval ranking from –roughly– .6 at the beginning of the sample to around .7-.8 at the end for high and low skilled –respectively–. Overall, there is an upwards-slopping trend implying that immigrants are becoming relatively less productive, with average growth rates of 2.19% and 3.04% for high and low skilled –respectively–. As noted earlier, given that the underlying primitives are assumed to be fixed across time all variation comes through changes on labour relative supply. To investigate further how responsive the MRTS is to changes on the relative labour supply recall that –the negative of– the elasticity of complementarity –i.e. the inverse of the elasticity of substitution– is

$$\frac{d \ln MRTS_Q(N_Q/I_Q)}{d \ln N_Q/I_Q} = \rho_Q - 1 \ (Q = H, L) \tag{7}$$

This implies that a 1% increase on the native–to–immigrant supply induces a $\rho_H - 1$ and $\rho_L - 1$ increase on the MRTS of high and low skilled, respectively. Given our data –at the aggregate level– this translates into

Table 9: Annual Growth Rates (%)

Year	N_H/I_H	$MRTS_H$	N_L/I_L	$MRTS_L$
2001	-11.25	4.16	-5.03	1.86
2002	-7.14	2.64	-10.61	3.92
2003	-3.41	1.26	-2.81	1.04
2004	-2.21	0.82	-9.14	3.38
2005	-4.37	1.62	-9.06	3.35
2006	-5.97	2.21	-9.68	3.58
2007	-5.25	1.94	-9.69	3.58
2008	-1.56	0.58	-9.92	3.67
2009	-2.71	1.00	-4.71	1.74
2010	-0.60	0.22	-3.79	1.40
2011	-12.88	4.76	-16.95	6.27
2012	-5.25	1.94	0.75	-0.28
2013	2.68	-0.99	-5.62	2.08
2014	-5.61	2.08	-5.20	1.92
Mean	-4.68	1.73	-7.25	2.68

ρ_H and ρ_L are from the baseline specification

We observe that the native-to-immigrant relative labour supply at the aggregate level has been decreasing for most of our time series for both high and low skilled. With average growth rates of -4.68% and -7.25% respectively, this translates on increasing MRTS or –what is the same– decreasing immigrant relative productivity. More specifically, the MRTS has been growing at an average rate of 1.73% for high skilled and 2.68% for low skilled[39].

4 Robustness

4.1 Changes on Underlying Characteristics, Specification and Sample

Even though we have extended our specification to include two occupations, it could be the case that within these, natives and immigrants differ in terms of other characteristics such as age, education or sex. To account for this we could extend the number of nests (e.g. see Manacorda et al. 2012). But doing so without turning to wage information would have proved challenging in terms of estimation. Instead, we use fitted-wage-based weights to create a new labour measure that accounts for changes on underlying individual level characteristics –this is similar to the efficiency units in Acemoglu and Autor (2011) and Autor et al. (2008)–. Our weights account for changes on immigrant and natives sex, education[40], age and full-time/par-time status composition. By using fitted rather than actual wages, we do not introduce other effects such as wage discrimination in our

[39] Note that figures in table 9 are national level aggregates. If we use weighted averages –or unweighed– these are heavily driven by outlier markets with very small immigrant labour figures. Note that the proportional mapping we use to homogenize industry and occupation codes can produce employment figures that are not integers and that are smaller than one.

[40] Measure as age when left full-time education.

estimates. When we compare head counts and fitted-wage weighted employment –at the aggregate level– we obtain the following table

Table 10: Headcount and Weighted Measures

	Weighted/Head Count		Ratio
	Immigrant	Native	
High Skilled			
2000	1.058	0.937	1.129
2003	1.096	0.978	1.121
2005	1.106	0.978	1.131
2014	1.126	0.999	1.128
Low Skilled			
2000	1.067	0.955	1.117
2003	1.079	0.962	1.121
2005	1.088	0.976	1.115
2014	1.125	1.009	1.115

Source: Labour Force Survey, own computation.

In table 10 we see that immigrants tend to have higher than average fitted wages, i.e. within industry-region-occupation there is positive selection on the observables used to form the weights[41]. Furthermore, differences are fairly homogeneous across occupations and time, with weighted to head count ratio between immigrant and native labour being around 11-12% higher. This is, the relative supply of immigrant-to-native when using the weighted measure is 12% higher –at the aggregate level–. In table A.3 we replicate table 8 using the weighted labour measure. The general picture is unchanged, point estimates signal towards immigrants being more productive than natives and confidence intervals show the same behaviour as before.

In section 2, we noted that employment from LFS is typically lower than the same figures from Workforce Jobs Dataset. As a robustness check, we use employment proportions from LFS to input employment levels from Workforce Jobs data, and perform estimation again. Results are displayed in tables A.4, A.5, A.6 and A.7. The two first ones display estimates for the single nest specification with predetermined inputs and using IV –respectively–. Table A.6 reports estimates for the two nest specification and A.7 reports the same estimates using fitted-wage weights. All estimates are close to the ones obtained with LFS employment measures but standard errors are typically smaller.

Another possible measure we can use for employment are hours of work[42]. Workers in high skilled occupations tend to provide more hours of work than low skill and immigrants more than natives –see table 11 –. Over time there has been a decrease on the number of hours provided, more noticeable for immigrants.

[41] See equation (A.1) in the appendix

[42] We choose to use total hours usually worked as with this we account for differences on overtime.

Table 11: Supply of Hours of Work

	Hour per Week and Worker		Ratio
	Immigrant	Native	
High Skilled			
2000	42.440	41.663	1.019
2003	43.249	41.914	1.032
2005	42.720	41.534	1.029
2014	41.912	41.256	1.016
Low Skilled			
2000	39.068	37.811	1.033
2003	38.428	37.143	1.035
2005	38.257	36.919	1.036
2014	36.389	36.202	1.005

Source: Labour Force Survey, own computation.

When we use hours to measure labour –table A.8 to A.10–, we obtain MRTS estimates comparable to the ones obtained using headcount. With point estimates statistically not different from one or with confidence intervals bounded in the region where immigrants are more productive than natives. Nonetheless, there are changes on the production function parameters. Most noticeable, the elasticity of substitution parameter from both single and two nest specification increases to around .9-, implying an elasticity of substitution between immigrant and native employment of 10. This is larger than the estimate for the UK provided in Manacorda et al. (2012) but smaller than US estimates in Card (2009) and Ottaviano and Peri (2012).

Furthermore, up to now we have kept fixed the nesting structure. Imposing capital and labour to be complementaries and a free elasticity of substitution between different types of labour –with the restriction of within nest constant elasticity of substitution–. We now explore if the implications derived from our estimates vary when we set high skilled labour to be complementary to a capital-low skilled labour composite input. Where capital and low skilled labour is allowed to have any feasible elasticity of substitution. Results are displayed in table A.16. We observe that the native efficiency and elasticity of substitution parameters are within a neighbourhood of those obtained with our main specification. In terms of MRTS, point estimates are always below one but confidence intervals are broader and typically include one. Moreover, in appendix A we provide further robustness tests differentiating EEA and non-EEA immigrants; using wage bill information, introducing region-industry interactions in TFP and present results using Peri (2012) methodology. Point estimates under these specifications are generally noisier, and some times lay outside any economically-meaningful space.

Finally, we addressed endogeneity concerns in the two occupation specification by using an control function approach. Specifically, we iteratively estimate production function parameters and use them to construct marginal prices. The differential between these marginal prices and the actual observed wage is interpreted as a transitory wage shock. And we use it as a regressor in the next iteration of the production function. We repeat this process until parameters converge to a stable point. If workers select into a specific market according to wages only, then this procedure will control for common shocks that influence productivity and employment figures. In table 12 we observe that point estimates are close to those obtained without the control function. Furthermore, there is a positive and significant correlation between wage shocks and production for immigrants, but the same correlation is non-significant for natives. This is consistent with immigrants being more flexible than natives.

Table 12: Production Function With Capital and Two Nests: Control Function

	Immigrant Wage Shocks Only			Immigrant and Native Wage Shocks		
	Baseline	Quadratic Trend	Free ρ	Baseline	Quadratic Trend	Free ρ
Imm.Wage Shock	0.030 *	0.027 *	0.027 *	0.031 *	0.027 *	0.027 *
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)
Nat.Wage Shock	.	.	.	-0.002	-0.003	-0.003
	.	.	.	(0.022)	(0.022)	(0.022)
ν	0.511 ***	0.515 ***	0.982 *	0.511 ***	0.516 ***	0.977 *
	(0.084)	(0.085)	(0.389)	(0.084)	(0.085)	(0.382)
ρ	1.000	1.000	0.516 ***	1.000	1.000	0.516 ***
	.	.	(0.091)	.	.	(0.091)
δ	0.792 ***	0.787 ***	0.785 ***	0.793 ***	0.788 ***	0.785 ***
	(0.080)	(0.082)	(0.102)	(0.078)	(0.080)	(0.103)
δ_2	0.451 ***	0.437 ***	0.438 **	0.454 ***	0.441 ***	0.442 **
	(0.128)	(0.125)	(0.140)	(0.120)	(0.118)	(0.133)
ρ_2	0.569 *	0.597 *	0.597 *	0.565 *	0.591 *	0.591 *
	(0.282)	(0.282)	(0.289)	(0.277)	(0.277)	(0.286)
$\overline{MRTS_H}$	0.360	0.357	0.359	0.362	0.359	0.362
	(0.109)	(0.107)	(0.115)	(0.105)	(0.104)	(0.111)
95% CI‡	[0.200, 0.651]	[0.199, 0.643]	[0.192, 0.672]	[0.205, 0.639]	[0.204, 0.634]	[0.198, 0.661]
$\overline{MRTS_L}$	0.363	0.359	0.361	0.364	0.362	0.364
	(0.108)	(0.106)	(0.115)	(0.104)	(0.103)	(0.111)
95% CI‡	[0.202, 0.651]	[0.201, 0.642]	[0.194, 0.673]	[0.208, 0.638]	[0.207, 0.632]	[0.200, 0.661]
Observations	1563	1563	1563	1563	1563	1563

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$. All columns include industry dummies, a London dummy and a linear trend. Market clustered standard errors in parenthesis. Estimator's limiting distribution with degrees of freedom correction.‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2). Wage shocks are Z-scores to get a similar scale to the dummies in the TFP specification.

4.2 Immigration Affecting Productivity Through Other Channels

So far, we have explored the link between immigration and productivity exclusively through changes on the input mix, assuming –implicitly– no changes induced on other factors. We now explore possible immigration induced changes on native employment, capital stock and TFP. To estimate these relations we use the same sample we used for estimation of the two nest production function specification. Recall that for each market in our sample we only have capital investment data. And that we generated the series of capital stock using an –up to some extend– arbitrary imputation procedure that employs labour figures at a base year. Thus it has the potential to induce spurious correlation between immigrant labour and capital stock. To account for this, we report estimates between immigrant labour an our capital stock figures, jointly with estimates at the national level between immigrant labour and capital stock for different assets for which we have ONS data.

Furthermore, TFP is typically obtained as a residual. On a linear specification with immigration on the right-hand-side TFP is orthogonal to immigration by construction. However, due to the structure of our estimating equation, we can identify the link with TFP by using any specification underlying table 8 extending its TFP specification to include immigration[43]. Alternatively, we can take estimates for the share of capital –ν– and labour elasticities from the literature jointly with wage information assuming perfectly competitive labour markets to extract a measure of TFP that is not orthogonal to immigration –see Peri (2012)–. To the best of our knowledge there is no other paper that has estimated the elasticity of substitution between high and low skilled occupations –ρ– for the UK. Manacorda et al. (2012) report estimates of the elasticity of substitution between natives and immigrants for the UK. We use their estimate and the typical value of .67 for ν –see Peri (2012)– to extract a TFP measure from the production function that does not separate between high and low skilled –equation (1), see results in appendix A.7–. Finally, to explore the link between immigrant and native employment we fit the following regressions

$$\ln N_H = D_i^H + D_r^H + D_t^H + \beta_H^H I_H + \beta_L^H I_L \tag{8}$$

$$\ln N_L = D_i^L + D_r^L + D_t^L + \beta_H^L I_H + \beta_L^L I_L \tag{9}$$

Where D_i, D_r and D_t are dummies for industry, region and year[44]. From these equations, we get the correlation between immigrant labour and log-native labour for each occupational level. This is, the βs in (8) and (9) are semi-elasticities between immigrant and native labour. We re-scale immigrant figures on the right hand side of (8) and (9) to be expressed in terms of thousands so that the βs can be interpreted as a one thousand increase on immigrant labour correlates with a $\beta * 100$ percent increase on native employment. In table A.21 we report OLS and IV estimates from fitting equations (8) and (9) using the same sample as in table 8. Low skilled immigrant labour is negatively correlated with both high and low skilled native labour but the effect is small –the largest estimate imply a .2% drop on low skilled native employment for each 1000 increase on immigrant labour of the same type– and non-significant. The estimates for high skilled immigrant labour are similar in magnitude although typically with the opposite sign. The instrument passes the typical rule of thumb for weak instruments and we reject the null of non-endogeneity at 95% confidence level. Other than this, OLS estimates appear to be upwards biased.

In table A.22 we show estimates for capital using a similar specification. As before immigrant employment figures are expressed in thousands and estimates can be read as semi-elasticities. Both OLS and IV estimates show a positive correlation although OLS estimates for high skilled are five times the size of IV thus signalling towards upwards bias, the null of non-endogeneity is rejected at 95% confidence level. As a robustness check in table A.24 we perform similar regressions using capital stock at the national level for which there is data available. Results are comparable to the ones observed in A.22 with positive albeit small in magnitude and typically non-significant estimates.

To explore the effects of immigration on TFP without turning to pre-existing estimates for production function parameters; we extend our TFP specification to be

$$A = \exp(D_i + D_r + D_t + \beta_1 I_H + \beta_2 I_L + \beta_3 N_H + \beta_4 N_L + \beta_5 I_H/N_H + \beta_6 I_L/N_L + \epsilon_{irt})$$

[43] Note that orthogonality conditions are with respect to the Jacobian, as long as the columns of this are linearly independent we can identify the extra channel for immigration through TFP.

[44] At risk of minimum confusion we obviate the residual terms.

In table A.23 we present estimates for the βs in the new TFP specification using the same production function specification as in column 5 of table 8. Our estimates imply mild, non-significant changes on output given by immigration through TFP.

