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THE CROSS-OCCUPATIONAL EFFECTS OF IMMIGRATION ON NATIVE WAGES IN THE UK

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Cross-Occupational Effects of Immigration on Native Wages in the U.K.

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Abstract

This paper estimates the effect of immigration into an occupation on the wages of natives working in other, better paid occupations. Using Annual Population Survey data from the UK we rank occupations by real hourly wage and find that increases in the migrant/native ratio raise average wages of natives working in the next higher paid occupation by around 0.13 percent. We find that these effects operate through migrants' higher educational attainments raising workplace productivity more broadly and supporting specialization in tasks. Our findings have important implications for policy and public discourse. They suggest that debates over the economic impacts of migration often ignore the potential spill-over benefits that a migrant can bring to the outcomes for native workers elsewhere in the wage distribution, particularly in lower wage occupations.

JEL Classifications: J21, J31, J61

Keywords: Immigration, Impact, Wage distribution

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1 Introduction

The impact of immigration on the wages of natives remains a topic of intense debate, both in economic policy circles and the wider public discourse. The magnitude and even direction of this effect appears to vary based on setting and approach taken (Dustmann et al., 2016). Studies typically investigate whether natives and migrants either compete with or complement each other in similar jobs or skill groups, often referred to as cells. There is a rich body of evidence looking at whether or not migrants either compete with or complement natives in the same part of the wage distribution—i.e. within the same cell. However, whether or not these same migrants yield benefits or costs to native workers just above or below them in the wage distribution—i.e. in an adjacent cell—has remained relatively unexplored.

In this paper, we estimate the effect of immigration into an occupation on wages of natives working in higher paid occupations. Such *cross-occupational* effects of immigration may arise by migrants increasing the productivity of workers (Peri et al., 2015; Ottaviano et al., 2018 for instance) or by migrant inflows allowing natives to specialize in more complex, better remunerated tasks (Peri and Sparber, 2009; for example). Such effects may be even more likely in countries such as the UK, where migrants have been found to downgrade upon arrival thus leading to an inflow of over-qualified workers (Dustmann et al., 2013). Whilst we do not detect any meaningful effect of immigration within the same occupation-region group, we find that immigration into one occupation increases wages of natives working in the occupation ranked above by around 0.13 percent. Our findings are consistent with migrants increasing productivity and allowing natives to specialise.

To estimate the effect of immigration into an occupation on wages of natives working in higher paid occupations we use Office for National Statistics (ONS) data and divide workers in each of the 13 U.K. regions into 9 occupational categories based on the Standard Occupational Classification (SOC). To identify adjacent occupations, we first rank all 9 occupations according to the mean hourly wage of their employees with Managers, Directors and Senior Officials at the top and Elementary Occupations at the bottom. For each occupation o, we define the occupation *below* $(o - 1)$ as the occupation with mean hourly earnings are one rank lower than o. Similarly, the occupation *above* $(o + 1)$ is the occupation with mean hourly earnings one rank higher than o. Using these definitions, we regress yearly changes in native wages in occupation o on yearly changes the migrant-native ratio in occupations o, $o - 1$, $o + 1$. As such, this paper builds upon Dustmann et al. (2013) in trying to identify the underlying cross-effects of migration within these regions. Following standard practice in the literature, we instrument migration flows using past-migration in the 1991 Census. According to Dustmann et al. (2016) this approach is good for identifying the distributional impact of migration between occupation groups.

We first describe the occupational distribution of migrants and find that migrants tend to cluster at the top and the bottom of the wage distribution. Moreover, in late years, migrants are increasingly found working at low paying occupations. When we use the methodology adopted by Dustmann et al. (2013) we find positive albeit insignificant effects of migration of a very similar magnitude to the authors with the exception of the recession years where migration decreases native wages. To estimate cross-occupational effects in the same setting, we construct an occupation-region-year panel. We find that wages of natives working in occupation o are increased by immigration into the occupation *below*. Our point estimates suggest that a 1 percent increase in the change in the migrant-native ratio in occupation $o-1$ results in a 0.128 percent increase in native wages in occupation o. By contrast, we find no effects of immigration into the same occupation (o) or into the occupation above ($o+1$). These results are robust to differing occupation orders. Moreover, we find that the positive wage effect from migrants working in occupations *below* natives is concentrated in occupations located at the lower end of the wage distribution. For this sample, however, we also find a negative effect of migrants working in occupations above those of natives.

We consider productivity, peer effects and specialisation as possible channels of impact. Peer effects may impact productivity and therefore native wages as a result of social pressure to work harder and/or through knowledge spillovers (Cornelissen et al., 2017). To provide evidence on this mechanism we first show that higher migrant inflows into an occupation are associated with higher levels of education in that same occupation. This is partly a consequence of the fact that migrants' educational attainments exceed that of natives and in part due to migrants downgrading upon arrival to the UK (Dustmann et al., 2013). In a second step we show that native wages within an occupation o are positively associated with the average educational attainments of employees working in the occupation *below*, $o-1$. Taken together, these two pieces of evidence suggest that migrants may lead to *cross-occupational* wage impacts by due to their exceptionally high levels of education.

An alternative pathway of impact through which migrants increase the wage of those natives working in occupations above their own is by allowing natives to specialise in better paid tasks. Peri and Sparber (2009) show when migrants have a comparative advantage in 'lower' skilled, manual occupations then natives are pushed to specialise in 'higher' skilled occupations with complex communicative, interactive and better remunerated tasks. We investigate this channel of impact by focusing on in-job training received by natives. Training is a likely pre-requisite for specialising in more complex tasks and accordingly we find that migration flows into occupation $o-1$ induce natives in occupations above, o, to either take up or to be offered in-job training. These results tally with findings by Campo et al. (2018), who find that immigration is associated with higher native training, albeit only at a regional level.

By allowing immigration into one section of the labour force to affect natives in different occupations, this study provides evidence on a novel impact of migrants on native wages. As such, our results complement the large literature on the effect of immigration on native labour market outcomes. Dustmann et al. (2016) categorised this literature into three key methodological approaches which would drive the disparity in results throughout the literature. Firstly, the national skill cell approach which uses variation across skill-experience groups and identifies the relative wage effect of immigration by experience within a skill group and tends to find significant negative results (Borjas, 2003, 2014; Aydemir and Borjas, 2007; Card and Peri, 2016). Secondly, the spatial approach which uses regional variation in migration and measures the absolute effect on native wages on a particular skill group and this finds a variety of results results which can be negative, insignificant or positive depending on the context (Card, 1990; Altonji and Card, 1991; Lemos and Portes, 2013; Dustmann et al., 2013, 2017; Foged and Peri, 2016; Peri and Yasenov, 2019). Recent literature using this approach has found that migrant outflows have no positive effects on natives labour outcomes Clemens et al. (2018); Lee et al. (2019). Thirdly, the mixed approach which uses both spatial and skill variation and measures the relative impact of migration on native wages across skill groups and finds overall either a small negative effect or no effect (LaLonde and Topel, 1991; Card, 2001, 2009; Borjas, 2006; Lewis, 2011; Glitz, 2012; Dustmann and Glitz, 2015; Nickell and Saleheen, 2015). This paper uses a mixed-approach to investigate the cross-occupational effects of migration. Using occupation-spatial variation as opposed to occupation-experience variation allows us to investigate the cross-effects of skill specific migration while still providing a meaningful coefficient on the relative impacts of migration between skill groups.