5 Counter-Factual Productivity

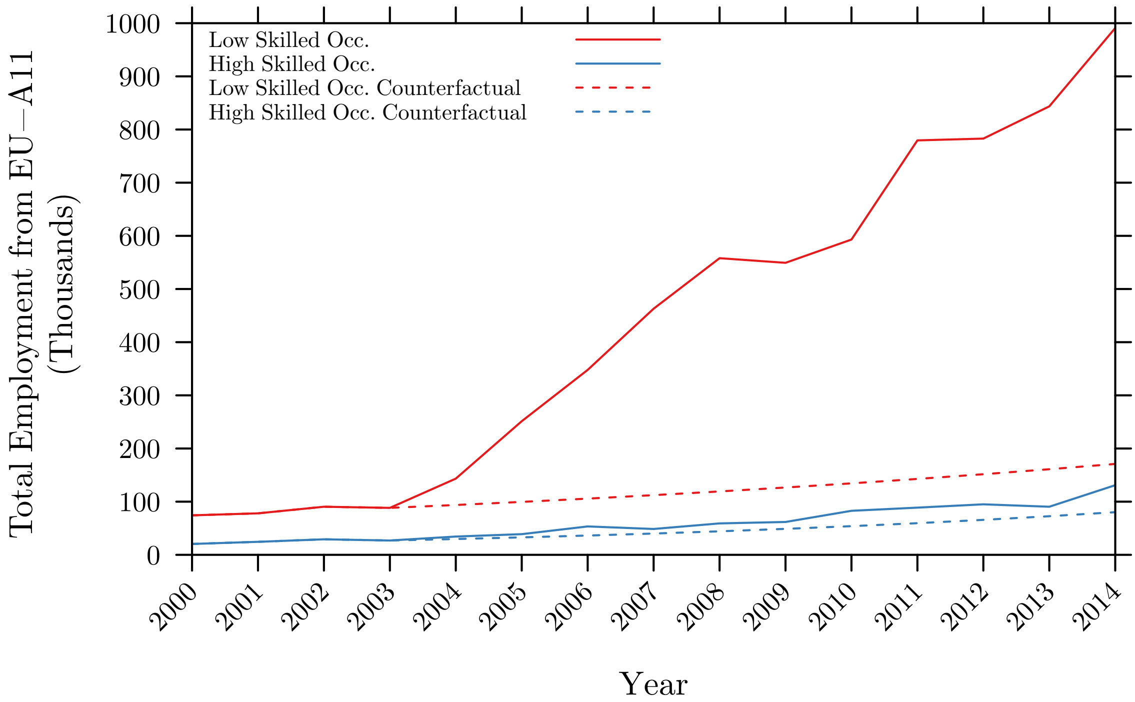
We now use estimates in table 8 to explore a counter-factual environment. In particular, we ask the question of what would have been the evolution of UK productivity if accession were not to have happened and immigration from EU-A11[45] countries were to be growing at pre-2004 rates. Arguably, accession of EU-A11 countries produced a large in-flow of immigrant workers in the UK and moreover this flow was fast, in the sense of large and immediate increases on its growth rate right after 2004[46]. With this in mind we claim that other inputs at least in the neighbourhood of 2004 did not have time to respond and adjust to the increased labour supply from EU-A11 countries. This allows us to produce a counter–factual without correcting for other inputs response that is reliable at least for a neighbourhood around 2004.

To create our counter-factual we computed EU-A11 average annual growth rate at the national level using years 2000-2003 for both high and low skilled and use these and 2003 employment levels to get the counter-factual figures at the national level. Then we imputed the national figures to each of the markets using the market contribution to total EU-A11 employment for both high and low skilled and each year from 2004-2014. To gain some visual understanding of the factual and counter-factual data, we have plotted the two series in figure 2. As mentioned before following 2004 EU-A11 labour experience a sharp increase, mostly into low skilled occupations. For example total, low skilled employment in 2003 was below 100 thousand raising to roughly 200 thousand two years after. In comparison, our counter–factual figures show a smooth upwards slopping trend with a difference between factual and counter–factual at the end of the sample of roughly 800 thousand low skilled and 50 thousand high skilled EU-A11 workers. These differences when we aggregate all immigrants are less striking but still salient –see figure C.7–.

[45]In our counter-factual we treat Bulgaria, Romania and Croatia as EU-A8 countries even though their accession happened later on. In practice this distinction does not make much of a difference.

[46]See Vargas-Silva and Markaki (2017)

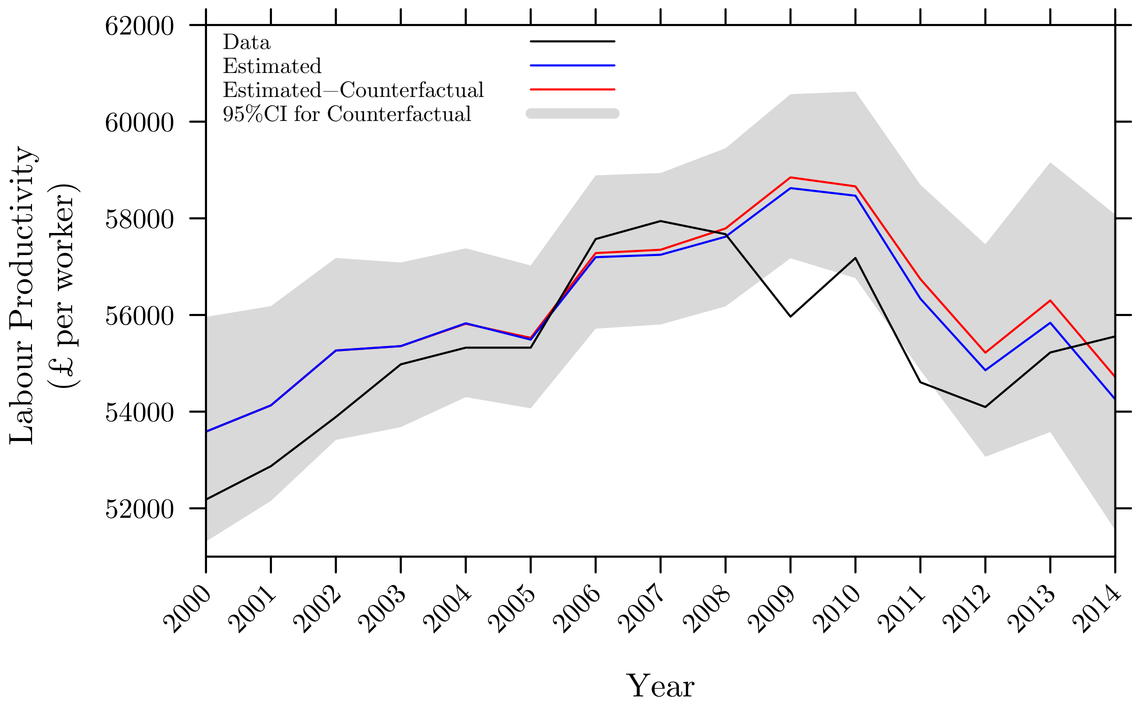
Figure 2: EU-A10 Labour Force Evolution and Counter-factual



We use the counter-factual labour series and estimates from table 8 to simulate a counter-factual sample of output for each market and year in our estimation sample. Then we aggregate output and employment at the national level and compute output per worker, the typical measure of labour productivity. We choose to use estimates from column 4 in table 8. In figure 3 we plot the simulated counter-factual with its 95% confidence intervals, the simulated series when we use the actual inputs –we refer to this as treatment– and actual output per worker. For all the series but 2009, both the treatment and the actual figure lie inside the counter-factual confidence interval. Right after accession –2005-2006– the simulated counter-factual labour productivity is tight to the treatment figure, implying no differences in the neighbourhood of 2004 when we expect other inputs to be fixed. From 2008 onwards the counter-factual simulation upper-bounds the other two figures but is rather close to the factual simulation and never point significantly different. Overall, we find that if immigration growth from EU-A11 countries were to be at pre-2004 levels, labour productivity would have been virtually unchanged. Nonetheless, we note that the effect of immigration in labour productivity could also come through its effect on other inputs that become more flexible in the long run. For example, on the typical model we think about capital as being fixed in the short run and adapt in the long run, while labour is fully flexible. In such environment even comparison around accession time can be misleading due to native employment adjustment. However, we have already made the claim when discussing the instrument and endogeneity concerns that labour and particularly native labour is sticky. Unlike the sand-box labour supply model, workers in reality face switching costs. Changing jobs can imply –among others– losing job-specific human capital, expend time searching for a new job or moving home;

and the implied costs are typically non-negligible[47]. Moreover, in section 4.2 we showed that immigration has mild and –typically– non-significant correlation with other inputs[48].

Figure 3: Simulation Under EU-A10 Labour Force Counter-factual



6 Conclusions

Throughout this paper we have addressed two questions, what is the relative productivity of immigrants with respect to natives in the UK and what is the link between immigration and productivity. In order to offer an answer to this we collected data from the UK Labour Force Survey and ONS regional accounts from which we estimated the parameters of an underlying production function. We started with a simple specification CES production function where each industry–region uses two types of labour –immigrant and native– and capital to produce an homogeneous output. We estimated the parameters using a variety of restrictions and estimators both under an exogeneity assumption over all inputs and using a past-settlement instrument to correct for possible immigrant endogeneity. Then we progressed towards a more comprehensive specification where both native and immigrant labour are divided into low and high skilled according to the occupation they perform. Due to the complexities of this specification we are restricted in terms of the estimators available but we show that our estimates are robust to changes on specification, sample and parametric restrictions. Overall, we find that immigrant

[47]For example, switching costs for inter-state relocation in the US are estimated around the hundred of thousand dollars (see Kennan and Walker 2011).

[48]In unreported results we used estimates in section 4.2 to allow for input adjustment in our simulations. The simulated effects were still small and point-non-significant.

labour is at least as productive as native. Out of all our estimates only in the two most restrictive specifications, where we do not control for differences on capital stock and make parametric restrictions based upon assumption or out of sample estimates we can reject a null-hypothesis of equality of productivity against native labour being more productive than immigrant. All other estimates show either non-statistically significant differences or immigrant labour being significantly more productive. When we allow for differences across skill levels, we find that immigrants –at the margin– are typically significantly more productive than natives. Furthermore, given ours estimates we ask the question of what would have been the evolution of labour productivity if immigration from EU-A11 countries were to be stable at pre-accession levels. The large and almost instantaneous inflows following accession give us a nice set-up to explore this question at least on the short run where capital is fixed and the adjustment of native labour is limited by switching costs. We simulate counter-factuals finding that the relation between accession and labour productivity in the UK is mild and non-significant. Given our data and specification we cannot distinguish between the counter-factual and treatment.

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A Robustness Results

We now present a battery of robustness checks where we address possible concerns relating to specification and employment measure.

A.1 Estimates with Trimmed Sample

The reader might be concerned about whether sampling error may drive the MRTS plotted in figures C.6 or our estimates. In terms of the figures, we note that given the estimates in 8 the MRTS for both high and low skilled is a strictly positive, decreasing and convex function, i.e. the effect of outlier observations for native-to-immigrant relative supply is mitigated when we take the expectation of the MRTS rather than computing the MRTS at the expectation of the native-to-immigrant relative supply. To illustrate this point, in figures C.4 and C.5 –for the baseline estimates– we plot alternative measures for the MRTS –specifically– mean, GVA weighted mean and median MRTS; and the MRTS at the GVA weighted mean of native-to-immigrant relative supply. As expected the MRTS evaluated at the –weighted– mean relative employment show more instability than the other three measures. Mean, weighted mean and median MRTS are within an acceptable neighbourhood and our preferred measure –weighted mean– upper-bounds the others. Furthermore, we re-estimate the parameters of the production function dropping observations for which the native-to-immigrant supply for either or both high and low skilled are above the 95% percentile –table A.1–. The estimates we obtain from the trimmed sample are close to their whole sample counterparts in table 8.

Table A.1: Production Function With Capital and Two Nests: upper 5% Trimmed Sample

	Baseline	Changes on TFP Specification		Changes on Parametric Restrictions (w quadratic time trend)		
		Quadratic Trend	Industry Trends	Free ρ	Free ρ, δ_H, δ_L	Unrestricted
ν	0.502 ***	0.506 ***	0.375 ***	0.506 ***	0.492 ***	0.501 ***
	(0.081)	(0.082)	(0.075)	(0.087)	(0.097)	(0.108)
ρ	1.000	1.000	1.000	0.998 *	0.865 †	0.896 †
	.	.	.	(0.399)	(0.447)	(0.455)
δ	0.807 ***	0.800 ***	0.842 ***	0.800 ***	0.796 ***	0.770 ***
	(0.082)	(0.084)	(0.078)	(0.103)	(0.095)	(0.106)
ρ_H	.	.	.	.	.	0.347
	.	.	.	.	.	(0.414)
δ_H	.	.	.	.	0.405 **	0.478 *
	.	.	.	.	(0.139)	(0.234)
ρ_L	.	.	.	.	.	0.790
	.	.	.	.	.	(0.760)
δ_L	.	.	.	.	0.490 *	0.401
	.	.	.	.	(0.223)	(0.322)
δ_2	0.471 **	0.452 **	0.636 **	0.452 **	.	.
	(0.141)	(0.137)	(0.206)	(0.153)	.	.
ρ_2	0.499	0.540 †	0.166	0.540 †	0.552 †	.
	(0.307)	(0.305)	(0.416)	(0.319)	(0.315)	.
$\overline{MRTS_H}$	0.348	0.347	0.398	0.347	0.292	0.277
	(0.104)	(0.103)	(0.162)	(0.108)	(0.126)	(0.117)
95% CI‡	[0.194, 0.625]	[0.194, 0.620]	[0.179, 0.882]	[0.189, 0.637]	[0.126, 0.679]	[0.121, 0.633]
$\overline{MRTS_L}$	0.351	0.349	0.415	0.349	0.415	0.442
	(0.104)	(0.102)	(0.180)	(0.108)	(0.245)	(0.253)
95% CI‡	[0.197, 0.627]	[0.196, 0.620]	[0.177, 0.970]	[0.190, 0.640]	[0.130, 1.320]	[0.144, 1.358]
Observations	1635	1635	1635	1635	1635	1635

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$. All columns include industry dummies, a London dummy and a linear trend. Market clustered standard errors in parenthesis. Estimator's limiting distribution with degrees of freedom correction.‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2).

A.2 Accounting for Compositional Changes

To compute our efficiency unit weights, we use LFS micro-data selecting natives only from the first quarter of years 2011-2014. And we run the following mincerian wage equation

$$\ln w = \beta_0 + D_i + D_r + D_t + \beta_1 edage + \beta_2 edage^2 + \beta_3 age + \beta_4 age^2 + \beta_5 sex + \beta_6 ftptw + \epsilon \quad \text{(A.1)}$$

Where *edage* is age when left full-time education and *ftptw* indicates whether the individual is a full- or part-time employee. Using β_1 to β_6 we compute fitted wages for every worker in the sample we use to produce estimates in table 8. Then for every market-occupation we compute the average wage and we weight every observation using its predicted wage over the mean in the relevant market-occupation[49]. This translates into individuals having a weight larger than one if their predicted wage is larger than mean, equal to one if predicted wage equal to mean and lower than one otherwise.

Table A.2: Characteristic Loadings

cons	2.056***
	(0.141)
age	0.081***
	(0.003)
age^2	-0.001***
	(0.000)
edage	0.164***
	(0.012)
edage^2	-0.003***
	(0.000)
Part-Time	-0.866***
	(0.017)
Female	-0.187***
	(0.009)
Observations	35,303

Market clustered standard errors. Include region, industry and year dummies. *edage* stands for age when left full-time education. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[49] For earlier than 2011 the procedure implies some more steps due to the industry and occupation translation. In unreported estimates we also tried year-market-occupation and occupation means for standardization obtaining similar results.