Our paper also contributes to the literature on the mechanisms through which migrants affect native outcomes. By considering cross-occupational effects, we show that migrants do not have to work in the same occupation as natives for previously highlighted mechanisms to arise. Previous studies have highlighted many reasons that migration can increase productivity including diversity (Ottaviano and Peri, 2006; Kerr and Lincoln, 2010; Ortega and Peri, 2014; Peri et al., 2015; Kemeny and Cooke, 2018), cost-reduction (Ottaviano et al., 2013) and bilateral trade(Gould, 1994; Rolfe et al., 2013; Ottaviano et al., 2018). Recent studies find migration increases labour productivity within firms in the UK (Ottaviano et al., 2018) and within UK regions (Campo et al., 2018). In this paper we focus on two other channels, peer effects and native specialisation. We apply previously highlighted rationales for peer effects affecting wages through productivity spillovers Cornelissen et al. (2017), to migrant peers across occupations, which is in line with the wider literature on workplace productivity (Mas and Moretti, 2009; Falk and Ichino, 2006; Waldinger, 2012; Azoulay et al., 2010; Jackson and Bruegmann, 2009). We also highlight that migrants may allow natives to specialise in more complex communicative and interactive tasks speaks to the literature on specialisation in the workplace (Peri, 2012; D'Amuri and Peri, 2014; Bisello, 2014; Foged and Peri, 2016).

The remainder of the paper is as follows: Section 2 describes the data sources. In section 3 we define how we order occupations, our empirical specification and identification strategy. We then show how we will investigate the mechanisms behind spillovers. In Section 4 we discuss our estimation results and discuss potential pathways of impact in section 5. Section 6 concludes.

2 Data, Measurements and Descriptive Statistics

To estimate the effect of changes in the migrant stock within a particular occupation on native wages in other, related occupations, we use data from the UK Annual Population Survey (APS) from 2004-2016. Using the Standard Occupational Code system (SOC) provided by the APS we divide employees into nine occupations and rank these nine occupation by the mean real hourly earnings of their employees. For each occupation o we then estimate whether changes in the migrant stock in occupations *below* and *above* occupation o have an effect of natives working in occupation o.

2.1 Data

We use the Annual population survey (APS), which provides detailed data on labour outcomes and migration for a large, representative sample for the UK with boosted samples for smaller regions. The APS consists of repeated cross sections and contains year data for the years 2004 to 2016. The APS is a survey of private households in the UK conducted by the Office of National Statistics (ONS) in Great Britain and by the Northern Ireland Statistics and Research Agency(NISRA) in Northern Ireland. The sample size of the APS is made up of around 320,000 households in each survey, which the widest ranged household survey in the UK. It allows the generation of statistics for smaller UK regions, as it utilises sample boosts from the Local Labour Force Survey and APS boost in 2004 and 2005. These local boosts allows us to break down the data to regional levels while maintaining a good sample size and accuracy. The APS contains data on employment, unemployed, income as well as informations on age, education, and occupation. Details about the sampling employed by the APS are reported in appendix A.

2.2 Measurements

We define *migrants* as those individuals interviewed by the APS that were not born in the UK. The APS records gross weekly wages and total hours worked per week. Using these two pieces of information we calculate gross hourly wages, which we deflate by the 2015 CPI. Gross weekly wages have a top threshold at £788 which makes up 7.38 percent of our working age sample which is employed.

We construct an occupation-region-year panel for the years 2004 to 2016 by aggregating wages for those who are of working age, between the ages of 16 to 65. We divide the UK into 13 regions, 10 regions in England (Northeast, Northwest, Merseyside, Yorkshire & Humberside, East Midlands, West Midlands, Eastern, London, Southeast and Southwest) as well as Wales, Scotland and Northern Ireland. We allocate workers to 9 occupations by using the 1-digit SOC definitions as follows: i) managers, directors and senior officials; ii) professionals; iii) associate professional and technical; iv) administrative and secretarial; v) skilled trades; vi) caring, leisure and other services; vii) sales and customer service; viii) process, plant and machine; and ix) elementary occupations. Occupations definitions change in the year 2011 and we report the definitions for the previous years in appendix B.

Following standard practice in the literature, we instrument country-specific migrant shares in year t using country-migrant shares before the sample period, in our case 2004 to 2016. For this, we merge the 1991 United Kingdom Census to our occupation-region-year panel. Using information on area of residence, occupations and country of birth, we then calculate the share of migrants in each region coming from well-defined parts of the world, who work in a certain occupation. Since the occupation definition in the 1991 Census differs from both the SOC2000 and SOC2010 definitions, we adjusted occupations, see Appendix B for more details.

2.3 Summary statistics

Table 1 reports selected characteristics for natives and migrants working for the years 2004 and 2016. Whilst in 2004 real hourly wages of migrants exceeded those for natives, the opposite is true for the last year of our analysis, 2016. Across both time periods, migrants in work are slightly younger compared to natives. The percentage of women working is also slightly higher for migrants. In terms of education, working migrants are—on average—better educated compared to working natives. Whilst average educational attainment improves from 2004 to 2016, the gap between natives and migrants remains relatively constant.

	Natives		Migrants	
	2004	2016	2004	2016
Real Hourly Wage	13.06	13.83	14.33	13.56
Age	41.34	42.58	39.94	39.85
Female(%)	52	52	54	54
Education				
Higher	0.01	0.02	0.07	0.10
High	0.15	0.22	0.29	0.37
Intermediate	0.59	0.59	0.45	0.39
Low	0.19	0.10	0.11	0.07
None/Still in	0.06	0.07	0.08	0.08

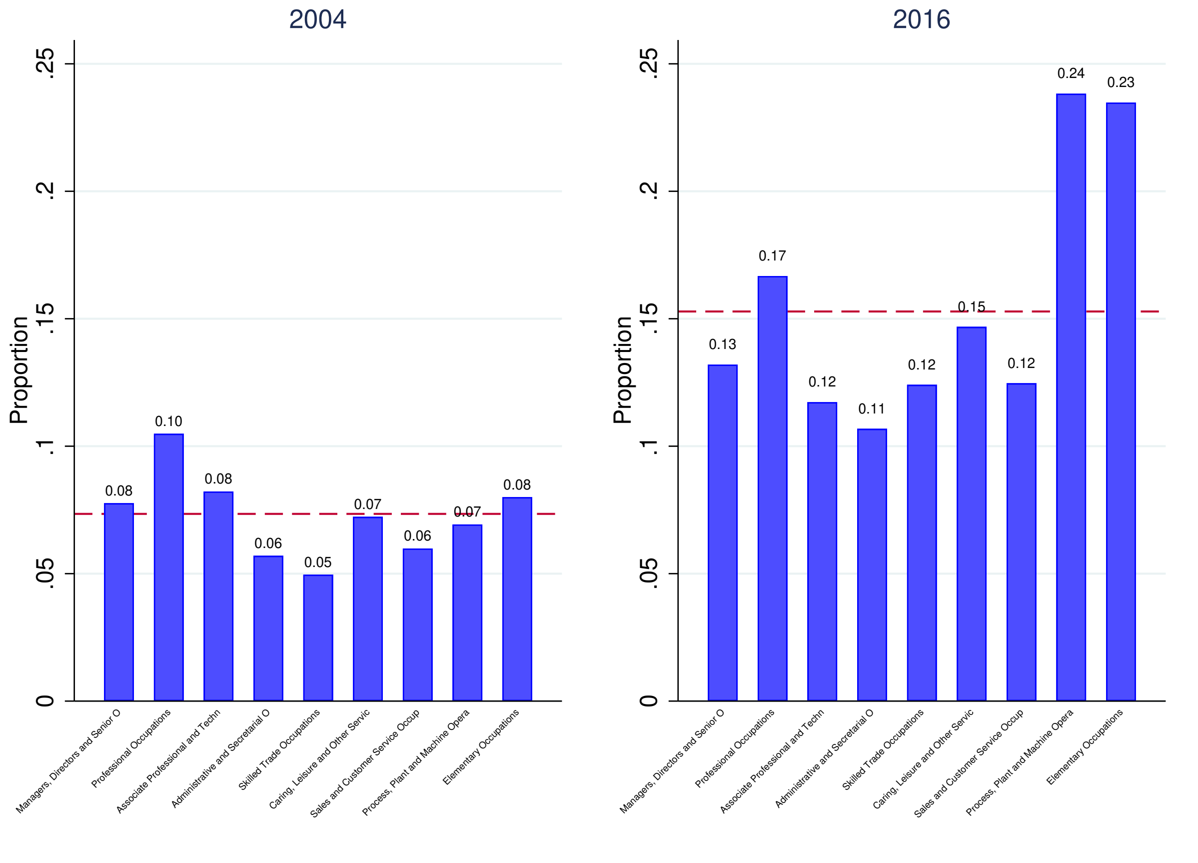
Entries are for working age(16-65) natives and immigrants for the average real hourly wage, average age, the percentage of female and the share in each education group in 2004 and 2016. Higher education: left full-time education after age 25, High education: left full-time education between age 20-24, Low education: left full-time education between age 16-19, None/Still in: Left education at age 15 or below or is still in education. Source: APS 2004, 2016