Table A.3: Production Function With Capital and Two Nests: Skill

	Baseline	Changes on TFP Specification		Changes on Parametric Restrictions (w quadratic time trend)		
		Quadratic Trend	Industry Trends	Free ρ	Free ρ, δ_H, δ_L	Unrestricted
ν	0.481 ***	0.482 ***	0.366 ***	0.478 ***	0.467 ***	0.473 ***
	(0.076)	(0.077)	(0.072)	(0.081)	(0.090)	(0.098)
ρ	1.000	1.000	1.000	1.107 *	0.983 *	1.065 †
	.	.	.	(0.442)	(0.488)	(0.550)
δ	0.806 ***	0.800 ***	0.834 ***	0.813 ***	0.809 ***	0.799 ***
	(0.079)	(0.080)	(0.077)	(0.100)	(0.093)	(0.094)
ρ_H	.	.	.	.	.	0.480
	.	.	.	.	.	(0.424)
δ_H	.	.	.	.	0.442 **	0.480 †
	.	.	.	.	(0.142)	(0.247)
ρ_L	.	.	.	.	.	0.761
	.	.	.	.	.	(0.681)
δ_L	.	.	.	.	0.513 *	0.444
	.	.	.	.	(0.212)	(0.289)
δ_2	0.502 ***	0.489 ***	0.591 **	0.483 **	.	.
	(0.142)	(0.138)	(0.176)	(0.153)	.	.
ρ_2	0.561 †	0.588 †	0.379	0.586 †	0.597 †	.
	(0.305)	(0.303)	(0.333)	(0.314)	(0.305)	.
$\overline{MRTS_H}$	0.451	0.448	0.483	0.436	0.377	0.362
	(0.149)	(0.148)	(0.177)	(0.150)	(0.178)	(0.171)
95% CI‡	[0.235, 0.862]	[0.235, 0.856]	[0.236, 0.990]	[0.222, 0.857]	[0.150, 0.952]	[0.143, 0.912]
$\overline{MRTS_L}$	0.456	0.453	0.494	0.441	0.506	0.509
	(0.150)	(0.149)	(0.186)	(0.152)	(0.288)	(0.277)
95% CI‡	[0.239, 0.870]	[0.238, 0.862]	[0.236, 1.033]	[0.224, 0.865]	[0.165, 1.547]	[0.175, 1.480]
Observations	1800	1800	1800	1800	1800	1800

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$. All columns include industry dummies, a London dummy and a linear trend. Market clustered standard errors in parenthesis. Estimator's limiting distribution with degrees of freedom correction.‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2).

A.3 Employment Measured from Workforce Jobs

Table A.4: Production Function With Capital: Deep Parameters Workforce Jobs

	Log-approx	Log-approx	Log-approx	Kmenta	NLS
ρ	1.000	0.872	0.598	0.134***	0.598*
	(.)	(.)	(.)	(0.024)	(0.268)
δ	0.509***	0.532***	0.625***	0.848***	0.431***
	(0.074)	(0.066)	(0.056)	(0.047)	(0.120)
ν	0.606***	0.610***	0.600***	0.546***	0.640***
	(0.092)	(0.089)	(0.083)	(0.075)	(0.115)
$\overline{MRTS}$	1.036	0.877	0.771	1.222	0.350
	(0.306)	(0.233)	(0.186)	(0.437)	(0.071)
95% CI‡	$[0.580, 1.850]$	$[0.521, 1.476]$	$[0.481, 1.236]$	$[0.606, 2.465]$	$[0.234, 0.521]$
Spe.Test (P-val)	0.080	0.077	0.075	0.084	
Observations	1908	1908	1908	1908	1908

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors other than for NLS are delta method from market clustered variance-covariance matrix estimate. All regressions but NLS include additive dummies for industry, region and a linear time trend. NLS includes controls for industry, London and a time trend. ‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2)

Table A.5: Production Function With Capital: Deep Parameters Workforce Jobs (IV)

	Log-approx	Log-approx	Log-approx
ρ	1.000	0.872	0.598
	(.)	(.)	(.)
δ	0.349***	0.401***	0.673**
	(0.085)	(0.095)	(0.238)
ν	0.750***	0.717***	0.579***
	(0.170)	(0.153)	(0.132)
$\overline{MRTS}$	0.537	0.517	0.951
	(0.200)	(0.205)	(1.026)
95% CI‡	$[0.259, 1.115]$	$[0.238, 1.124]$	$[0.115, 7.890]$
F-Stat	14.722	18.520	36.453
Endog Stat	2.226	1.276	0.052
Endog P-val	0.136	0.259	0.820
Spe.Test (P-val)	0.063	0.062	0.071
Observations	1908	1908	1908

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are delta method from market clustered variance-covariance matrix estimate. All regressions include additive dummies for industry, region and a linear time trend. ‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2)

Table A.6: Production Function With Capital and Two Nests: Workforce Jobs Employment

	Baseline	Changes on TFP Specification		Changes on Parametric Restrictions (w quadratic time trend)		
		Quadratic Trend	Industry Trends	Free ρ	Free ρ, δ_H, δ_L	Unrestricted
ν	0.654 ***	0.658 ***	0.520 ***	0.641 ***	0.624 ***	0.633 ***
	(0.104)	(0.105)	(0.104)	(0.106)	(0.119)	(0.122)
ρ	1.000	1.000	1.000	1.387 **	1.143 **	1.177 **
	.	.	.	(0.476)	(0.434)	(0.417)
δ	0.774 ***	0.769 ***	0.795 ***	0.822 ***	0.803 ***	0.785 ***
	(0.060)	(0.061)	(0.072)	(0.082)	(0.071)	(0.069)
ρ_H	.	.	.	.	.	0.541 †
	.	.	.	.	.	(0.324)
δ_H	.	.	.	.	0.349 **	0.416 *
	.	.	.	.	(0.105)	(0.167)
ρ_L	.	.	.	.	.	0.905 †
	.	.	.	.	.	(0.462)
δ_L	.	.	.	.	0.428 ***	0.371 *
	.	.	.	.	(0.127)	(0.171)
δ_2	0.436 ***	0.427 ***	0.538 ***	0.413 ***	.	.
	(0.093)	(0.090)	(0.139)	(0.104)	.	.
ρ_2	0.691 **	0.713 ***	0.502 †	0.710 **	0.735 ***	.
	(0.214)	(0.211)	(0.261)	(0.223)	(0.215)	.
$\overline{MRTS_H}$	0.418	0.419	0.447	0.393	0.314	0.293
	(0.103)	(0.104)	(0.129)	(0.102)	(0.136)	(0.118)
95% CI‡	$[0.258, 0.678]$	$[0.258, 0.682]$	$[0.254, 0.787]$	$[0.236, 0.655]$	$[0.135, 0.733]$	$[0.133, 0.647]$
$\overline{MRTS_L}$	0.420	0.421	0.453	0.395	0.442	0.485
	(0.103)	(0.104)	(0.132)	(0.103)	(0.149)	(0.211)
95% CI‡	$[0.260, 0.679]$	$[0.260, 0.683]$	$[0.256, 0.800]$	$[0.238, 0.657]$	$[0.228, 0.856]$	$[0.207, 1.136]$
Observations	1800	1800	1800	1800	1800	1800

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$. All columns include industry dummies, a London dummy and a linear trend. Market clustered standard errors in parenthesis. Estimator's limiting distribution with degrees of freedom correction.‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2).

Table A.7: Production Function With Capital and Two Nests: Workforce Jobs Employment Skill

	Baseline	Changes on TFP Specification		Changes on Parametric Restrictions (w quadratic time trend)		
		Quadratic Trend	Industry Trends	Free ρ	Free ρ, δ_H, δ_L	Unrestricted
ν	0.539 ***	0.541 ***	0.422 ***	0.476 ***	0.492 ***	0.497 ***
	(0.086)	(0.087)	(0.089)	(0.069)	(0.084)	(0.084)
ρ	1.000	1.000	1.000	10.424	9.938	10.384
	.	.	.	(15.948)	(14.298)	(14.823)
δ	0.798 ***	0.793 ***	0.812 ***	1.000 ***	1.000 ***	1.000 ***
	(0.066)	(0.067)	(0.067)	(0.001)	(0.001)	(0.004)
ρ_H	.	.	.	.	.	-0.113
	.	.	.	.	.	(0.858)
δ_H	.	.	.	.	0.566 **	0.775 *
	.	.	.	.	(0.179)	(0.300)
ρ_L	.	.	.	.	.	0.570 †
	.	.	.	.	.	(0.333)
δ_L	.	.	.	.	0.523 ***	0.498 ***
	.	.	.	.	(0.129)	(0.133)
δ_2	0.567 ***	0.557 ***	0.639 ***	0.518 ***	.	.
	(0.120)	(0.116)	(0.138)	(0.130)	.	.
ρ_2	0.497 †	0.520 *	0.341	0.476 †	0.465	.
	(0.254)	(0.249)	(0.262)	(0.283)	(0.290)	.
$\overline{MRTS_H}$	0.527	0.526	0.557	0.418	0.499	0.574
	(0.162)	(0.160)	(0.190)	(0.116)	(0.237)	(0.399)
95% CI‡	$[0.289, 0.963]$	$[0.289, 0.956]$	$[0.286, 1.086]$	$[0.243, 0.719]$	$[0.197, 1.264]$	$[0.147, 2.243]$
$\overline{MRTS_L}$	0.535	0.533	0.572	0.424	0.427	0.456
	(0.164)	(0.161)	(0.199)	(0.117)	(0.112)	(0.126)
95% CI‡	$[0.294, 0.975]$	$[0.294, 0.965]$	$[0.289, 1.131]$	$[0.247, 0.730]$	$[0.255, 0.714]$	$[0.265, 0.783]$
Observations	1800	1800	1800	1800	1800	1800

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$. All columns include industry dummies, a London dummy and a linear trend. Market clustered standard errors in parenthesis. Estimator's limiting distribution with degrees of freedom correction.‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2).

A.4 Using Hours Instead of Headcount

Table A.8: Production Function With Capital: Deep Parameters Hours

	Log-approx	Log-approx	Log-approx	Kmenta	NLS
ρ	1.000	0.872	0.930	0.033	0.930**
	(.)	(.)	(.)	(0.130)	(0.318)
δ	0.602***	0.597***	0.597***	0.962***	0.238*
	(0.094)	(0.077)	(0.083)	(0.050)	(0.112)
ν	0.440***	0.447***	0.444***	0.417***	0.522***
	(0.082)	(0.082)	(0.082)	(0.072)	(0.091)
$\overline{MRTS}$	1.512	1.112	1.264	4.201	0.267
	(0.593)	(0.354)	(0.437)	(5.256)	(0.075)
95% CI‡	$[0.701, 3.261]$	$[0.595, 2.077]$	$[0.642, 2.491]$	$[0.362, 48.794]$	$[0.154, 0.464]$
Spe.Test (P-val)	0.077	0.074	0.076	0.078	
Observations	1908	1908	1908	1908	1908

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors other than for NLS are delta method from market clustered variance-covariance matrix estimate. All regressions but NLS include additive dummies for industry, region and a linear time trend. NLS includes controls for industry, London and a time trend. ‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2)

Table A.9: Production Function With Capital: Deep Parameters Hours (IV)

	Log-approx	Log-approx	Log-approx
ρ	1.000	0.872	0.930
	(.)	(.)	(.)
δ	0.324**	0.376**	0.349**
	(0.107)	(0.122)	(0.114)
ν	0.533***	0.521***	0.528***
	(0.143)	(0.139)	(0.141)
$\overline{MRTS}$	0.478	0.453	0.458
	(0.235)	(0.236)	(0.230)
95% CI‡	$[0.183, 1.251]$	$[0.163, 1.259]$	$[0.172, 1.223]$
F-Stat	15.926	18.365	17.112
Endog Stat	1.943	1.232	1.571
Endog P-val	0.163	0.267	0.210
Spe.Test (P-val)	0.074	0.073	0.073
Observations	1908	1908	1908

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are delta method from market clustered variance-covariance matrix estimate. All regressions include additive dummies for industry, region and a linear time trend. ‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2)

Table A.10: Production Function With Capital and Two Nests: Total Hours of Work

	Baseline	Changes on TFP Specification		Changes on Parametric Restrictions (w quadratic time trend)		
		Quadratic Trend	Industry Trends	Free ρ	Free ρ, δ_H, δ_L	Unrestricted
ν	0.504 ***	0.509 ***	0.390 ***	0.511 ***	0.497 ***	0.502 ***
	(0.086)	(0.086)	(0.078)	(0.092)	(0.097)	(0.100)
ρ	1.000	1.000	1.000	0.946 *	0.777	0.820
	.	.	.	(0.436)	(0.503)	(0.533)
δ	0.720 ***	0.713 ***	0.775 ***	0.707 ***	0.694 ***	0.687 ***
	(0.098)	(0.098)	(0.102)	(0.108)	(0.101)	(0.105)
ρ_H	.	.	.	.	.	0.844
	.	.	.	.	.	(0.577)
δ_H	.	.	.	.	0.206	0.264
	.	.	.	.	(0.130)	(0.261)
ρ_L	.	.	.	.	.	1.114 †
	.	.	.	.	.	(0.618)
δ_L	.	.	.	.	0.292 †	0.263
	.	.	.	.	(0.169)	(0.210)
δ_2	0.289 *	0.280 *	0.403 *	0.280 *	.	.
	(0.135)	(0.131)	(0.196)	(0.135)	.	.
ρ_2	0.929 *	0.960 **	0.749 †	0.963 **	1.011 **	.
	(0.356)	(0.353)	(0.408)	(0.347)	(0.347)	.
$\overline{MRTS_H}$	0.343	0.353	0.382	0.356	0.266	0.250
	(0.118)	(0.127)	(0.138)	(0.123)	(0.155)	(0.120)
95% CI‡	$[0.175, 0.671]$	$[0.175, 0.712]$	$[0.188, 0.775]$	$[0.180, 0.702]$	$[0.085, 0.835]$	$[0.097, 0.642]$
$\overline{MRTS_L}$	0.344	0.354	0.388	0.357	0.423	0.470
	(0.113)	(0.121)	(0.137)	(0.118)	(0.213)	(0.332)
95% CI‡	$[0.181, 0.657]$	$[0.181, 0.691]$	$[0.193, 0.777]$	$[0.187, 0.683]$	$[0.157, 1.136]$	$[0.118, 1.877]$
Observations	1795	1795	1795	1795	1795	1795

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$. All columns include industry dummies, a London dummy and a linear trend. Market clustered standard errors in parenthesis. Estimator's limiting distribution with degrees of freedom correction.‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2).

A.5 Distinguishing EEA and non-EEA

We now introduce some changes on specification. First we explore whether we can identify differences between EEA and non EEA. To do this we re-specify our production function as

$$
\begin{aligned}
Y &= AK^{1-\nu}\psi^{\frac{\nu}{\rho}} \\
\psi &= [\delta H^{\rho/\rho_H} + (1-\delta)L^{\rho/\rho_L}] \\
H &\equiv \left[N_H^{\rho_H} + \theta_1^H EEA_H^{\rho_H} + \theta_2^H O_H^{\rho_H}\right] \\
L &\equiv \left[N_L^{\rho_L} + \theta_1^L EEA_L^{\rho_L} + \theta_2^L O_L^{\rho_L}\right]
\end{aligned}
$$

Where without further loss of generality we have performed a different normalization on the native efficiency parameters. Now –for example– EEA are more productive than natives at a point EEA $\approx$ N if $\theta > 1$. We applied a similar change to the one nest specification. In terms of the estimates we observe that efficiency parameters are typically noisily estimated and –for the single nest specification– sometimes outside the economically meaningful space. Moreover, given this estimates and the noise they carry we are not able to detect any difference between EEA and non EEA. Finally, in terms of the IV, we see that we have a weak instrument problem.

Table A.11: Reduced Form With Capital: EEA and non-EEA

	OLS			IV		
	$\rho = 1$	$\rho = .87$	$\rho = .44$	$\rho = 1$	$\rho = .87$	$\rho = .44$
$\ln N$	0.515***	0.521***	0.519***	0.553***	0.558***	0.450***
	(0.075)	(0.075)	(0.075)	(0.115)	(0.120)	(0.127)
$\ln K$	0.910***	0.905***	0.899***	0.914***	0.905***	0.948***
	(0.157)	(0.157)	(0.156)	(0.184)	(0.180)	(0.195)
EEA/N	0.783**			-0.170		
	(0.247)			(1.117)		
O/N	0.023			1.619		
	(0.206)			(1.120)		
$(EEA/N)^{.87}$		0.756**			0.108	
		(0.227)			(0.999)	
$(O/N)^{.87}$		0.029			1.332	
		(0.196)			(0.989)	
$(EEA/N)^{.44}$			0.576***			0.072
			(0.166)			(0.766)
$(O/N)^{.44}$			-0.069			-0.388
			(0.158)			(0.624)
	1st Stage			(EEA/N)	$(EEA/N)^{.87}$	$(EEA/N)^{.44}$
$\widetilde{EEA/N}$				0.416**		
				(0.134)		
$\widetilde{O/N}$				-0.033		
				(0.094)		
$(\widetilde{EEA/N})^{.87}$					0.376***	
					(0.111)	
$(\widetilde{O/N})^{.87}$					-0.026	
					(0.086)	
$(\widetilde{EEA/N})^{.44}$						0.279***
						(0.057)
$(\widetilde{O/N})^{.44}$						-0.052
						(0.069)
	2nd Stage			(O/N)	$(O/N)^{.87}$	$(O/N)^{.44}$
$\widetilde{EEA/N}$				-0.032		
				(0.187)		
$\widetilde{O/N}$				0.609**		
				(0.187)		
$(\widetilde{EEA/N})^{.87}$					-0.022	
					(0.140)	
$(\widetilde{O/N})^{.87}$					0.544***	
					(0.159)	
$(\widetilde{EEA/N})^{.44}$						-0.053
						(0.050)
$(\widetilde{O/N})^{.44}$						0.367***
						(0.070)
F-Stat				5.277	6.335	8.684
Endog Stat				2.957	2.332	0.598
Endog P-val				0.228	0.312	0.742
Spe.Test (P-val)	0.020	0.019	0.019	0.024	0.023	0.024
Observations	1,740	1,740	1,740	1,740	1,740	1,740

Market clustered standard errors in parenthesis. All regressions include region and industry dummies; and a linear time trend. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.12: Production Function With Capital: EEA and non-EEA

	Log-approx	Log-approx	Log-approx	NLS
ρ	1.000	0.872	0.445	0.445
	(.)	(.)	(.)	(0.306)
θ_1	1.521***	1.265***	0.493***	1.044
	(0.418)	(0.337)	(0.137)	(0.970)
θ_2	0.044	0.048	-0.059	0.858
	(0.223)	(0.183)	(0.071)	(0.606)
ν	0.515***	0.521***	0.519***	0.532***
	(0.075)	(0.075)	(0.075)	(0.095)
$\overline{MRTS}_{EEA}$	0.657	0.527	0.386	0.182
	(0.181)	(0.140)	(0.107)	(0.061)
95% CI‡	$[0.383, 1.127]$	$[0.313, 0.888]$	$[0.224, 0.666]$	$[0.094, 0.352]$
$\overline{MRTS}_{O}$	22.761	15.167	-4.893	0.337
	(115.459)	(57.346)	(5.887)	(0.116)
95% CI‡	$[0.001, 4.732e^5]$	$[0.009, 2.508e^4]$	[., .]	$[0.171, 0.662]$
Spe.Test (P-val)	0.020	0.019	0.019	
Observations	1740	1740	1740	1740

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors other than for NLS are delta method from market clustered variance-covariance matrix estimate. All regressions but NLS include additive dummies for industry, region and a linear time trend. NLS includes controls for industry, London and a time trend. ‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2)

Table A.13: Production Function With Capital: EEA and non-EEA (IV)

	Log-approx	Log-approx	Log-approx
ρ	1.000	0.872	0.445
	(.)	(.)	(.)
θ_1	-0.307	0.168	0.071
	(2.646)	(2.073)	(1.071)
θ_2	2.925***	2.083***	-0.384***
	(0.064)	(0.036)	(0.020)
ν	0.553***	0.558***	0.450***
	(0.115)	(0.120)	(0.127)
$\overline{MRTS}_{EEA}$	-3.261	3.967	2.686
	(28.129)	(48.892)	(40.622)
95% CI‡	[., .]	$[0.000, 1.227\text{e}^{11}]$	$[0.000, 2.013\text{e}^{13}]$
$\overline{MRTS}_{O}$	0.342	0.353	-0.754
	(0.007)	(0.006)	(0.039)
95% CI‡	[0.328, 0.357]	[0.341, 0.365]	[., .]
F-Stat	5.277	6.335	8.684
Endog Stat	2.957	2.332	0.598
Endog P-val	0.228	0.312	0.742
Spe.Test (P-val)	0.024	0.023	0.024
Observations	1740	1740	1740

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are delta method from market clustered variance-covariance matrix estimate. All regressions include additive dummies for industry, region and a linear time trend. ‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2)

Table A.14: Production Function With Capital and Two Nests: EEA and non-EEA

	Baseline	Free ρ
ν	0.516 ***	0.527 ***
	(0.089)	(0.101)
ρ	1.000	0.804 *
	.	(0.362)
δ	0.843 ***	0.811 ***
	(0.065)	(0.105)
ρ_2	0.597 *	0.606 *
	(0.288)	(0.292)
θ_2	0.896	0.919
	(0.789)	(0.812)
θ_3	1.081	1.045
	(0.773)	(0.829)
$\overline{MRTS}_H^{EEA}$	0.299	0.300
	(0.140)	(0.137)
95% CI‡	$[0.119, 0.751]$	$[0.123, 0.733]$
$\overline{MRTS}_H^{Other}$	0.375	0.396
	(0.147)	(0.173)
95% CI‡	$[0.174, 0.807]$	$[0.168, 0.932]$
$\overline{MRTS}_L^{EEA}$	0.331	0.332
	(0.151)	(0.146)
95% CI‡	$[0.136, 0.811]$	$[0.140, 0.788]$
$\overline{MRTS}_L^{Other}$	0.363	0.384
	(0.142)	(0.167)
95% CI‡	$[0.169, 0.782]$	$[0.163, 0.901]$
Observations	1400	1400

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$. All columns include industry dummies, a London dummy and a quadratic trend. Market clustered standard errors in parenthesis. Estimator's limiting distribution with degrees of freedom correction.‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2).

A.5.1 Free Native Efficiency Parameters

Recall that –given competitive labour markets– workers are paid their marginal product. We can use this to let free the native efficiency parameters –variation within market-years– and recover then from relative-aggregate-wages. It follows from the firm first-order conditions that

$$\begin{aligned}\delta_{qirt} &= \frac{w_{Nqirt} N_{qirt}^{1-\rho_q}}{w_{Iqirt} I_{qirt}^{1-\rho_q} + w_{Nqirt} N_{qirt}^{1-\rho_q}} \\ &= \frac{WB_{Nqirt} N_{qirt}^{-\rho_q}}{WB_{Iqirt} I_{qirt}^{-\rho_q} + WB_{Nqirt} N_{qirt}^{-\rho_q}}\end{aligned} \tag{A.2}$$

Where the second equality follows from noting that if we use mean wages to measure wage paid in a given market-year-country of birth-occupational level $-w_{Nqirt}-$ we can re-express them in terms of the wage bill $-WB_{Nqirt}-$ and labour $-N_{qirt}-$. A similar extraction procedure is followed in Peri (2012) with the caveat that we let the quantity as a function of the unknown parameter ρ_q $(q = H, L)$ that is to be estimated. Note that (A.2) implies that we a have a noiseless measure of the market-year-occupation-immigration status wage bill[50] and that all variation within market-years is due to structural change on the native efficiency parameter, what can be rather stringent. We can substitute (A.2) into (6) to obtain

$$\begin{aligned} Y_{irt} &= A_{irt}K_{irt}^{1-\nu}[\delta H_{irt}^{\rho} + (1-\delta)L_{irt}^{\rho}]^{1/\rho} \\ H_{irt} &= \left[\frac{WB_{NHirt} + WB_{IHirt}}{WB_{IHirt}I_{Hirt}^{-\rho_H} + WB_{NHirt}N_{Hirt}^{-\rho_H}}\right]^{1/\rho_H} \\ L_{irt} &= \left[\frac{WB_{NLirt} + WB_{ILirt}}{WB_{ILirt}I_{Lirt}^{-\rho_L} + WB_{NLirt}N_{Lirt}^{-\rho_L}}\right]^{1/\rho_L} \end{aligned} \tag{A.3}$$

It is clear from the system in (A.3) that now there are two parameters less to be estimated. When we try to fit the tow nest specification we are only able to achieve convergence for the Baseline specification –restricted $\rho_H = \rho_L = \rho_2$–; and the estimated immigrant native elasticity of substitution parameter is very noisy.

[50]Note that wages do not need to be deflated, any common proportional factor drops out of (A.2).

Table A.15: Production Function With Capital and Two Nests: Free Efficiency Parameters

	Baseline
ν	0.356 ***
	(0.083)
ρ	1.000
	.
δ	0.788 ***
	(0.085)
ρ_2	1.534 ***
	(0.245)
$\overline{MRTS}_H$	1.047
	(.)
95% CI[‡]	[., .]
$\overline{MRTS}_L$	1.221
	(.)
95% CI[‡]	[., .]
Observations	1563

[†] $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$. All columns include industry dummies, a London dummy and a quadratic trend. Market clustered standard errors in parenthesis. Estimator's limiting distribution with degrees of freedom correction.[‡] Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2).

A.5.2 Changes on the Nesting Structure

To make the new specification explicit let us write

$$\begin{aligned} Y &= AH^{(1-\varphi)/\rho_H} C^{\varphi/\vartheta} \\ H &= [\delta_H N_H^{\rho_H} + (1-\delta_H) I_H^{\rho_H}] \\ C &= [K^{\vartheta} + \varpi L^{\vartheta/\rho_L}] \\ L &= [\delta_L N_L^{\rho_L} + (1-\delta_L) I_L^{\rho_L}] \end{aligned} \tag{A.4}$$

Where we have made changes on notation for those parameters that change interpretation. Furthermore, for estimation we need to re-parametrize the model such that we normalize the capital efficiency parameter to one and let the low skilled labour efficiency parameter –ϖ– free. We observe that the native efficiency and elasticity of substitution parameters are within a neighbourhood of those obtained with our main specification. In terms of MRTS, point estimates are always below one but confidence intervals are only bounded below one in the second column for high and low skilled; and in the last two for high skilled.

Table A.16: Production Function With Capital and Two Nests: Nested Capital

	Baseline	Free φ	Free δ_H, δ_L	Unrestricted
φ	0.500	0.672 ***	0.671 ***	0.680 ***
	.	(0.070)	(0.067)	(0.067)
ϑ	0.272	0.244	0.244	0.278
	(0.827)	(0.420)	(0.416)	(0.412)
ϖ	0.193	0.380	0.380	0.352
	(0.188)	(0.260)	(0.271)	(0.274)
ρ_H	.	.	.	0.992 **
	.	.	.	(0.349)
δ_H	.	.	0.392 *	0.284 †
	.	.	(0.154)	(0.145)
ρ_L	.	.	.	0.362
	.	.	.	(0.958)
δ_L	.	.	0.387	0.551
	.	.	(0.244)	(0.480)
δ_2	0.490 ***	0.390 *	.	.
	(0.137)	(0.181)	.	.
ρ_2	0.794 **	0.764 *	0.762 *	.
	(0.279)	(0.379)	(0.365)	.
$\overline{MRTS_H}$	0.632	0.397	0.400	0.391
	(0.174)	(0.110)	(0.118)	(0.118)
95% CI‡	[0.368, 1.086]	[0.230, 0.684]	[0.224, 0.713]	[0.217, 0.706]
$\overline{MRTS_L}$	0.635	0.398	0.392	0.380
	(0.175)	(0.110)	(0.250)	(0.244)
95% CI‡	[0.370, 1.088]	[0.231, 0.686]	[0.113, 1.367]	[0.108, 1.339]
Observations	1800	1800	1800	1800

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$. All columns include industry dummies, a London dummy and a quadratic trend. Market clustered standard errors in parenthesis. Estimator's limiting distribution with degrees of freedom correction.‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2).

A.6 Region-Industry Interactions

We now produce estimates for the single nest specification introducing region-industry dummies in the TFP specification. Introducing market fix effects implies that now our instrument lives out of market-year/region-year/industry-year level –or lower–; as permanent shocks at the industry, region or market level are accounted for by the dummies. Goldsmith-Pinkham et al. (2017) show that identification with instruments of the form share at a base level times growth rates, relies on variation in terms of the shares, while the growth rate component gives us first-stage power. In our set-up, variation of the base level is at the market level thus by introducing market fix effects we may leave few to no variation for the instrument to identify the parameters of interest. Indeed we see that –now– the native efficiency parameters are very noisily estimated –standard errors up to twice the size of the estimate, see also the underlying reduced form parameters in table A.17–; and the MRTS we compute from them are either outside any economically meaningful space or informative-less due to the length of their confidence intervals.

Table A.17: Reduced Form Parameters With Capital: Region-Industry Interactions

	OLS				IV			
	$\rho = 1$	$\rho = .87$	$\rho = .55$	Kmenta	$\rho = 1$	$\rho = .87$	$\rho = .55$	Kmenta
I/N	0.104				-0.033			
	(0.074)				(0.321)			
$(I/N)^{.87}$		0.102				-0.015		
		(0.071)				(0.337)		
$(I/N)^{.55}$			0.077				0.019	
			(0.064)				(0.297)	
$\ln N$	0.198***	0.198***	0.197***	0.180***	0.184***	0.185***	0.189***	0.201***
	(0.041)	(0.042)	(0.042)	(0.040)	(0.050)	(0.054)	(0.055)	(0.052)
$\ln I$				0.012				-0.016
				(0.013)				(0.057)
$(\ln N/I)^2$				0.001				-0.004
				(0.001)				(0.005)
$\ln K$	0.111	0.110	0.105	0.103	0.099	0.101	0.103	0.092
	(0.106)	(0.106)	(0.106)	(0.106)	(0.092)	(0.092)	(0.096)	(0.105)
	1$^{\text{st}}$ Stage							$(\ln N/I)^2$
$(\ln \tilde{N/I})^2$								-0.218***
								(0.048)
$\ln \tilde{I}$								-4.332***
								(1.064)
	1$^{\text{st}}$ Stage				I/N	$(I/N)^{.87}$	$(I/N)^{.55}$	$\ln I$
$\tilde{I/N}$					0.619***			
					(0.161)			
$(\tilde{I/N})^{.87}$						0.559***		
						(0.153)		
$(\tilde{I/N})^{.55}$							0.469***	
							(0.112)	
$\ln \tilde{I}$								0.506***
								(0.079)
$(\ln \tilde{N/I})^2$								0.020***
								(0.003)
F-Stat					14.858	13.266	17.455	3.118
Endog Stat					0.243	0.157	0.045	1.275
Endog P-val					0.622	0.692	0.832	0.529
Spe.Test (P-val)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	1,908	1,908	1,908	1,908	1,908	1,908	1,908	1,908

Market clustered standard errors in parenthesis. All regressions include region and industry dummies; and a linear time trend.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.18: Production Function With Capital: Region-Industry Interactions

	Log-approx	Log-approx	Log-approx	Kmenta
ρ	1.000	0.872	0.555	0.208*
	(.)	(.)	(.)	(0.101)
δ	0.655***	0.690***	0.821***	0.935***
	(0.161)	(0.146)	(0.117)	(0.066)
ν	0.198***	0.198***	0.197***	0.192***
	(0.041)	(0.042)	(0.042)	(0.042)
$\overline{MRTS}$	1.902	1.717	1.964	3.532
	(1.353)	(1.173)	(1.565)	(4.297)
95% CI‡	$[0.471, 7.672]$	$[0.450, 6.551]$	$[0.412, 9.361]$	$[0.325, 38.328]$
Spe.Test (P-val)	0.000	0.000	0.000	0.000
Observations	1908	1908	1908	1908

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors other than for NLS are delta method from market clustered variance-covariance matrix estimate. All regressions but NLS include additive dummies for industry, region and a linear time trend. NLS includes controls for industry, London and a time trend. ‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2)

Table A.19: Production Function With Capital: Region-Industry Interactions (IV)

	Log-approx	Log-approx	Log-approx
ρ	1.000	0.872	0.555
	(.)	(.)	(.)
δ	1.222	1.077	0.946
	(2.661)	(1.857)	(0.769)
ν	0.184***	0.185***	0.189***
	(0.050)	(0.054)	(0.055)
$\overline{MRTS}$	-5.502	-10.754	7.564
	(53.943)	(239.690)	(114.773)
95% CI‡	[., .]	[., .]	$[0.000, 6.220\text{e}^{13}]$
F-Stat	14.858	13.266	17.455
Endog Stat	0.243	0.157	0.045
Endog P-val	0.622	0.692	0.832
Spe.Test (P-val)	0.000	0.000	0.000
Observations	1908	1908	1908

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are delta method from market clustered variance-covariance matrix estimate. All regressions include additive dummies for market, industry, region and a linear time trend. ‡ Confidence intervals computed with modified metric such that they are constrained in $[0, \infty)$ (see appendix B.2)

A.7 Production Function Decomposition

We now use a similar decomposition to Peri (2012). Differently from the main body of this paper, now we do not estimate the parameters of the underlying production function but reduced form effects on different quantities determining the production function. We make some modifications on our production function to make it more similar to Peri (2012). However, note that we do not use Peri (2012) exact specification. In his work, the production function takes two types of labour differentiated by education with no explicit differentiation between immigrant and native labour. For internal consistency we modify his specification to take immigrant and native labour. Let the new specification be

$$Y = K^{\alpha}[XA\psi(h)]^{1-\alpha}$$
$$\psi(h) = \left[(\beta h)^{(\sigma-1)/\sigma} + ((1-\beta)(1-h))^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)}$$

Where X are total hours supplied for both immigrants and natives and h is the share of hours supplied by natives. We fix $\alpha = .33$, and σ to Manacorda et al. (2012) estimate. Native efficiency parameters –β– are pinned down from wage information in a similar way to section A.5.1. We also define the following quantities, $E = N + I$, $y = Y/E$, $k = K/Y$ and $x = X/E$.