Table 1: Summary statistics for those employed in 2004 and 2016

In Figure 1 we show the proportion of migrants and natives working in each occupation in 2004 and 2016. When compared to the UK average (shown as a red horizontal line), migrants tend to work at both the high and the low end of the occupational distribution. From 2004 to 2016, however, we see a compositional shift towards occupations on the low end of the occupation distribution. This is mainly driven by increases in migrants working in Process, Plant and Machinery Occupations and Elementary Occupations. Whereas the proportion of migrants among workers in Process, Plant and Machinery Occupations in 2004 was 7% (below the UK average), this occupation reports the highest migrant share in 2016, 24%. Elementary Occupations follow a similar pattern, with increases from 8% to 23%. By contrast, the proportion of migrants in the two highest earning occupations (managerial and professionals) decreases in 2016 relative to the average for the whole workforce.

This compositional shift into occupations at the lower end of the occupational distribution could perhaps explain why average wages for migrants have fallen relative to natives despite the large increase in education. These results fit with Salvatori (2018), who finds that between 1979 and 2012 in the UK relative to natives, migrants increased the employment share in bottom paid occupations.

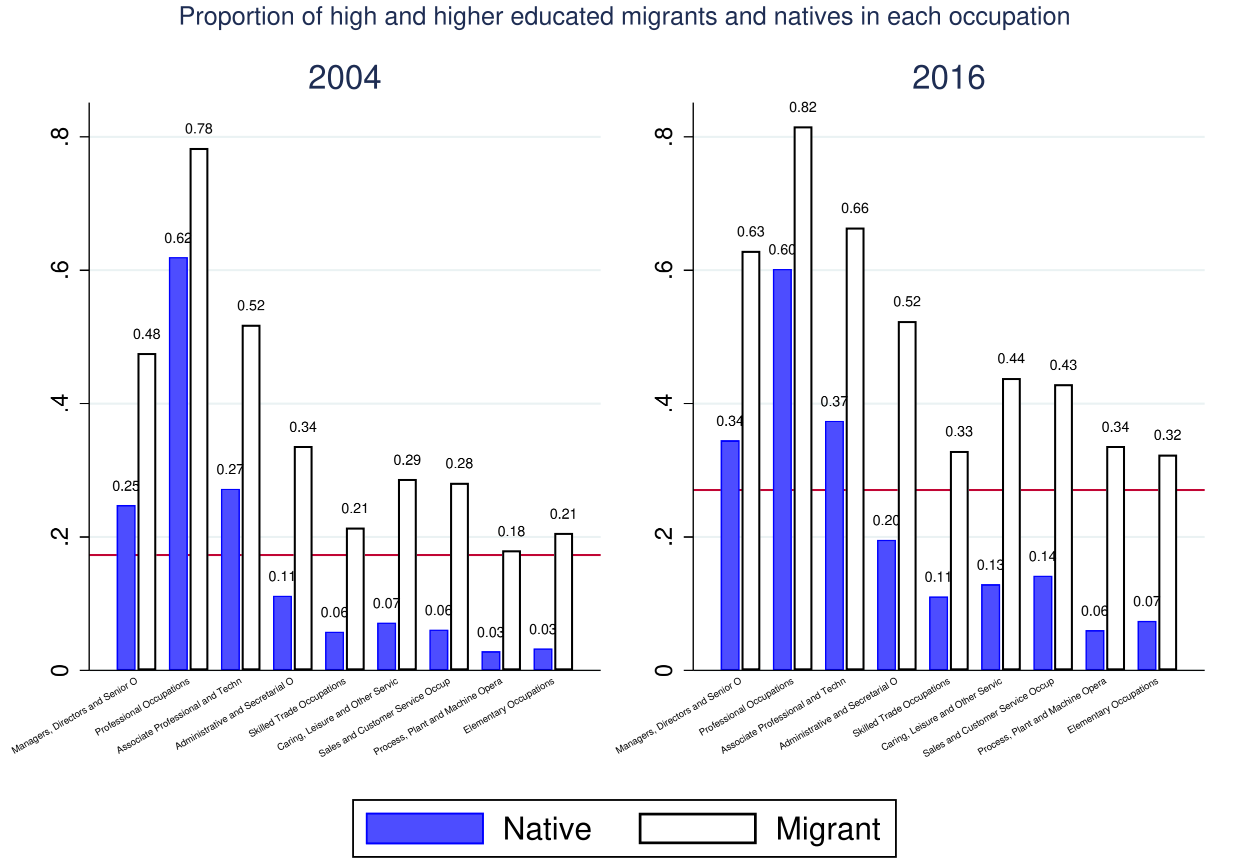
Figure 2 shows the proportion of highly educated workers (defined as individuals who left full time education from age 20 and above) for each of the 9 occupations for migrants and natives. When compared to the UK average (shown as a red horizontal line), the figure shows that migrants are better educated compared to natives across all occupations. Over time these differences increase, especially for workers employed in lower occupations. In



This figure shows the proportion of migrants in each occupation in 2004 and 2016. Where occupations are defined by the 9 1-digit SOC. The red line indicates the average proportion of the employed working age sample who are migrants. Source: APS 2004, 2016.

Figure 1: Proportion of Occupation who are Migrants in 2004 and 2016

fact, migrants working in elementary occupations show higher educational attainments than the UK average for all occupations. In Elementary Occupations in 2016, 32 percent of migrants are highly educated compared to just 7 percent of natives. Compared to 2004, this corresponds to an increase of 11 percentage points for migrants compared to 4 percentage points for natives. This pattern is consistent with results presented by Dustmann et al. (2013) where the authors show that many migrants concentrate initially at the low end of the wage distribution.



This figure shows the proportion of migrants and natives of working age(16-65) with high or higher education in each of the 9 1-digit SOC occupations in 2004 and 2016. The red line indicates the average proportion with high and higher education who are of working age. Source: APS 2004, 2016.

Figure 2: Proportion of high and higher educated migrants and natives in each occupation in 2004 and 2016

3 Empirical methodology

To lay out our empirical strategy, we first discuss how we rank occupations and set up our econometric specification, which expands on the mixed approach in the literature by including migration into adjacent occupations.

3.1 Ordering Occupations

Our paper tests the hypothesis that migrant inflow into occupations adjacent to occupation o, i.e. either *below* or *above*, affects native wages in occupation o. For this purpose, we rank occupations according to the mean hourly wage of their employees. This approach is motivated by the finding that migrants—at least initially—often concentrate at the low end of the wage distribution (Dustmann et al., 2013). We show our ranking in column (1) of table 2. As a robustness check, we also rank occupation using the default ordering of the SOC definition provided by the ONS, see column (2) of table 2.

		(1)	(2)
Order	**Rank**	**Real hourly wage ordering**	**ONS ordering**
Highest	1	Managers, Directors and Senior Officials	Managers, Directors and Senior Officials
	2	Professional Occupations	Professional Occupations
	3	Associate Professional and Technical Occupations	Associate Professional and Technical Occupations
	4	Skilled Trades Occupations	Administrative and Secretarial Occupations
	5	Administrative and Secretarial Occupations	Skilled Trades Occupations
	6	Process, Plant and Machine Operatives	Caring, Leisure and Other Service Occupations
	7	Caring, Leisure and Other Service Occupations	Sales and Customer Service Occupations
	8	Sales and Customer Service Occupations	Process, Plant and Machine Operatives
Lowest	9	Elementary Occupations	Elementary Occupations

This table shows how we rank 9 1-digit SOC occupations from Highest to Lowest. Column 1 ranks them by the average UK real hourly wage for each occupation and Column 2 is the standard ordering provided by the ONS.

Table 2: Ranking of occupations

To highlight our methodology, consider Professional occupations as an illustrative example. The occupation adjacent and above to *Professionals* are *Managers, Directors and Senior Officials* whereas the occupation adjacent and below to *Professionals* are *Associate Professional and Technical Occupations*. Since managers are the highest and elementary the lowest occupations, we are dropping these occupations from our estimations.

Using occupations to define skill groups has the advantage that it allows us to avoid the issue of migrant downgrading upon arrival in the UK, which is where migrants with high levels of education tend to work in jobs below that skill level. In such a case, parameter estimates would over-estimate the number of highly educated migrants competing with highly educated natives where in reality these highly educated migrants are also competing with lower educated natives. By using occupations to define skill groups we overcome the issue of downgrading and assume that managers compete with managers, professionals with professionals and so on.

3.2 Empirical Model

Our methodology builds upon the analysis by Dustmann et al. (2013), where the authors use UK data to estimate the total effect of migration into a region on native wages across the wage distribution within that region using the following specification

$$\triangle lnW^N_{prt} = \beta_p \triangle m_{rt} + \triangle X_{prt} + \gamma_t + \triangle\epsilon_{ort}$$

where $\triangle lnW^N_{prt}$ is the yearly change ($lnW^N_{prt} - lnW^N_{prt-1}$) in average log native wages in percentile p, region r and time t and $\triangle m_{rt}$ is the yearly change in the migrant native ratio within a region r and time t. The migrant native ratio is defined as $m_{rt} = \frac{M_{rt}}{N_{rt}}$, i.e. the number of migrants working divided by the total number of natives in region r in year t. Moreover, the authors control for region characteristics X_{rt}, and time fixed effects, γ_t.

In order to estimate cross-occupational effects of migrants, we build off this model and divide each region-year observation into 9 occupations. Our dependent variable, thus, becomes the yearly change in average log native wage, $\triangle lnW^N_{ort}$, in occupation group o in region r in year t. Using the occupational ranking outlined in section 3.1, we relate changes in native wages to three migration measures: i) yearly changes in the migrant-native ratio in the same occupational group o ($\triangle m_{ort}$), ii) yearly changes in the migrant-native ratio in the occupational group above o ($\triangle m_{o+1rt}$), and iii) yearly changes in the migrant-native ratio in the occupational group below o ($\triangle m_{o-1rt}$) in region r and year t as follows

$$\triangle lnW^N_{ort} = \alpha + \beta_2 \triangle m_{ort} + \beta_2 \triangle m_{o+1rt} + \beta_2 \triangle m_{o-1rt} + \beta_2 \triangle X_{ort} + \gamma_t + \triangle \epsilon_{ort} \tag{1}$$

where X_{ort} denotes controls for the average age for natives and migrants and education controls, defined by the age they left education, for the proportion of migrants and natives with higher(25>), high(20-24), intermediate(16-19) and low education(16 <) all within an occupation-region-time group and time fixed effects. The remaining variables are defined as above. We estimate robust standard errors clustered at the occupation specific regional level. One key issue when allowing for spatial variation is that it is possible for natives to react to migration, by for example moving to a different region. This would result in our coefficient being biased towards zero. We follow Dustmann et al. (2013) and use broad definitions of spatial regions which will reduce the likelihood of this being the case.[1]

When estimating the impact of migration on native wages we must consider the endogenous allocation of migration into occupations and regions. Results would be biased if migrants move to occupations and regions experiencing high growth. Following studies such as Bartel (1989) and Munshi (2003) the literature has utilised the findings that immigrants tend to migrate to where there is other migrants. Following Dustmann et al. (2013) and Altonji and Card (1991) we use settlement patterns from past migration as an instrument.[2] However, unlike previous studies we must also instrument for the endogeneity of migration into below and above occupations. We use a 2SLS approach where our first stage regresses the migrant native ratio of those employed in occupation o, and region r, in 1991. We use

[1] Dustmann et al 2013 test this using LFS data and find no evidence for a native response

[2] We use a simple past migration instrument as opposed to the alternative used in Card (2001) due to our current absence in country of origin data which is forthcoming

the same controls and time fixed effects outlined in Equation 1.

There are some potential issues with measurement error due to the sample being split into occupation, region, time groups. Where our sample size for migrants can be quite small in some groups, in for example regions like Northern Ireland, which can be exacerbated by first differencing our regression as pointed out by Dustmann et al. (2013). However, according to the authors using an instrumental variable estimation will account for this measurement error as long as the instrumental variable's measurement error is not correlated with the measurement error of our variable of interest. Furthermore, as we use the 1991 Census for our instrument we do not expect our lagged measure of migration's measurement error to be correlated with our main main measure of migration's measurement error as it is a different dataset taken over 10 years before the beginning of our own. If this was not the case our instrument would be invalid, as pointed out by (Aydemir and Borjas, 2011).

Finally, following Dustmann et al. (2013) we do not use APS sample weights which are calculated for the whole population, and not migrants and natives separately.

4 Results

As a starting point we replicate the results presented by Dustmann et al. (2013). Thereafter, we estimate reduced form results for cross-occupational effects of migrants on wages for the whole of the UK and along the occupational distribution.