Table A.20: Peri (2012) Decomposition

	OLS		IV	
	Level	First Diff	Level	First Diff
$\ln E$	0.501	0.614***	3.396	1.022**
	(0.444)	(0.160)	(1.796)	(0.386)
$\ln y$	-0.436	-0.652***	4.105	-1.098**
	(0.338)	(0.155)	(2.616)	(0.407)
$\frac{\alpha}{1-\alpha} \ln k$	0.038	0.081	-4.062	0.174
	(0.686)	(0.073)	(3.894)	(0.285)
$\ln A$	0.868	0.511**	8.447	-0.693
	(0.977)	(0.191)	(5.991)	(0.846)
$\ln x$	-0.879***	-0.823***	0.297	-0.167
	(0.062)	(0.035)	(0.564)	(0.454)
$\ln \psi$	-0.463***	-0.421***	-0.577***	-0.412
	(0.044)	(0.064)	(0.158)	(0.241)
$\ln h$	-0.601***	-0.539***	-0.782***	-0.459***
	(0.045)	(0.034)	(0.229)	(0.072)
$\ln \beta$	-0.595***	-0.554***	-0.614*	-0.557
	(0.074)	(0.121)	(0.281)	(0.315)
	First Stage		$\frac{I}{I+N}$	
$\frac{\tilde{I}}{\tilde{I}+N}$			0.646***	1.228***
			(0.093)	(0.310)
F-Stat			48.743	15.702
Endog Stat			3.119	1.473
Endog P-val			0.077	0.225
Observations	1,692	1,508	1,692	1,508

Market clustered standard errors in parenthesis. All regressions include region, industry and year dummies. Estimates are scaled up by a factor of 1000 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.8 Immigration Through Other Channels

Table A.21: Native Employment and Immigration

	$\ln N_L$		$\ln N_H$	
	OLS	IV	OLS	IV
I_L	-0.001	-0.002	-0.001	-0.001
	(0.001)	(0.002)	(0.001)	(0.002)
I_H	0.009	0.004	0.007	-0.001
	(0.004)	(0.003)	(0.005)	(0.003)
		First Stage I_H		
$\tilde{I}_L$		-0.108***		-0.108***
		(0.021)		(0.021)
$\tilde{I}_H$		0.748***		0.748***
		(0.066)		(0.066)
		First Stage I_L		
$\tilde{I}_L$		0.614***		0.614***
		(0.113)		(0.113)
$\tilde{I}_H$		0.246*		0.246*
		(0.112)		(0.112)
F-Stat		50.234		50.234
Endog Stat		6.036		6.306
Endog P-val		0.049		0.043
Observations	1,800	1,800	1,800	1,800

Market clustered standard errors in parenthesis. All regressions include region, industry and year dummies. Estimates are scaled up by a factor of 1000 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.22: GFCF and Immigration

	OLS	IV
I_H	0.010	0.002
	(0.005)	(0.003)
I_L	0.001	0.001
	(0.002)	(0.002)
	First Stage I_H	
$\tilde{I_H}$		0.748***
		(0.066)
$\tilde{I_L}$		-0.108***
		(0.021)
	First Stage I_L	
$\tilde{I_H}$		0.246*
		(0.112)
$\tilde{I_L}$		0.614***
		(0.113)
F-Stat		50.234
Endog Stat		5.908
Endog P-val		0.052
Observations	1,800	1,800

Industry clustered standard errors in parenthesis. All regressions include region, industry and year dummies. Estimates are scaled to represent changes in thousands of immigrants. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.23: TFP and Immigration: Two Nest Immigration Through TFP

	Ratio	Level	Level and Ratio
β_1	.	0.001	0.000
	.	(0.001)	(0.001)
β_2	.	0.001	0.001
	.	(0.000)	(0.000)
β_3	.	.	0.000
	.	.	(0.001)
β_4	.	.	0.000
	.	.	(0.000)
β_5	-0.031	.	0.028
	(0.203)	.	(0.179)
β_6	0.091	.	0.089
	(0.320)	.	(0.299)
$\frac{\partial \ln TFP}{\partial I_H} 100$	-0.001	0.071	0.026
	(0.007)	(0.084)	(0.092)
$\frac{\partial \ln TFP}{\partial I_L} 100$	0.000	0.069	0.051
	(0.001)	(0.045)	(0.043)
Observations	1800	1800	1800

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$. All columns include industry dummies, a London dummy and a quadratic trend. ρ fix at 1. Market clustered standard errors in parenthesis. Estimates scaled to represent changes in thousands of immigrant employment. TFP semi-elasticities computed at weighted means.

A.9 Immigration and Capital Stock by Asset Type

Here we complement the immigration and capital investment estimates in section 4.2 with immigration and capital stock estimates at the national level by asset type, for which there is data available produced by UK ONS.

Table A.24: Capital and Immigration

	Total	Buildings	IPP	Software	Other Mach.
			OLS		
I_H	0.001	0.001	-0.000	0.002*	0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
I_L	0.001*	0.001**	0.002*	0.001	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
			IV		
I_H	0.000	0.000	0.001	0.005**	0.003
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
I_L	0.001	0.001	0.000	-0.001	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
			First Stage I_H		
$\tilde{I_H}$	0.834***	0.834***	0.834***	0.833***	0.834***
	(0.085)	(0.085)	(0.085)	(0.085)	(0.085)
$\tilde{I_L}$	-0.095**	-0.095**	-0.095**	-0.095**	-0.095**
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
			First Stage I_L		
$\tilde{I_H}$	0.671*	0.671*	0.671*	0.672*	0.671*
	(0.271)	(0.271)	(0.271)	(0.271)	(0.271)
$\tilde{I_L}$	0.709***	0.709***	0.709***	0.709***	0.709***
	(0.177)	(0.177)	(0.177)	(0.177)	(0.177)
F-Stat	24.689	24.689	24.689	24.717	24.689
Endog Stat	2.048	5.400	4.722	5.124	1.061
Endog P-val	0.359	0.067	0.094	0.077	0.588
Observations	558	558	558	556	558

Industry clustered standard errors in parenthesis. All regressions include region, industry and year dummies. Estimates are scaled to represent changes in thousands of immigrants.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Technical Appendix

B.1 Deep-parameters and Reduced Forms

B.1.1 Kmenta (1967)

Actual equation

$$\ln Y_{irt} \approx \ln A_{irt} + \nu\delta \ln(N_{irt}) + (1-\delta)\nu \ln(I_{irt}) + \frac{\nu\delta(1-\delta)\rho}{2}\left(\ln \frac{N_{irt}}{I_{irt}}\right)^2$$

Reduced form

$$\ln(\hat{Y}) = b_0 + b_1 \ln(N) + b_2 \ln(I) + b_3 \left(\ln \frac{N}{I}\right)^2$$

Parameters

$$\hat{\nu} = b_1 + b_2$$
$$\hat{\delta} = \frac{b_1}{b_1 + b_2}$$
$$\hat{\rho} = \frac{2b_3(b_1 + b_2)}{b_1 b_2}$$

B.1.2 Log-Approximation

Actual equation

$$\ln Y_{irt} \approx \ln A_{irt} + \nu \ln \delta + \nu \ln N_{irt} + \frac{\nu}{\rho}\frac{(1-\delta)}{\delta}\left(\frac{I_{irt}}{N_{irt}}\right)^\rho \tag{B.1}$$

Reduced form

$$\ln(\hat{Y}) = b_0 + b_1 \ln(N) + b_2 \left(\frac{I}{N}\right)^{\bar{\rho}}$$

Where $\bar{\rho}$ is some number in $(-\infty, 1]$ that has been imposed.
Parameters

$$\hat{\nu} = b_1$$
$$\hat{\delta} = \frac{b_1}{b_1 + b_2\bar{\rho}}$$

B.1.3 Log-Approximation: EEA and Non-EEA

Actual equation

$$\ln Y_{irt} \approx \ln A_{irt} + \nu \ln N_{irt} + \frac{\nu}{\rho}\theta_1\left(\frac{EEA_{irt}}{N_{irt}}\right)^\rho + \frac{\nu}{\rho}\theta_2\left(\frac{NEEA_{irt}}{N_{irt}}\right)^\rho$$

Reduced form

$$\ln(\hat{Y}) = b_0 + b_1 \ln(N) + b_2 \left(\frac{EEA}{N}\right)^{\bar{\rho}} + b_3\left(\frac{NEEA}{N}\right)^{\bar{\rho}}$$

Where $\bar{\rho}$ is some number in $(-\infty, 1]$ that has been imposed.

Parameters

$$\hat{\nu} = b_1$$
$$\hat{\theta}_1 = \frac{b_2\bar{\rho}}{b_1}$$
$$\hat{\theta}_2 = \frac{b_3\bar{\rho}}{b_1}$$

B.2 Estimated MRTS and its Variance

We estimate the MRTS by using weighted means, where weights are obtained from the GVA contribution of each market to the national economy aggregated across time, i.e.

$$\overline{MRTS} = \frac{\sum_i \sum_r \sum_t MRTS_{irt} * GVA_{irt}}{\sum_i \sum_r \sum_t GVA_{irt}}$$

Then we use the covariance matrix for ρ and δ and the Jacobian of $\overline{MRTS}$ to estimate its variance. Where the non-zero elements of the Jacobian are

$$\frac{\partial \overline{MRTS}}{\partial \delta} = \sum_i \sum_r \sum_t \frac{1}{(1-\delta)^2} \left(\frac{N_{irt}}{I_{irt}}\right)^{\rho-1} \left(\sum_i \sum_r \sum_t GVA_{irt}\right)^{-1}$$
$$\frac{\partial \overline{MRTS}}{\partial \rho} = \sum_i \sum_r \sum_t \frac{\delta}{1-\delta} \left(\frac{N_{irt}}{I_{irt}}\right)^{\rho-1} \ln\left(\frac{N_{irt}}{I_{irt}}\right) \left(\sum_i \sum_r \sum_t GVA_{irt}\right)^{-1}$$

B.2.1 MRTS Confidence Interval

The MRTS is only economically meaningful within $[0, \infty)$. To constraint our confidence intervals to the non-negative segment of the real line we apply the following change of metric.

$$g(MRTS) = \log(MTRS)$$

Where the standard error of $g(MRTS)$ is given by

$$\text{SE}(g(MRTS)) = \frac{\text{SE}(MRTS)}{MRTS}$$

Then we can construct confidence intervals in $[0, \infty)$ for MRTS as

$$\left[\exp\left(\log(MRTS) - \text{crit} * \frac{\text{SE}(MRTS)}{MRTS}\right), \exp\left(\log(MRTS) + \text{crit} * \frac{\text{SE}(MRTS)}{MRTS}\right)\right]$$

Where crit is the relevant critical value and $\text{SE}(MRTS)$ has been computed as explained in the previous section.

C Reduced Form Parameters

Table C.1: Production Function: Reduced Form

	OLS				IV			
	$\rho = 1$	$\rho = .87$	$\rho = .74$	Kmenta	$\rho = 1$	$\rho = .87$	$\rho = .74$	Kmenta
I/N	0.394***				1.301**			
	(0.092)				(0.399)			
$(I/N)^{.87}$		0.479***				1.493***		
		(0.099)				(0.428)		
$(I/N)^{.74}$			0.576***				1.654***	
			(0.104)				(0.434)	
$\ln N$				0.771***				-0.391
				(0.059)				(0.329)
$\ln I$				0.232***				1.672***
				(0.032)				(0.373)
$(\ln N/I)^2$				0.017***				0.242***
				(0.003)				(0.067)
	1st Stage							$(\ln N/I)^2$
$\tilde{I}$								0.000
								(0.000)
$\ln \tilde{I}$								-1.231***
								(0.284)
	1st Stage				I/N	$(I/N)^{.87}$	$(I/N)^{.74}$	$\ln I$
$\widetilde{I/N}$					1.155***			
					(0.260)			
$(\widetilde{I/N})^{.87}$						0.973***		
						(0.211)		
$(\widetilde{I/N})^{.74}$							0.809***	
							(0.159)	
$\ln \tilde{I}$								0.191***
								(0.027)
$\tilde{I}$								0.000***
								(0.000)
F-Stat					19.678	21.256	25.776	3.529
Endog Stat					9.425	8.973	8.247	16.126
Endog P-val					0.002	0.003	0.004	0.000
Observations	5,878	5,878	5,878	5,878	5,878	5,878	5,878	5,878

Market clustered standard errors in parenthesis. All regressions include region and industry dummies; and a linear time trend. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.2: Production Function with Capital: Reduced Form

	OLS				IV			
	$\rho = 1$	$\rho = .87$	$\rho = .55$	Kmenta	$\rho = 1$	$\rho = .87$	$\rho = .55$	Kmenta
I/N	0.175				1.283			
	(0.103)				(0.957)			
$(I/N)^{.87}$		0.235*				1.180		
		(0.105)				(0.915)		
$(I/N)^{.55}$			0.327*				0.430	
			(0.126)				(0.672)	
$\ln N$	0.408***	0.415***	0.426***	0.359***	0.523***	0.517***	0.437***	-0.335
	(0.067)	(0.067)	(0.068)	(0.060)	(0.126)	(0.130)	(0.116)	(0.382)
$\ln I$				0.054				1.100
				(0.028)				(0.581)
$(\ln N/I)^2$				0.003				0.119
				(0.002)				(0.068)
$\ln K$	0.946***	0.942***	0.935***	0.941***	0.895***	0.893***	0.928***	0.649***
	(0.169)	(0.170)	(0.170)	(0.169)	(0.157)	(0.154)	(0.165)	(0.151)
	1st Stage							$(\ln N/I)^2$
$\tilde{I}$								0.000*
								(0.000)
$\ln \tilde{I}$								-1.261
								(0.652)
	1st Stage				I/N	$(I/N)^{.87}$	$(I/N)^{.55}$	$\ln I$
$\tilde{I/N}$					0.484***			
					(0.127)			
$(\tilde{I/N})^{.87}$						0.439***		
						(0.109)		
$(\tilde{I/N})^{.55}$							0.354***	
							(0.071)	
$\ln \tilde{I}$								0.166**
								(0.052)
$\tilde{I}$								-0.000
								(0.000)
F-Stat					14.536	16.224	24.979	7.207
Endog Stat					2.197	1.599	0.027	3.170
Endog P-val					0.138	0.206	0.869	0.205
Spe.Test (P-val)	0.061	0.058	0.054	0.057	0.066	0.065	0.063	0.042
Observations	1,908	1,908	1,908	1,908	1,908	1,908	1,908	1,908