4.1 Spatial Results

Before considering cross-occupational effects of migration, we show that we can replicate the results of the paper that is the basis for our analysis (Dustmann et al., 2013) pretty closely. In table 3 we divide the UK into 13 regions and estimate the average effect of migration within a region for three time periods. The dependent variable is the change in the log native wage within a region, time cell and we control for migrants' and natives' average age and the proportion of migrants and natives with low, intermediate, high and higher education within a region, time cell as well as for time fixed effects. Columns 1 and 2 present our OLS and Columns 3 and 4 our 2SLS results where we instrument the migrant-native ration using the 1991 census. Columns 1 and 3 present results with time fixed effects but no extra controls and Columns 2 and 4 present results with both time fixed effects and extra controls. We split our sample into three time periods, pre-recession, recession and post-recession. When we focus on the years before the recession (2004-2007), we find a positive coefficient of 0.300, which remarkably close to the one estimated by Dustmann et al. (2013) of 0.256. Our results are less precisely estimated, which is most likely due to a considerably smaller sample size. When we focus on the two recession years in panel B, we find a very precisely estimated negative effect of -0.237. This finding tallies with Peri (2010) who finds using a similar approach that in the short-run during a downturn the effect of migration on the average income per worker is slightly negative(point estimate of -0.55). Finally, in panel C we focus on the post-recession years 2010-2016 and find a positive coefficient of 0.162, which is smaller in size compared to the 0.256 estimated by Dustmann et al. (2013).

	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
Panel A: Pre-Recession(2004-2007)				
mignat_ratio	0.114	-0.0155	-0.104	0.300
	(0.230)	(0.275)	(0.127)	(0.277)
Observations	39	39	39	39
Panel B: Recession(2008-2009)				
mignat_ratio	-0.564**	-0.314	-0.536***	-0.237
	(0.190)	(0.221)	(0.192)	(0.242)
Observations	26	26	26	26
Panel C: Post-Recession(2010-2016)				
mignat_ratio	0.119**	0.0949	0.0549*	0.162**
	(0.0455)	(0.0550)	(0.0316)	(0.0724)
Observations	91	91	91	91
Controls	N	Y	N	Y
Time FE	Y	Y	Y	Y

Entries are estimated regression coefficients of the yearly change in native log real hourly wages on the yearly change in the employed migrant to native ratio, $\triangle m_{ort}$ in the for three different time periods. Pre-recession(2004-2007) in Panel A, Recession (2008-2009) in Panel B and Post-Recession(2010-2016) in Panel C. All estimations are at a regional level using 13 government office regions. Additional covariates are controls for migrants and natives separately and include the average age, the proportion with higher, high, intermediate and low education and year fixed effects. Clustered standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Impactof migration on native wages across regions

4.2 Main results

The results shown in panel A of Table 4 are based on a panel dataset where for each year between 2004 and 2016 we divide the UK into 13 regions and each region again into 9 occupational groups (although the bottom and the top drop out). As explained in section 3.1, we rank these 9 occupations by the mean hourly wage of their employees. The dependent variable is the change in the log native wage within an occupation, region, time cell. Our controls are as follows: migrant and natives average age and the proportion of migrants and natives with low, intermediate, high and higher education within an occupation, region, time cell. Following Dustmann et al. (2013), we also control for time fixed effects.

Columns 1 and 2 present our OLS and Columns 3 and 4 our 2SLS results where migrant native ratio in 1991 is the instrument. Columns 1 and 3 present results with time fixed effects but no extra controls and Columns 2 and 4 present results with both time fixed effects and extra controls. Across all four models, the migrant-native ratio in the same region and occupation show coefficients that are very small in size. By contrast, when we consider the migrant-native ratio in the occupation *below*, the 2SLS results suggest that a 1 percent increase in the change in the migrant native ratio in the occupation below a native's own occupation, within the same region and time, resulted in a relative increase of between 0.128 and 0.190 percent. We cannot reject the hypothesis that the coefficients are statistically different from zero. These results are smaller yet still comparable in size with Card (2001) (-0.11) and Dustmann et al. (2013) (between 0.213-0.256). Furthermore, they are not too dissimilar to the cross-effects from high school dropouts found by Borjas and Monras (2017) for the Mariel Boatlift which varies between 0.131-0.589. For the migrant-native ratio in the occupations *above*, however, the estimates are smaller in absolute size and imprecisely estimated.

When comparing the OLS and 2SLS results for the migrant-native ration in the same occupation and in occupations above and below, the coefficient sizes increase (in absolute magnitude). One possible reason for this change is that the OLS estimates suffer from classical measurement error, which biases coefficients towards zero. By removing this bias, the 2SLS estimates show the true effect, which is considerably larger (in absolute magnitude).

As a robustness check, we re-estimate our regressions maintaining the SOC's default occupation order in Appendix C. Whilst the point estimates for the migrant-native ratio in occupations below and above increase, the patterns in the estimates is very similar to the one shown in panel A of table 4.

4.3 Results along the occupational distribution

In table 5 we investigate cross-occupational effects along the occupational distribution by splitting our sample into High, Medium and Low occupations.[3] As before, cross-occupational

[3] High skilled occupations are defined as Managers, Directions and Senior Officials, Professionals and Associate Professional and Technical Occupations. Medium skilled occupations are defined as Skilled Trade and Administrative and Secretarial Occupations and Low Occupations are defined as Process, Plant and Machine Operatives; Caring, Leisure and Other Services; Sales and Customer Service and Elementary Occupations.

Dependent Variable $\triangle lnW^N$	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
$\triangle$ m own occupation	0.0438	0.0259	-0.0430	0.0210
	(0.0402)	(0.0377)	(0.123)	(0.0984)
$\triangle$ m below occupation	0.0503	0.0248	0.190***	0.128***
	(0.0365)	(0.0399)	(0.0532)	(0.0399)
$\triangle$ m above occupation	-0.0281	-0.0116	-0.150	-0.126
	(0.0513)	(0.0508)	(0.117)	(0.0930)
Observations	1092	1092	1092	1092
Controls	N	Y	N	Y
Time FE	Y	Y	Y	Y

Entries are estimated regression coefficients of the yearly change in native log real hourly wages on the yearly change in the employed migrant to native ratio, $\triangle m_{ort}$ in the own, below and above occupations for the years 2004-2016. All estimations include 9 occupation groups ordered by real hourly wages and are estimated using 13 government office regions. Additional covariates are controls for migrants and natives separately and include the average age, the proportion with higher, high, intermediate and low education and year fixed effects. Clustered standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Impact of migration on native wages: Ordered by Real Hourly Wage

effects cannot be estimated for the highest and lowest occupation. The final groups, therefore, consist of two High skilled occupations, two Medium skilled occupations and three Low skilled occupations. The results of table 5 show that the positive effect of the migrant-native ratio for occupations below is concentrated in low occupations. For low occupations, the migrant-native ratio in occupations below increases native wages by 0.145 percent. By contrast, for the migrant-native ratio on occupations above decreases native real hourly wages by 0.121 percent. In terms of migrant spillovers, low occupations may be where we are likely to find a strong effect. This could be a result of the large increase in migrant downgrading in low skilled occupations, which is where Cornelissen et al. (2017) find the strongest peer effects. When we order occupations by the standard SOC ordering in Appendix C our results are comparable.

Dependent Variable $\triangle lnW^N_{ort}$	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
High				
$\triangle$ m own occupation	0.117	0.168*	-1.412	-0.815*
	(0.109)	(0.0943)	(0.865)	(0.439)
$\triangle$ m below occupation	0.0992*	0.0270	0.0321	-0.680
	(0.0566)	(0.0372)	(0.847)	(1.153)
$\triangle$ m above occupation	-0.0120	0.0285	1.332	2.253
	(0.0599)	(0.0912)	(2.593)	(2.573)
Observations	312	312	312	312
Medium				
$\triangle$ m own occupation	0.0763	0.0850	0.0438	-0.0680
	(0.0833)	(0.0807)	(0.102)	(0.160)
$\triangle$ m below occupation	-0.0314	-0.0719*	0.152	-0.354
	(0.0468)	(0.0386)	(0.315)	(0.496)
$\triangle$ m above occupation	0.139*	0.181**	-0.254	0.586
	(0.0730)	(0.0671)	(0.561)	(0.878)
Observations	312	312	312	312
Low				
$\triangle$ m own occupation	-0.00112	-0.0179	0.0391	0.0525
	(0.0549)	(0.0450)	(0.0352)	(0.0464)
$\triangle$ m below occupation	0.0722	0.0495	0.185***	0.145**
	(0.0635)	(0.0708)	(0.0701)	(0.0646)
$\triangle$ m above occupation	-0.0908	-0.0675	-0.164***	-0.121***
	(0.0877)	(0.0941)	(0.0391)	(0.0341)
Observations	468	468	468	468

Entries are estimated regression coefficients of the yearly change in native log real hourly wages on the yearly change in the employed migrant to native ratio, $\triangle m_{ort}$ in the own, below and above occupations in High, Medium and Low occupations for years 2004-2016. There are 9 occupations in total, ranked by real hourly wage where High Occupations are defined as the 3 highest paid occupations, Medium Occupations are defined as the next two highest paid occupations, and Low Occupations are the four lowest paid and are estimated using 13 government office regions. Additional covariates are controls for migrants and natives separately and include the average age, the proportion with higher, high, intermediate and low education and year fixed effects. Clustered standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: The impact of migration on native wages in high, medium and low occupations: Ordered by Real Hourly Wage

5 Potential Mechanisms

After presenting the reduced form cross-occupational effects, we explore the role of two potential mechanisms through which the results may operate. First, we concentrate on productivity changes and second we investigate whether migrant inflow into occupations below can allow natives to specialise into better remunerated tasks.

5.1 Productivity

A consequence of migrants downgrading (Dustmann et al., 2013), relatively higher educated migrants take up employment in low paying occupations, especially just after arriving in the UK. This inflow of highly educated migrants into a region-occupation cell likely increases the average level of education in that particular cell. To investigate this, we estimate how the change in the migrant-native ratio, m_{ort} correlates with the change in the proportion of the total sample with high or higher education, within occupation, region, time groups. We define an individual as having high or higher education if he or she finished education aged 20 or later. For this, we create a variable for the change in the proportion of sample in each cell with high or higher education, $\triangle Educ^{H}_{ort}$, and regress yearly changes of this variable on yearly changes in the migrant native ratio in that particular cell, $\triangle m_{ort}$, in a specification similar to the one outlined in equation 1. We also control for changes in the average age and the proportion with low education the the proportion with intermediate education for both migrants and natives separately.

The results in table 6 document a strong, consistent and statistically significant correlation between the migrant-native ratio in an occupation and the proportion of highly educated individuals in that occupation. For the whole sample, an increase in the migrant native ratio is correlated with an increase in the overall proportion with high and higher education across all occupations at 0.105. We decided to define High, Medium and Low occupations like section 5.3 to keep consistency in our definitions[4]. We find that the correlation between migrants and educational attainment is similar along the occupational distribution.

As a next step, we estimate whether wages in an occupation relate to changes in the proportion of highly educated native workers in occupations above and below. For this, we regress changes in native log real wages, $\triangle lnW^{N}_{ort}$ on the changes in the proportion of *all* workers in the same occupation ($\triangle Educ^{H}_{ort}$), the occupation above ($\triangle Educ^{H}_{o+1rt}$) and the occupation below ($\triangle Educ^{H}_{o-1rt}$), who have high or higher education in a regression. We use a regression framework similar to the one outlined in equation 1 and include controls for the

[4]This results in an uneven number of groups in each category

Dependent Variable $\triangle Educ^H_{ort}$	(1) All Educ	(2) All Educ
All Occ		
$\triangle$ m own occupation	0.104***	0.105***
	(0.0162)	(0.0204)
Observations	1404	1404
High Occ		
$\triangle$ m own occupation	0.0863	0.0967***
	(0.0703)	(0.0281)
Observations	468	468
Medium Occ		
$\triangle$ m own occupation	0.0915	0.109**
	(0.0581)	(0.0490)
Observations	312	312
Low Occ		
$\triangle$ m own occupation	0.0976***	0.102***
	(0.0194)	(0.0224)
Observations	624	624
Controls	No	Yes
Time FE	Yes	Yes

Entries are estimated regression coefficients of the yearly change in the overall proportion with high and higher education on the yearly change in the employed migrant to native ratio, $\triangle m_{ort}$ in the own, below and above occupations for All, High, Medium and Low occupations for years 2004-2016. There are 9 occupations in total ranked by real hourly wage where High Occupations are defined as the 3 highest paid occupations, Medium Occupations are defined as the next two highest paid occupations, and Low Occupations are the four lowest paid and are estimated using 13 government office regions. Additional covariates are controls for migrants and natives separately and include the average age, the proportion with intermediate and low education and year fixed effects. Clustered standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Correlations between migration and education

total average proportion of low and intermediate educated workers in the same occupation, region, time group and age controls and time dummies.

Unsurprisingly, column 1 table 7 shows that the proportion of highly educated individuals working in occupation o is positively associated with mean wages in occupation o. More relevant to our purposes, however, we find a positive association between changes in educational attainments of employees in an occupation below occupation o and changes in native wages in occupation o. This result suggest that there are wage spillovers from increased education, even when these occur in different occupations, particularly occupations with lower mean

Dependent Variable $\triangle lnW^{N}_{ort}$	(1) All	(2) High	(3) Medium	(4) Low
$\triangle Educ^{L}$	0.280	0.175	-0.324	0.384
	(0.219)	(0.700)	(0.576)	(0.235)
$\triangle Educ^{I}$	0.378*	0.258	-0.246	0.507**
	(0.222)	(0.569)	(0.512)	(0.239)
$\triangle Educ^{H}$ own	0.530**	0.616	0.123	0.377
	(0.242)	(0.555)	(0.492)	(0.317)
$\triangle Educ^{H}$ Below	0.167*	0.0602	0.0764	0.334
	(0.0988)	(0.0899)	(0.101)	(0.198)
$\triangle Educ^{H}$ Above	0.0936	-0.0360	0.0462	0.317**
	(0.0641)	(0.103)	(0.0921)	(0.121)
Observations	1092	312	312	468
Controls	Yes	Yes	Yes	Yes

Entries are estimated regression coefficients of the yearly change in native log real hourly wages on the yearly change in the overall proportion with high and higher education in the own, below and above occupations for All, High, Medium and Low occupations for years 2004-2016. There are 9 occupations in total ranked by real hourly wage where High Occupations are defined as the 3 highest paid occupations, Medium Occupations are defined as the next two highest paid occupations, and Low Occupations are the four lowest paid and are estimated using 13 government office regions. Additional covariates are controls for migrants and natives separately and include the average age, the proportion with intermediate and low education and year fixed effects. Clustered standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Correlation between education changes and wages- Ordered by Real Hourly Wage

wages.