Market clustered standard errors in parenthesis. All regressions include region and industry dummies; and a linear time trend.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.1 Descriptives

Table C.3: Employment figures, Occupational Distribution and Labour Productivity

	Primary Sector	Manufactures	Construction	Services	Total
	Total Employment (Thousands)				
Immigrant	126.315	644.570	260.292	3685.161	4716.338
Native	707.599	2428.059	1834.180	17739.757	22709.595
	Proportion in High Skilled Occupations				
Immigrant	0.322	0.214	0.175	0.301	0.282
Native	0.189	0.267	0.198	0.307	0.291
	Labour Productivity (£ per worker)				
	69889.614	53260.459	46846.604	58845.149	57638.986

Source: Labour Force Survey 2014 and UK ONS Regional Accounts

Table C.4: Immigrant to Native Ratios

	Primary Sector	Manufactures	Construction	Services	Total
	Immigrant/Native				
1998	0.046	0.069	0.036	0.085	0.077
2003	0.054	0.090	0.048	0.107	0.098
2005	0.077	0.123	0.061	0.121	0.114
2014	0.179	0.265	0.142	0.208	0.208
	Immigrant/Native High Skilled				
1998	0.095	0.071	0.054	0.104	0.096
2003	0.107	0.100	0.076	0.138	0.128
2005	0.135	0.125	0.077	0.144	0.137
2014	0.304	0.213	0.125	0.203	0.202
	Immigrant/Native Low Skilled				
1998	0.038	0.068	0.033	0.079	0.071
2003	0.045	0.088	0.043	0.096	0.088
2005	0.067	0.122	0.058	0.112	0.106
2014	0.149	0.285	0.146	0.210	0.210
	Ratio High to Low Skilled Relative Supplies †				
1998	2.524	1.036	1.657	1.323	1.347
2003	2.367	1.139	1.774	1.432	1.462
2005	2.032	1.023	1.321	1.287	1.292
2014	2.037	0.747	0.858	0.968	0.961

Source: Labour Force Survey and UK ONS Regional Accounts, own computation. †The last panel shows the ratio of immigrant–to–native in high skilled occupations over the same figure for low skilled.

Table C.5: Immigrant Share: Regions and Industries (32)

Industry	Immigrant Share											
	N. East	N. West	Yorksh/Humber	E. Midlands	W. Midlands	E. England	London	S. East	S. West	Wales	Scotland	N. Ireland	Total
A	0.000	0.099	0.132	0.218	0.145	0.195	0.586	0.239	0.109	0.047	0.138	0.018	0.151
B	0.000	0.215	0.243	0.000	0.000	0.229	0.479	0.388	0.000	0.000	0.108	0.000	0.179
CA	0.298	0.289	0.404	0.429	0.314	0.421	0.393	0.435	0.415	0.371	0.318	0.373	0.376
CB	0.117	0.307	0.249	0.374	0.310	0.111	0.452	0.206	0.226	0.000	0.000	0.000	0.246
CC	0.058	0.056	0.138	0.150	0.226	0.159	0.331	0.164	0.126	0.070	0.093	0.219	0.154
CD	0.122	0.000	0.170	0.000	0.000	0.689	0.342	0.093	0.000	0.000	0.090	0.000	0.125
CE	0.147	0.123	0.127	0.348	0.195	0.273	0.253	0.240	0.439	0.170	0.161	.	0.212
CF	0.303	0.093	0.445	0.327	0.162	0.276	0.705	0.370	0.000	0.000	0.126	0.281	0.281
CG	0.114	0.162	0.241	0.169	0.162	0.289	0.498	0.158	0.245	0.000	0.082	0.111	0.190
CH	0.030	0.147	0.077	0.173	0.111	0.168	0.531	0.178	0.133	0.000	0.107	0.128	0.128
CI	0.070	0.221	0.107	0.125	0.154	0.347	0.412	0.257	0.154	0.251	0.070	0.191	0.216
CJ	0.000	0.318	0.228	0.304	0.451	0.275	0.300	0.156	0.389	0.000	0.197	0.000	0.278
CK	0.185	0.153	0.198	0.203	0.178	0.235	0.637	0.166	0.196	0.196	0.151	0.248	0.208
CL	0.097	0.065	0.101	0.200	0.209	0.238	0.472	0.257	0.218	0.063	0.093	0.052	0.175
CM	0.072	0.113	0.141	0.133	0.146	0.180	0.384	0.173	0.116	0.094	0.050	0.120	0.148
D	0.077	0.092	0.035	0.131	0.138	0.129	0.178	0.169	0.132	0.069	0.132	0.000	0.121
E	0.052	0.145	0.239	0.044	0.243	0.175	0.365	0.174	0.170	0.000	0.125	0.000	0.163
F	0.085	0.061	0.069	0.069	0.079	0.074	0.419	0.099	0.059	0.048	0.084	0.058	0.124
G	0.069	0.101	0.095	0.160	0.135	0.141	0.404	0.161	0.091	0.070	0.099	0.070	0.151
H	0.134	0.165	0.145	0.186	0.238	0.186	0.424	0.193	0.179	0.098	0.069	0.101	0.211
I	0.189	0.285	0.203	0.200	0.299	0.252	0.709	0.336	0.272	0.205	0.217	0.222	0.330
J	0.066	0.139	0.162	0.147	0.155	0.178	0.344	0.214	0.140	0.145	0.170	0.208	0.220
K	0.095	0.066	0.081	0.123	0.140	0.079	0.308	0.147	0.113	0.070	0.079	0.098	0.171
L	0.115	0.148	0.071	0.156	0.150	0.181	0.322	0.129	0.105	0.000	0.054	0.000	0.152
M	0.096	0.082	0.109	0.128	0.112	0.145	0.287	0.157	0.101	0.121	0.121	0.031	0.166
N	0.091	0.116	0.168	0.185	0.165	0.177	0.528	0.189	0.116	0.118	0.140	0.130	0.221
O	0.070	0.065	0.078	0.094	0.066	0.141	0.235	0.119	0.075	0.080	0.086	0.033	0.110
P	0.075	0.083	0.077	0.078	0.085	0.094	0.309	0.123	0.069	0.056	0.076	0.066	0.117
Q	0.067	0.110	0.103	0.152	0.138	0.194	0.409	0.189	0.140	0.109	0.087	0.074	0.164
R	0.048	0.089	0.087	0.061	0.089	0.096	0.316	0.184	0.099	0.000	0.076	0.026	0.145
S	0.073	0.138	0.120	0.149	0.144	0.139	0.388	0.154	0.199	0.097	0.063	0.117	0.172
T	0.000	0.314	0.000	0.238	0.173	0.153	0.748	0.222	0.320	0.000	0.000	0.000	0.378
Total	0.088	0.117	0.122	0.153	0.145	0.160	0.380	0.175	0.129	0.088	0.105	0.093	0.172

Source: Labour Force Survey 2014

Table C.6: Labour Productivity: (12) Regions and (32) Industries

Industry	Labour Productivity (£ thousands per worker)											
	N. East	N. West	Yorksh/Humber	E. Midlands	W. Midlands	E. England	London	S. East	S. West	Wales	Scotland	N. Ireland	Total
A	42.993	37.313	47.607	49.261	48.980	53.327	2.660	26.558	48.994	25.263	40.336	28.864	39.798
B	107.693	35.313	31.590	125.262	31.179	32.215	12.359	38.509	128.424	25.625	59.838	62.096	52.093
CA	52.985	56.399	54.790	64.779	47.802	74.690	66.243	55.515	44.798	83.237	101.597	57.486	63.252
CB	26.764	54.422	47.335	64.318	29.198	44.225	53.753	23.261	42.657	17.534	52.047	19.531	44.855
CC	42.717	75.429	38.959	47.005	38.746	44.170	35.681	53.757	32.613	50.923	50.331	37.311	45.644
CD	7.843	110.902	41.526	22.148	34.945	43.256	3.200	40.495	62.654	28.809	42.348	24.363	40.280
CE	75.038	104.278	145.424	41.281	63.105	123.585	21.383	112.054	46.547	64.372	85.210	.	85.028
CF	157.761	221.019	124.295	45.203	22.194	94.077	32.308	57.263	124.484	66.440	149.962	28.298	97.177
CG	70.256	58.373	49.011	72.078	46.039	63.266	25.034	51.751	66.867	61.455	46.272	109.179	56.267
CH	48.298	62.522	47.978	70.425	50.486	52.626	54.363	51.820	43.080	48.350	69.182	44.850	53.334
CI	21.739	33.222	43.136	39.763	25.025	50.267	20.353	57.795	70.142	55.360	39.875	87.151	44.786
CJ	123.311	30.920	61.642	38.739	38.499	38.131	48.361	59.986	44.347	69.242	40.794	326.868	48.052
CK	68.367	40.132	36.333	40.783	40.780	59.416	16.079	62.480	28.348	32.965	54.337	48.560	44.249
CL	29.914	79.194	27.916	41.004	76.143	70.042	129.514	38.334	49.806	79.539	31.192	43.401	56.327
CM	27.346	36.591	26.195	37.254	30.878	29.859	30.813	41.959	30.355	79.114	43.224	30.957	36.353
D	125.541	79.355	120.021	141.247	156.079	87.276	126.150	152.556	98.288	103.671	131.560	190.059	122.702
E	55.132	60.153	65.535	69.953	50.969	69.543	112.529	123.293	106.700	64.177	100.539	56.518	79.621
F	35.651	39.211	35.710	44.585	39.463	64.644	62.244	58.390	36.559	31.120	41.932	35.088	46.847
G	37.619	48.450	34.874	45.784	47.291	45.781	71.687	64.682	44.094	31.296	50.029	53.590	50.167
H	37.359	35.756	40.044	39.920	36.412	52.051	80.469	61.166	43.761	36.466	44.782	54.874	50.920
I	23.174	32.263	27.350	28.317	33.906	32.445	56.248	39.809	34.831	28.318	34.102	26.576	36.337
J	84.181	67.317	50.051	49.853	65.347	73.924	115.255	101.860	51.899	50.787	73.181	55.426	85.291
K	96.522	108.411	83.552	81.721	109.166	95.783	106.530	126.027	100.923	98.587	92.538	71.523	103.012
L	404.682	374.188	492.940	645.221	605.220	653.557	952.804	657.951	526.685	418.434	447.034	806.550	607.700
M	46.182	59.903	46.146	43.112	44.238	51.742	81.770	69.884	42.771	43.929	68.801	45.392	61.898
N	35.863	51.965	43.743	44.250	49.561	52.068	103.342	59.179	56.279	32.402	46.635	29.851	59.033
O	49.992	46.194	48.313	47.253	40.792	42.259	53.059	46.083	42.344	50.831	57.230	41.356	47.720
P	28.801	30.100	37.695	30.763	30.852	32.364	54.610	32.938	36.888	30.093	36.262	23.985	35.639
Q	27.468	31.036	31.126	35.541	33.899	31.410	39.908	33.444	29.761	32.675	30.942	28.337	32.654
R	44.769	40.083	24.326	47.673	38.364	27.927	38.710	39.239	21.845	30.905	45.546	33.132	36.387
S	26.816	53.773	35.664	34.461	63.482	49.293	84.885	63.660	35.932	33.352	40.353	38.669	51.735
T	71.524	79.572	89.532	94.391	109.401	105.247	58.817	94.915	92.332	109.957	77.762	26.663	81.222
Total	45.258	52.634	45.420	49.397	50.461	55.809	83.740	65.473	50.103	45.900	54.216	44.391	57.639

Source: Labour Force Survey 2014 and UK ONS Regional Accounts

C.2 Extra Plots and Tables

Table C.7: Capital per Worker: (12) Regions and (11) Industries Workforce Jobs

Industry	Captial Stocks (£ thousands per worker)											
	N. East	N. West	Yorksh/Humber	E. Midlands	W. Midlands	E. England	London	S. East	S. West	Wales	Scotland	N. Ireland	Total
A	210.016	224.374	203.132	300.331	201.296	250.965	441.610	168.038	222.632	160.452	176.528	243.530	210.558
BDE	1167.682	934.169	1062.022	886.227	995.711	948.031	1100.657	1077.389	1118.347	939.441	1169.457	1074.714	1049.415
C	206.224	199.044	160.819	180.989	190.862	208.563	190.903	215.653	185.839	168.916	192.827	183.448	190.657
F	270.163	263.731	266.482	276.975	293.568	264.477	298.093	256.705	222.846	236.046	292.504	389.921	271.306
GHI	86.252	84.975	86.019	76.596	76.243	79.281	122.387	96.688	79.013	76.026	87.324	79.606	89.677
J	319.150	243.361	242.958	186.495	229.163	247.560	186.970	199.502	196.991	182.283	250.071	167.710	210.190
K	146.439	154.158	153.933	160.494	175.160	154.030	144.849	152.044	139.609	135.223	154.239	166.760	150.606
L	3829.737	4108.804	4904.251	6053.758	4366.617	5405.608	3842.882	5135.210	4128.214	4506.617	6475.815	10636.401	4713.840
MN	88.394	99.888	77.402	83.585	86.980	104.972	88.862	117.294	90.640	77.202	92.545	73.120	94.279
OPQ	71.499	72.281	74.384	79.280	70.017	80.820	82.157	82.912	78.334	73.206	93.129	70.067	78.528
RST	54.330	52.521	50.029	48.722	54.430	50.737	59.655	54.849	47.242	49.459	63.066	51.295	54.063
Total	188.308	188.936	187.941	192.829	190.904	199.833	204.634	213.445	203.340	181.476	227.974	229.235	201.349

Source: Workforce Jobs 2014 and Own Capital Stock

Table C.8: Labour Productivity: Regions and Industries (11) Workforce Jobs

Industry	Labour Productivity (£ thousands per worker)												
	N. East	N. West	Yorksh/Humber	E. Midlands	W. Midlands	E. England	London	S. East	S. West	Wales	Scotland	N. Ireland	Total
A	30.824	31.803	37.910	43.785	28.993	44.239	13.788	23.144	34.688	13.691	31.023	17.795	30.259
BDE	129.697	98.523	95.091	128.014	115.109	101.895	111.924	152.992	140.707	88.001	117.518	113.503	117.936
C	62.180	71.929	55.533	60.082	54.614	71.699	62.213	68.447	53.826	59.862	71.021	59.367	62.776
F	41.555	39.911	36.636	40.467	42.544	54.555	67.973	51.988	35.399	30.785	40.146	40.183	46.136
GHI	27.821	30.428	27.992	31.311	29.284	32.269	46.879	39.103	28.136	23.282	33.585	36.228	33.887
J	76.746	65.711	50.339	47.053	60.817	54.040	90.334	82.724	49.974	46.944	63.667	50.835	72.419
K	94.055	112.375	79.525	88.404	113.328	84.835	112.412	110.266	90.677	118.455	95.751	82.613	103.171
L	277.188	257.693	290.105	363.579	300.106	453.947	449.144	417.249	274.907	293.303	323.754	376.558	356.786
MN	26.834	31.346	25.024	22.879	28.172	26.440	53.405	36.573	31.082	23.866	36.309	25.914	35.405
OPQ	30.353	32.009	34.409	33.064	32.283	32.695	44.512	33.371	33.317	33.148	36.150	30.363	34.695
RST	31.358	33.359	25.110	29.092	40.113	33.625	43.236	34.547	24.993	25.838	34.783	28.205	34.019
Total	41.097	43.490	39.465	41.101	42.451	45.062	65.879	51.387	41.670	38.575	46.708	40.197	47.606