5.2 Specialisation

We also consider an alternative mechanism of impact where migrant inflow into lower occupations allows natives to specialise in more complex, better remunerated tasks. As previously highlighted by (Peri and Sparber, 2009; D'Amuri and Peri, 2014) migrant inflows can allow natives to specialise in jobs which are more concentrated in complex communicative and interactive tasks, for which they have a comparative advantage. This specialisation could result in an increase in overall productivity and therefore an increase in native wages. Currently we lack the necessary variables to map each occupation to a particular task. In the meantime, we approximate specialisation into more technical tasks by the proportion of natives either taking up or being offered 'Job Related Training or Education'. Since specialising

	(1)	(2)	(3)	(4)
	Train/Educ completed		Train/Educ offered	
mignat_change_4	0.0779**	0.0794**	0.0175	0.00981
	(0.0377)	(0.0376)	(0.0546)	(0.0552)
mignat_change_4_below	-0.00155	-0.00565	0.0852*	0.0681
	(0.0228)	(0.0216)	(0.0488)	(0.0444)
mignat_change_4_above	-0.0236	-0.0268	-0.0349	-0.0314
	(0.0240)	(0.0266)	(0.0521)	(0.0478)
Observations	1092	1092	1092	1092
Controls	N	Y	N	Y

Entries are estimated regression coefficients of the yearly change in the proportion of natives who have taken or have been offered but rejected job related training or education on the yearly change in the employed migrant to native ratio, $\triangle m_{ort}$ in the own, below and above occupations for years 2004-2016. All estimations include 9 occupation groups ordered by real hourly wages and are estimated using 13 government office regions. Additional covariates are controls for migrants and natives separately and include the average age, the proportion with higher, high, intermediate and low education and year fixed effects. Clustered standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Correlation between migration and native training- Ordered by Real Hourly Wage

into more technical tasks is likely to entail some re-training, the offer or completion of job related training might approximate natives specialising.

We define two averages, one for the proportion of natives undertaking 'Job Related Training or Education' and one for the proportion of natives being offered 'Job Related Training or Education'. We then regress yearly changes in these proportions on yearly changes in the migrant native ratio in the same occupation($\triangle m_{ort}$), in the occupation below ($\triangle m_{o+1rt}$), and in the occupation above ($\triangle m_{o+1rt}$) within a region, time cell. We use a framework analogous to equation 1 where we also control for the total average proportion of higher, high, intermediate and low educated native and migrant workers in the same occupation, region, time group and age controls and time dummies.

Table 8 shows, a weak but nonetheless detectable correlation between changes in the migrant-native ratio in occupations below and changes in native employees being offered 'Job Related Training or Education'. Whilst we cannot detect any correlations with completed educational courses, offers to show a correlation, albeit only marginally statically different from zero.

6 Conclusion

The results presented in this paper suggest that the wages of natives working in an occupation and a region are increased by immigration into lower paying occupations into the same region. This effect is particularly strong for low paying occupations, which tallies with results presented by Dustmann et al. (2013) showing that migrants to the UK downgrade upon arrival. These positive *cross-occupational* effects are likely to arise because of two mechanisms. First, we find that immigration into an occupation increases the average educational attainment of all employees working in that occupation. This effect arises mechanically by immigrants being more educated than natives. The average educational attainment of an occupation, in turn, is positively associated with wages in higher paying occupations. Second, we find that immigration into an occupation increases in-job training offers of natives working in better paid occupations, which possibly allows natives to specialise into better remunerated tasks. Our results have important implications for policy makers. Much of the policy debate surrounding migration focuses on how to attract high skilled migrants for high skilled jobs. Our results, however, suggest policymakers should consider the wider work environment and the complementarities that can occur across occupations. If countries stop migration into low skilled occupations then this could potentially reduce productivity spillovers to natives in higher paid occupations and thus harm real wage growth for natives, which in the UK has remained noticeably low since the financial crisis.

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A Data Sampling

The APS utilises the LFS, LLFS and the APS(B) data however these have different designs which influence the construction of the APS. The LFS uses a rotational sampling design, such that a household will be in the sample for five quarters, where each quarter a cohort will drop out, one cohort will be on their last interview in wave 5 and one cohort will newly join the survey and be on wave 1. Information is collected 1-4 week prior to the interview however questions on gross weekly wages and hours worked are only asked during the first and fifth interview. From the LFS the APS only utilises those who are either in their first interview(wave 1) and their last interview(wave 5). So within one year of the APS we will have 8 different sample groups from the LFS, two of which will be sampled each quarter which prevents the same household being included twice in one 4-quarter period. So this means between two consecutive years 50% of the sample will be in common. The LLFS sample is designed differently. Where households sampled will be interviewed in four annual waves, so the same household is interviewed four years in a row with the fieldwork spread equally across the four quarters. As such for each consecutive year 75% of the LLFS sample is in common and 25% is replaced. The LLFS sample is stratified by local area and the sample size is determined by a target number of Economically Active interviews. However if that target is achieved from wave 1 and 5 from the main LFS then no boost is required. This feeds into the APS weights. If we consider the 2014 data, 319,757 responding or imputed people are from 155,554 households. 42.1% came from the main LFS and the rest from the LLFS(ONS). The APS(B) data was a sample boost for England only in the years 2004 and 2005. This sample did not answer all of the sample questions and as such some estimates from the APS are based on a subset of the database.

B Occupation Definitions

In this paper we use three different SOC definitions shown in Table 9. X paper outlines three key changes. Firstly, within our main dataset we use both SOC2000 from 2004-2010 and SOC2010 occupations from 2011-2016. There were four main areas of change from the SOC2000. Firstly, managers were more strictly defined. Where, jobs with the manager title whose tasks did not involve significant responsibilities for strategic control over resources were reallocated to other major occupation groups. Secondly, there was a reallocation of most nursing occupations from associate professionals in group 3 and technical occupations to professional occupations in group 2. Thirdly, there was a reclassification of occupations

(1)	(2)	(3)
SOC1990	**SOC2000**	**SOC2010**
Managers and Administrators	Managers and Senior Officials	Managers, Directors and Senior Officials
Professional Occ.	Professional Occ.	Professional Occ.
Associate Professional and Technical Occ.	Associate Professional and Technical Occ.	Associate Professional and Technical Occ.
Clerical and Secretarial Occ.	Administrative and Secretarial Occ.	Administrative and Secretarial Occ.
Craft and Related Occ.	Skilled Trades Occ.	Skilled Trades Occ.
Personal and Protective Service Occ.	Personal Service Occ.	Caring, Leisure and Other Service Occ.
Sales Occ.	Sales and Customer Service Occ.	Sales and Customer Service Occ.
Plant and Machine Operatives	Process, Plant and Machine Operatives	Process, Plant and Machine Operatives
Other Occ.	Elementary Occ.	Elementary Occ.

This table show the changing definitions of 1-digit SOC occupations overtime.

Table 9: Definition of occupations

associated with information technologies however this did not impact their allocation across major occupation groups. Lastly, there was a creation of supervisory unit groups at the 4-digit level in major occupation groups 4, 5, 6 and 7. It does not seem this directly impacted potential movements between major occupations but would indirectly do so through the stricter definition of managers in major group 1.

The APS data provides a dual coding for occupations in 2010, such that we have the SOC2000 and the SOC2010 occupations, this is shown in table 10 for the working age population(16-65). As we can see the largest differences between definitions which are managers falls by around 5.3 percentage points, professional occupations increases by around 5 percentage points. This is to be expected by the redefinition of what a manager is for the former and for the latter it is most likely driven by the reallocation of nurses into the professional occupations category. With the third largest change being much smaller for Sales and Customer Service occupations increasing by 0.77 percentage points(most likely as a result those previously defined as managers being redefined as supervisors or similar). Despite these differences, at this moment, we do not account for this change in definition. This is mainly due to the current limitation of our dataset where we do not have the necessary 4-digit occupation definition to accurately backcast from SOC2000 to SOC2010.