Source: Workforce Jobs 2014 and UK ONS Regional Accounts

Figure C.1: ONS Capital Stock and Own Computation

(a) All Industries but Real State

(b) Real State

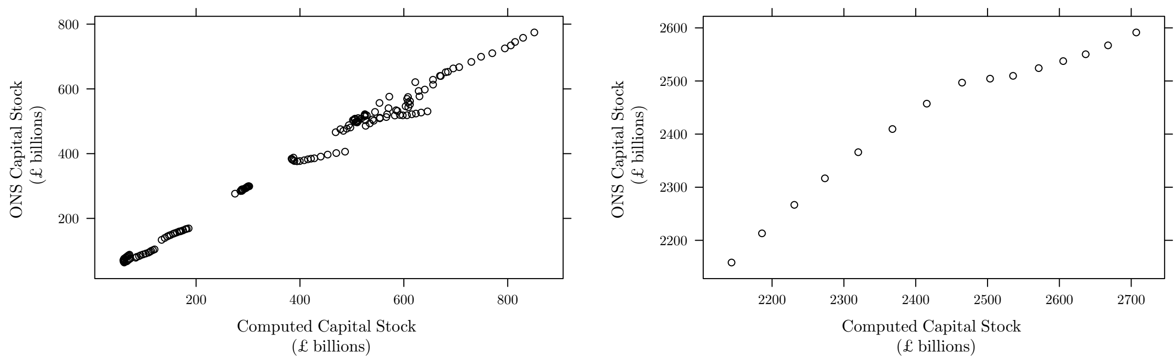


Figure C.2: Workforce Jobs and LFS: Measures of Employment

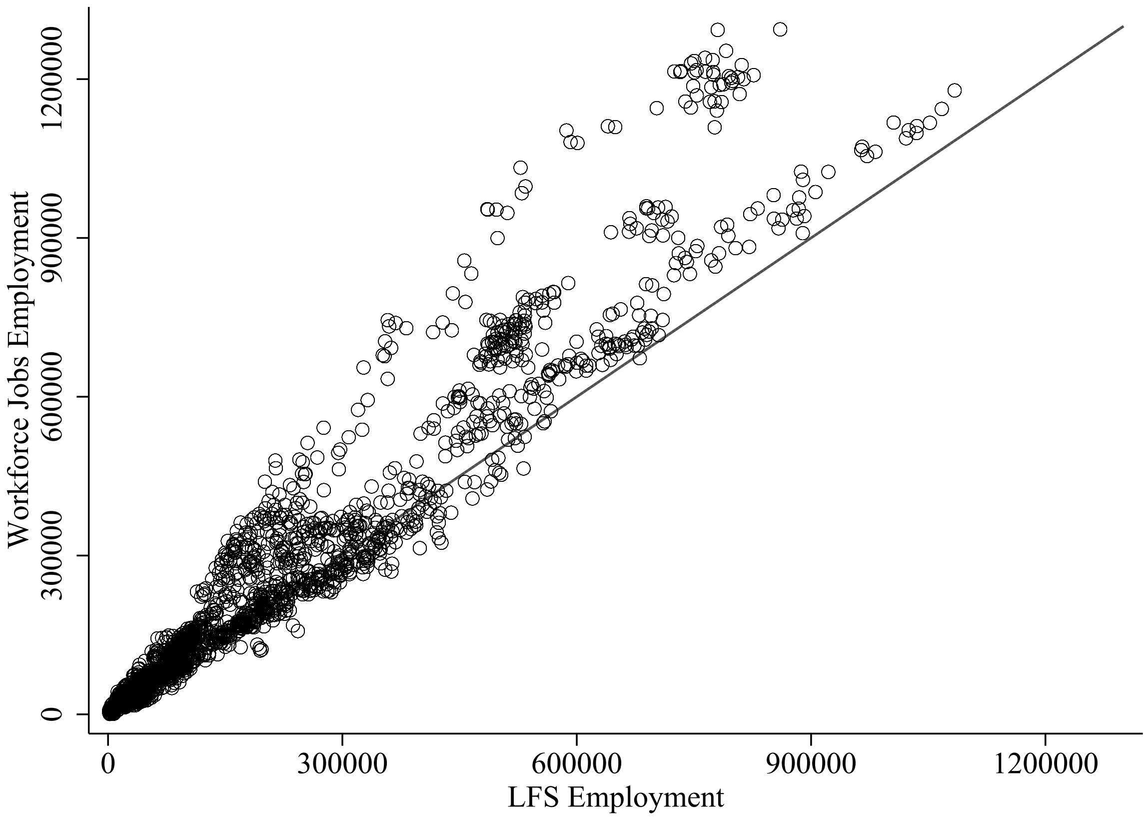


Figure C.3: Comparison of Wage Bill

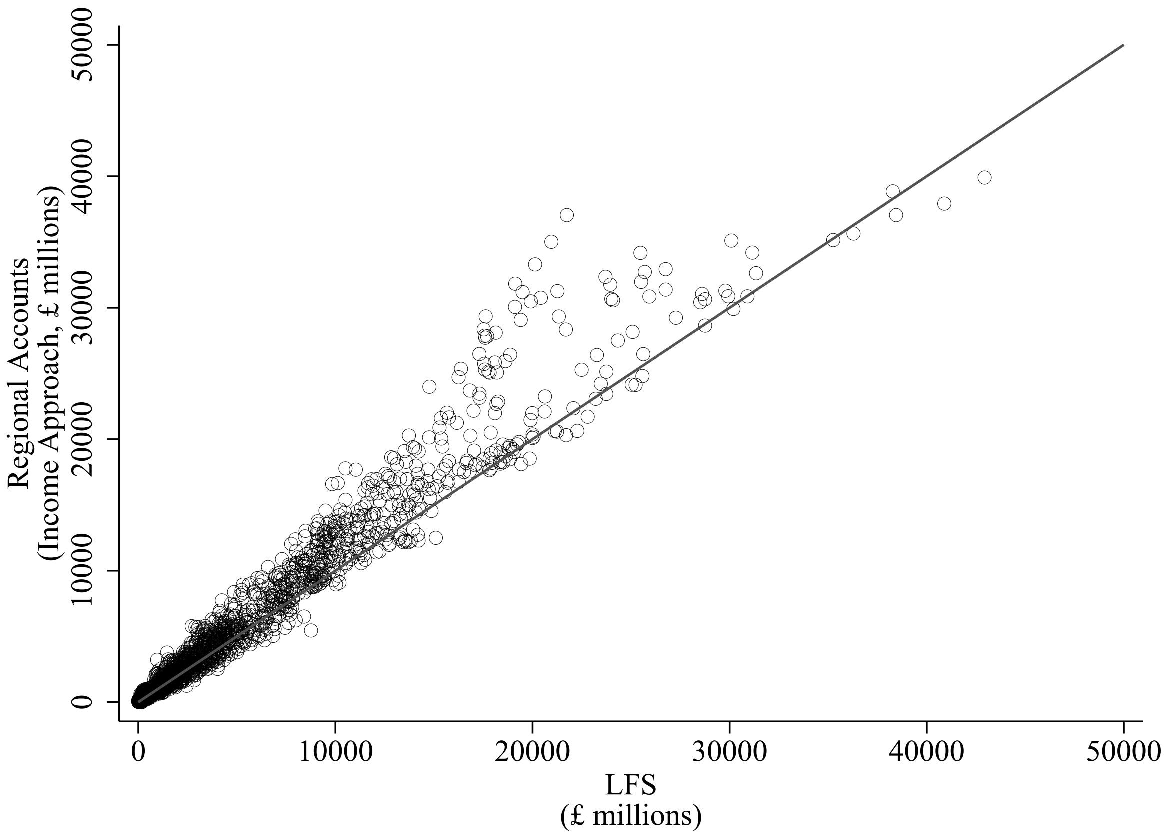


Table C.9: Wage Differentials

	1998-2014		2011-2014	
	Aggregate	Micro	Aggregate	Micro
Overall	-0.164	-0.016	-0.200	-0.049**
	(0.154)	(0.017)	(0.164)	(0.016)
Observations	6,492	797,936	1,524	151,082
High Skilled	0.196	0.024	-0.100	0.012
	(0.118)	(0.015)	(0.130)	(0.017)
Observations	6,258	218,864	1,420	45,908
Low Skilled	-0.291	-0.056***	-0.189	-0.073***
	(0.163)	(0.013)	(0.162)	(0.013)
Observations	6,483	579,072	1,516	105,174

Market clustered standard errors in parenthesis. All regressions include region, industry and year dummies. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure C.4: MRTS High Skilled Occupation: Comparison of Measures

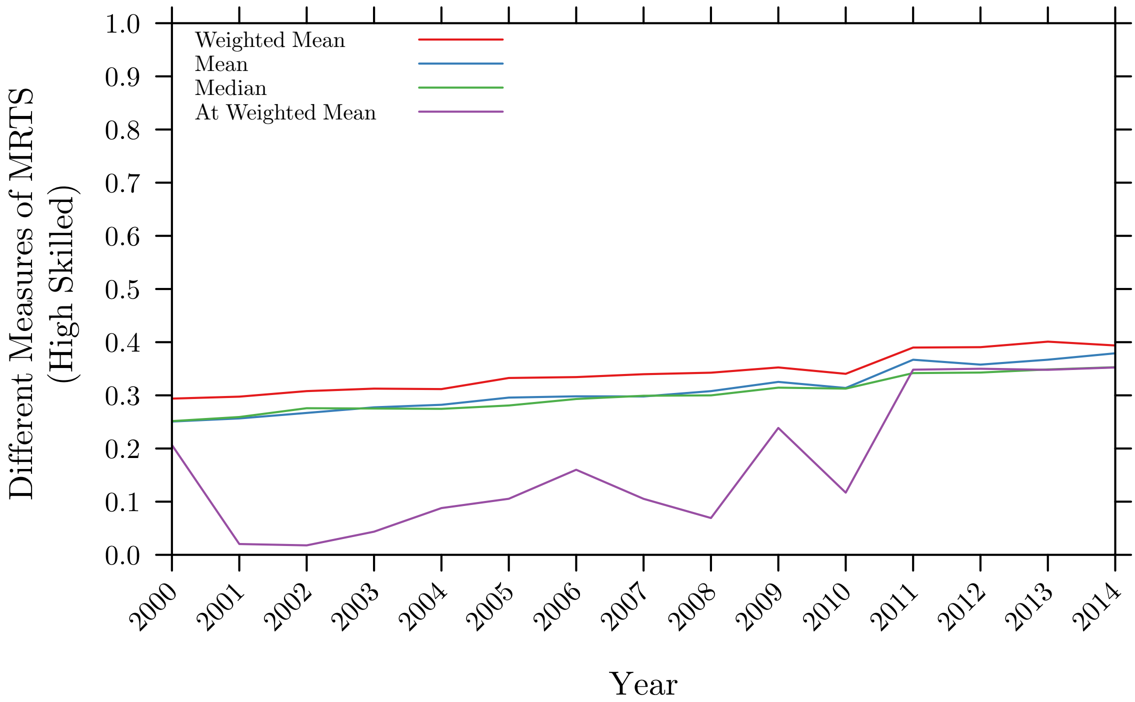


Figure C.5: MRTS Low Skilled Occupation: Comparison of Measures

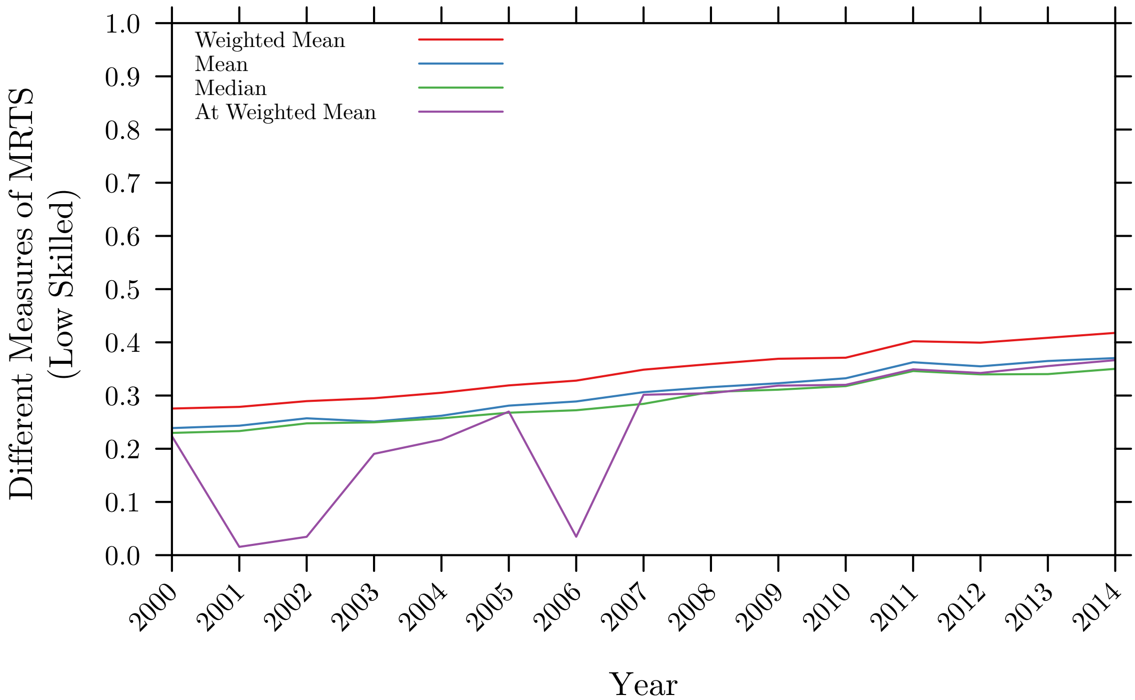


Figure C.6: MRTS Evolution: Estimates from Table 8

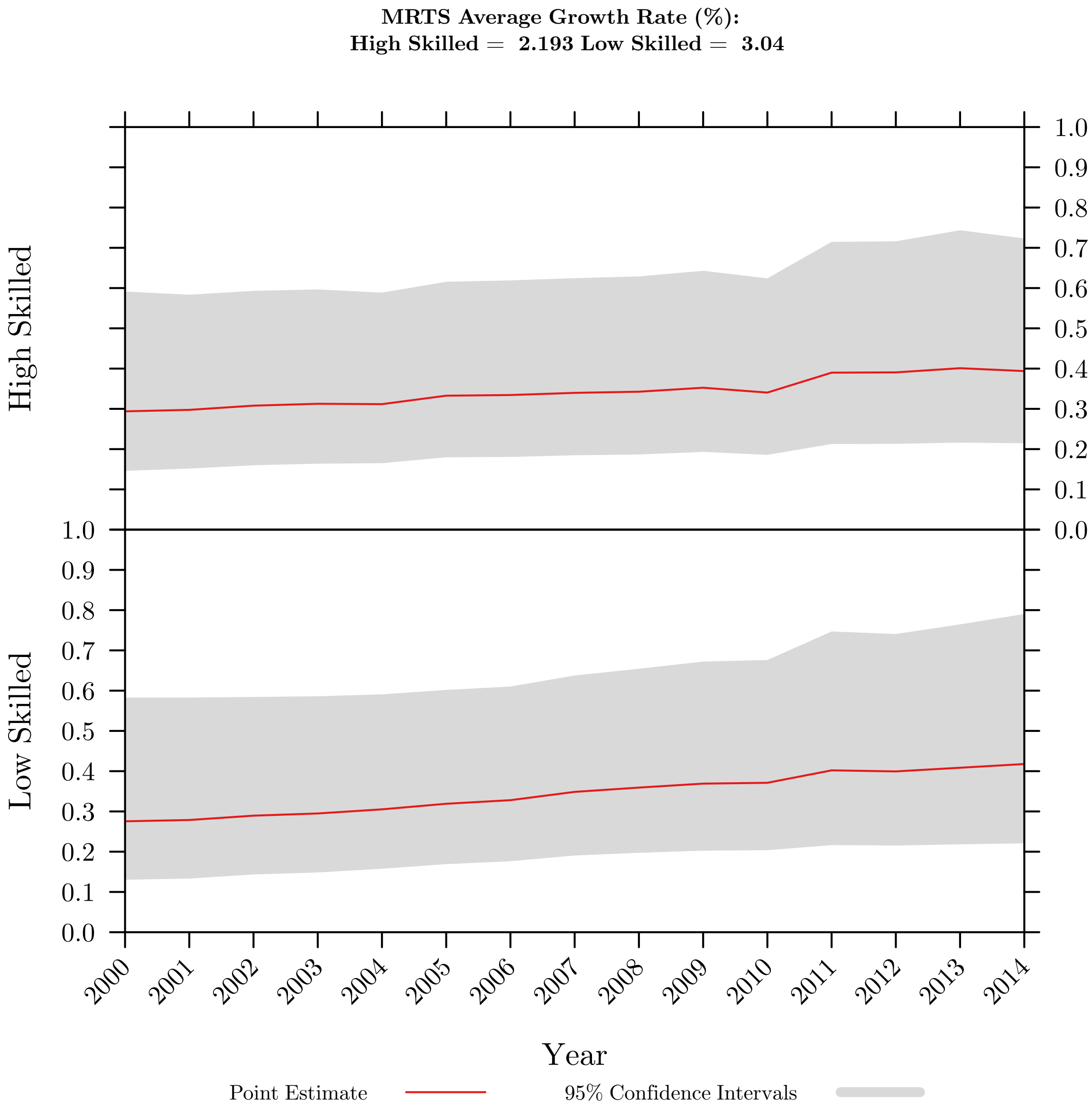
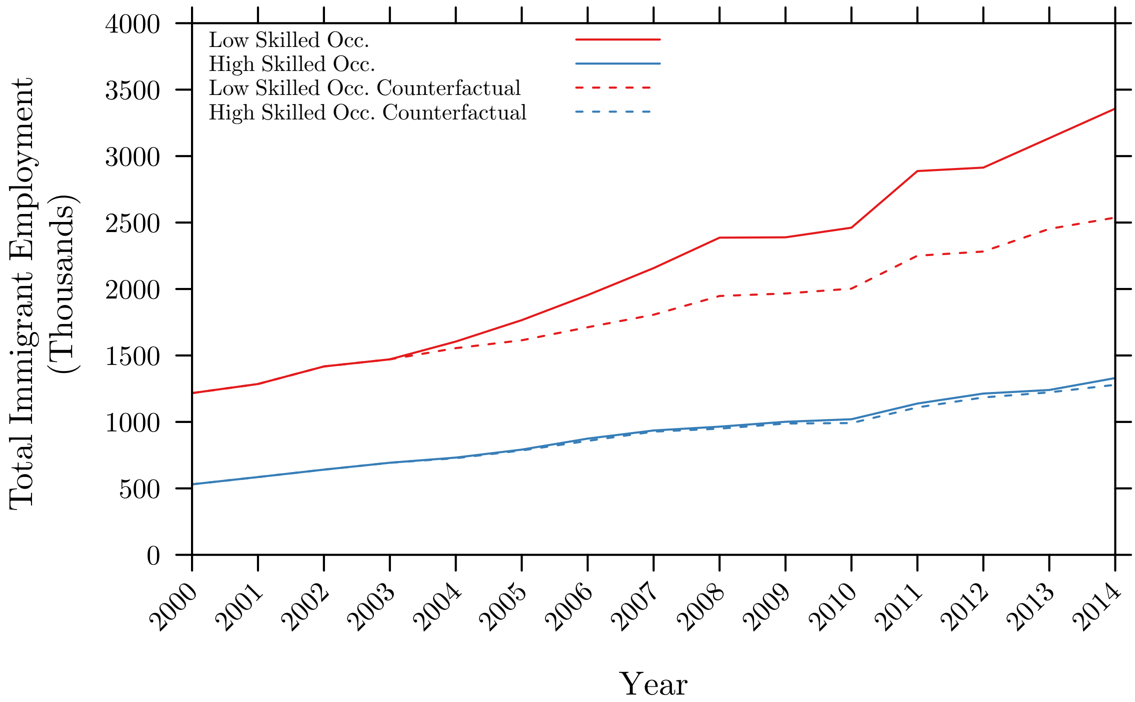


Figure C.7: Immigrant Labour Force Evolution and Counter-factual



C.3 Data Preparation

C.3.1 Special territories

There are a series of territories that depend or have special links with EU countries. If the country/territory is identifiable in LFS we include it as EU if it appears as such in the list available at https://ec.europa.eu/taxation_customs/business/vat/eu-vat-rules-topic/territorial-status-eu-countries-certain-territories_en. Individuals born in any UK overseas territories are coded as natives.

C.3.2 Changes on Industries and Occupations Coding

In 1991 the new SOC90 coding scheme was introduced in the LFS. In this year there are two variables reporting occupation, one is *KOS* that was used until 1991 and the other is *SOC/SOCMAIN* that uses the SOC90 coding scheme and is in place until 2001. Thanks to this we can create a mapping between the old coding and the new by cross tabulating the two variables using LFS 1991. As we are using aggregate quantities we choose to employ a probability mapping between schemes. Furthermore, some translations were imputed manually, see table C.10.

In 2001 there is a new change and occupations were coded under SOC00, during this year both the old *SOCMAIN* variable and the new *SOC2KM* were coded. However, only the later is provided in the end of user quarterly datasets available at the UK Data Archive with no occupational information provided at all in the first quarter. To overcome this issue, we use the last quarter of LFS 2000 and the second of 2001. Thanks to the panel dimension of LFS we can match observations that belong to the same individual in both quarters, and identify those who have not changed jobs. Then we use these observations to construct the mapping between occupational codes. While creating this map we imputed manually the following one-to-one correspondences

SOC90	**Manually Imputed SOC00**
491 tracers, drawing office assistants	3122 Draughtsperson
733 scrap dealers etc	1235 Recycling and refuse disposal managers
802 tobacco process operatives	8111 Food, drink and tobacco process operatives
890 washers etc in mines & quarries	8123 Quarry workers and related operatives

Finally, in the first quarter of 2011 there is a new change and occupations are now coded following SOC10. During this year in the end of user access datasets from the UK Data Archive there are available two occupational variables, one codes under SOC00 –*SC102KM*– and the other under SOC10 –*SOC10M*–; this allows us to create a mapping. With the three maps at hand we translate everything into SOC10 coding and then use MAC's NQF classification[51] to put workers in one of the 4 different groups, ranking 2, 3, 4 and 6.[52]

For industries there is a change between codes for the base years 1985-1990 and our first year of study, 1998; and between 2008 and 2009. We use proportional mappings from ONS and Dr. Jennifer Smith[53], to code pre 2008 LFS figures into SIC07. Due to availability constraints the matching for years 1985-1990 is performed using two digits industries while the matching for 1998-2008 is done using four digits.

[51]See https://www.gov.uk/guidance/immigration-rules/immigration-rules-appendix-j-codes-of-practice-for-skilled-wo

[52]SOC 2010 occupations (1171) Officers in armed forces, (2444) Clergy, (3311) NCOs and other ranks, (3314) Prison service officers (below principal officer), (3441) Sports players, and (3442) Sports coaches, instructors and officials; are given no classification as these are not eligible for Tier 2 visas.

[53]Available at http://www2.warwick.ac.uk/fac/soc/economics/staff/jcsmith/sicmapping/resources/proportional/.

Table C.10: Imputation from KOS (SOC80)

KOS (SOC80)	Imputed SOC90
453 SUPERVISORS- TRACERS DRAWING OFF ASSTS	491 Tracers, drawing office assistants
863 FOREMEN-WINDERS, REELERS ETC	813 Winders, reelers
1043 FOREMEN-CASE & BOX MAKERS	572 Case and box makers
1044 FOREMEN-PATTERN MAKERS (MOULDS)	573 Pattern makers (moulds)
1143 FOREMEN-WATCH & CHRONOMETER MAKERS & REPAIRERS	517 Precision instrument makers and repairers
1295 FOREMEN-ELECTRONICS WIREMEN	517 Precision instrument makers and repairers
1296 FOREMEN-COIL WINDERS	517 Precision instrument makers and repairers
1342 FOREMEN ASSEMBLERS-INSTRUMENTS	517 Precision instrument makers and repairers
1344 FOREMEN ASSEMBLERS-PAPER PROD & PRINTING PROCESSING	821 Paper, wood and related process plant operatives
1364 FOREMEN INSPECTORS VIEWERS ETC-RUBBER GOODS	824 Rubber process operatives, moulding machine operatives, tyre builders
1491 FOREMEN-RAILWAY GUARDS	881 Rail transport inspectors, supervisors and guards
1544 FOREMEN-SLINGERS	932 Slingers
1591 FOREMEN-LABOURERS UNSKILLED WORKERS NEC-TEXTILES(NOT TEXTILE GOODS)	559 Other textiles, garments and related trades nes
1592 FOREMEN-LABOURERS UNSKILLED WORKERS NEC-CHEMICALS & ALLIED TRADES	829 Other chemicals, paper, plastics and related process operatives nes
1594 FOREMEN-LABOURERS UNSKILLED WORKERS NEC-GIJWS & CERAMICS NEC	590 Glass product and ceramics makers
1595 FOREMEN-LABOURERS UNSKILLED WORKERS NEC-FOUNDRIES IN ENG ETC	911 Labourers in foundries
1602 LABOURERS UNSKILLED WORKERS NEC-CHEMICALS & ALLIED TRADES	829 Other chemicals, paper, plastics and related process operatives nes

Table C.11: Industry Groups

SIC07	Description
$[100, 322]$	A: Agriculture, forestry and fishing
$[510, 990]$	B: Mining and quarrying
$[1011, 1200]$	CA: Food products, beverages and tobacco
$[1310, 1520]$	CB: Textiles, wearing apparel and leather products
$[1610, 1820]$	CC: Wood and paper products and printing
$[1910, 1920]$	CD: Coke and refined petroleum products
$[2011, 2060]$	CE: Chemicals and chemical products
$[2110, 2120]$	CF: Basic pharmaceutical products and preparations
$[2211, 2399]$	CG: Rubber and plastic products
$[2410, 2599]$	CH: Basic metals and metal products
$[2611, 2680]$	CI: Computer, electronic and optical products
$[2711, 2790]$	CJ: Electrical equipment
$[2811, 2899]$	CK: Machinery and equipment not elsewhere classified
$[2910, 3099]$	CL: Transport equipment
$[3101, 3320]$	CM: Other manufacturing and repair
$[3511, 3530]$	D: Electricity, gas, steam and air-conditioning supply
$[3600, 3900]$	E: Water supply; sewerage and waste management
$[4110, 4399]$	F: Construction
$[4511, 4799]$	G: Wholesale and retail trade; repair of motor vehicles
$[4910, 5320]$	H: Transportation and storage
$[5510, 5630]$	I: Accommodation and food service activities
$[5811, 6399]$	J: Information and communication
$[6411, 6630]$	K: Financial and insurance activities
$[6810, 6832]$	L: Real estate activities
$[6910, 7500]$	M: Professional, scientific and technical activities
$[7711, 8299]$	N: Administrative and support service activities
$[8411, 8430]$	O: Public administration and defence; compulsory social security
$[8510, 8560]$	P: Education
$[8610, 8899]$	Q: Human health and social work activities
$[9001, 9329]$	R: Arts, entertainment and recreation
$[9411, 9609]$	S: Other service activities
$[9700, 9820]$	T: Activities of households
9900	U: Extraterritorial organisations

Table C.12: Industries into Sectors

Code	Description	Sector
1	A: Agriculture, forestry and fishing	Primary Sector
2	B: Mining and quarrying	Primary Sector
3	CA: Food products, beverages and tobacco	Manufactures
4	CB: Textiles, wearing apparel and leather products	Manufactures
5	CC: Wood and paper products and printing	Manufactures
6	CD: Coke and refined petroleum products	Manufactures
7	CE: Chemicals and chemical products	Manufactures
8	CF: Basic pharmaceutical products and preparations	Manufactures
9	CG: Rubber and plastic products	Manufactures
10	CH: Basic metals and metal products	Manufactures
11	CI: Computer, electronic and optical products	Manufactures
12	CJ: Electrical equipment	Manufactures
13	CK: Machinery and equipment not elsewhere classified	Manufactures
14	CL: Transport equipment	Manufactures
15	CM: Other manufacturing and repair	Manufactures
16	D: Electricity, gas, steam and air-conditioning supply	Primary Sector
17	E: Water supply; sewerage and waste management	Primary Sector
18	F: Construction	Construction
19	G: Wholesale and retail trade; repair of motor vehicles	Services
20	H: Transportation and storage	Services
21	I: Accommodation and food service activities	Services
22	J: Information and communication	Services
23	K: Financial and insurance activities	Services
24	L: Real estate activities	Services
25	M: Professional, scientific and technical activities	Services
26	N: Administrative and support service activities	Services
27	O: Public administration and defence; compulsory social security	Services
28	P: Education	Services
29	Q: Human health and social work activities	Services
30	R: Arts, entertainment and recreation	Services
31	S: Other service activities	Services
32	T: Activities of households	Services
33	U: Extraterritorial organisations	Not Included

Table C.13: Aggregate Industries to be used with Capital

Our Code	ONS GFCF
1	A
2	BCDE
3	C
4	F
5	GHI
6	J
7	K
8	L
9	MN
10	OPQ
11	RST

Table C.14: NQF Classification and Major Occupation

	NQF			
Major Occupation	2	3	4	6
Managers, Directors and Senior Officials	0.00	0.09	0.21	0.19
Professional Occupations	0.00	0.00	0.03	0.72
Associate Professional and Technical Occupations	0.02	0.17	0.33	0.03
Administrative and Secretarial Occupations	0.14	0.13	0.39	0.06
Skilled Trades Occupations	0.08	0.43	0.00	0.00
Caring, Leisure and Other Service Occupations	0.13	0.09	0.00	0.00
Sales and Customer Service Occupations	0.11	0.03	0.03	0.00
Process, Plant and Machine Operatives	0.30	0.04	0.00	0.00
Elementary Occupations	0.22	0.02	0.00	0.00

Table C.15: NQF Classification and Major Occupation: No NQF Match

Occupation	Description
1171	Officers in armed forces
2444	Clergy
3311	NCOs and other ranks
3314	Prison service officers (below principal officer)
3441	Sports players
3442	Sports coaches, instructors and officials

Table C.16: Country Groups

EU13	**EU-A11**
Austria	Czech Republic
Belgium	Estonia
Denmark	Hungary
Finland	Latvia
France	Lithuania
Germany	Poland
Greece	Slovakia
Italy	Slovenia
Luxembourg	Bulgaria
Netherlands	Romania
Portugal	Croatia
Spain	
Sweden	