A much larger issue is matching from SOC1990 to SOC2000 where the change in definitions were much more drastic. The ONS states that is impossible to backtrace the SOC1990 to the SOC2000, although they do provide tables which attempt to do this for the LFS from 1995-2000. Nickell and Saleheen(2015) propose a method which attempts to translate 3-digit SOC1990 occupations into 2-digit SOC2000 definitions. However, we currently do not have

Group	(1) SOC2000	(%)	(2) SOC2010	(%)
1	Managers and Senior Officials	15.21	Managers, Directors and Senior Officials	9.9
2	Professional Occupations	13.37	Professional Occupations	18.34
3	Associate Professional and Technical Occupations	14.51	Associate Professional and Technical Occupations	13.12
4	Administrative and Secretarial Occupations	11.2	Administrative and Secretarial Occupations	11.68
5	Skilled Trades Occupations	10.32	Skilled Trades Occupations	10.92
6	Personal Service Occupations	9.5	Caring, Leisure and Other Service Occupations	9.73
7	Sales and Customer Service Occupations	7.51	Sales and Customer Service Occupations	8.28
8	Process, Plant and Machine Operatives	7.03	Process, Plant and Machine Operatives	6.68
9	Elementary Occupations	11.36	Elementary Occupations	11.05

Entries in this table show the percentage of the working age(16-65) sample in each of the 1-digit SOC occupations using both the SOC2000 definition and the SOC2010 definition in 2010. Source: APS, 2010.

Table 10: Occupation distribution for those of working age in 2010(unweighted)

access to 3-digit SOC1990 definitions in the 1991 CENSUS data. Table 11 shows the occupational distribution of those who were in the QLFS in 2000Q4 and 2000Q2(so those who were in waves 1-3 in 2000Q4 and waves 3-5 in 2001Q2). As we can see the largest percentage point changes are in Elementary/Other occupations at 3.76, Personal Service/Personal and Protective serves at 3.61, Associate Professionals and Technical occupations at 2.28, Managers and Administrators/Senior Officials at 2.07, Professionals at 1.13% and Clerical/Administrative and Secretarial at 1.11. As this may be somewhat driven by seasonal changes in Table 12 I looked also at quarter 2 in both 2000 and 2001, where those who entered in wave 1 in 2000Q2 will be in wave 5 in 2001Q2. I find that these differences persist where only the gap between Professional occupations has lessened. This is not perfect where even though I have kept the same sample waves as comparison it is not neccesarily the case that the same people employed in 2000Q4 are also employed in 2001Q2 where there there is a change in the number of observations over this period. Currently we only match the Major group number one-to-one and do not attempt to match across definitions which could be an issue.

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(1)		(2)	
SOC1990	%	**SOC2000**	%
Managers and Administrators	15.94	Managers and Senior Officials	13.87
Professional Occupations	10.71	Professional Occupations	11.84
Associate Professional and Technical Occupations	10.76	Associate Professional and Technical Occupations	13.04
Clerical and Secretarial Occupations	14.98	Administrative and Secretarial Occupations	13.87
Craft and Related Occupations	11.5	Skilled Trades Occupations	11.83
Personal and Protective Service Occupations	11.33	Personal Service Occupations	7.72
Sales Occupations	8.15	Sales and Customer Service Occupations	7.81
Plant and Machine Operatives	8.64	Process, Plant and Machine Operatives	8.27
Other Occupations	7.99	Elementary Occupations	11.75
Observations	12,105		11,755

Entries in this table show the percentage of the working age(16-65) sample in each of the 1-digit SOC occupations using the SOC21990 definition in 2000Q4 and the SOC2000 in 2001Q2. The sample consists of observations which were present in both datasets as the QLFS is a rolling panel survey where participants drop out after 5 consecutive quarters. Source: QLFS, 2000Q2, 2001Q4

Table 11: Occupation distribution between 2000Q4 and 2001Q2

(1)	%	(2)	%
SOC1990		**SOC2000**	
Managers and Administrators	15.65	Managers and Senior Officials	13.87
Professional Occupations	11.08	Professional Occupations	11.84
Associate Professional and Technical Occupations	10.37	Associate Professional and Technical Occupations	13.04
Clerical and Secretarial Occupations	14.89	Administrative and Secretarial Occupations	13.87
Craft and Related Occupations	12.33	Skilled Trades Occupations	11.83
Personal and Protective Service Occupations	11.20	Personal Service Occupations	7.72
Sales Occupations	8.33	Sales and Customer Service Occupations	7.81
Plant and Machine Operatives	8.78	Process, Plant and Machine Operatives	8.27
Other Occupations	7.37	Elementary Occupations	11.75
Observations	12,755		11,755

Entries in this table show the percentage of the working age(16-65) sample in each of the 1-digit SOC occupations using the SOC21990 definition in 2000Q2 and the SOC2000 in 2001Q2. The sample consists of observations which were present in both datasets as the QLFS is a rolling panel survey where participants drop out after 5 consecutive quarters. Source: QLFS, 2000Q2, 2001Q2.

Table 12: Occupation distribution 2000Q2(w1) and 2001Q2(w5)

C Alternative occupation ordering

Dependent Variable $\triangle lnW^N$	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
$\triangle$ m own occupation	0.00398	-0.0164	-0.134*	-0.0700
	(0.0421)	(0.0401)	(0.0762)	(0.0773)
$\triangle$ m below occupation	0.141***	0.139***	0.297***	0.202***
	(0.0376)	(0.0356)	(0.0879)	(0.0677)
$\triangle$ m above occupation	-0.00976	-0.0169	-0.254*	-0.161
	(0.0699)	(0.0734)	(0.153)	(0.107)
Observations	1092	1092	1092	1092

Entries are estimated regression coefficients of the yearly change in native log real hourly wages on the yearly change in the employed migrant to native ratio, $\triangle m_{ort}$ in the own, below and above occupations for years 2004-2016. All estimations include 9 occupation groups using ONS ordering and are estimated using 13 government office regions. Additional covariates are controls for migrants and natives separately and include the average age, the proportion with higher, high, intermediate and low education and year fixed effects. Clustered standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Impact of migration on native wages: Ordered by default SOC

Dependent Variable $\triangle lnW^N_{ort}$	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
High				
$\triangle$ m own occupation	0.0935	0.154*	-1.736***	-0.530**
	(0.0993)	(0.0869)	(0.650)	(0.256)
$\triangle$ m below occupation	0.246**	0.144	-1.893	0.0373
	(0.0995)	(0.0916)	(2.551)	(0.684)
$\triangle$ m above occupation	-0.00613	0.0198	3.388	0.499
	(0.0575)	(0.0842)	(2.728)	(0.608)
Observations	312	312	312	312
Medium				
$\triangle$ m own occupation	0.0579	0.0670	-0.643	-0.625
	(0.129)	(0.103)	(1.979)	(1.361)
$\triangle$ m below occupation	0.111	0.120*	-0.116	-0.151
	(0.0883)	(0.0677)	(0.461)	(0.144)
$\triangle$ m above occupation	-0.119	-0.141	2.107	2.177
	(0.133)	(0.125)	(6.499)	(3.673)
Observations	312	312	312	312
Low				
$\triangle$ m own occupation	-0.0394	-0.0625	-0.103	-0.0604
	(0.0511)	(0.0436)	(0.0806)	(0.0893)
$\triangle$ m below occupation	0.104**	0.122**	0.291***	0.230***
	(0.0506)	(0.0512)	(0.0758)	(0.0700)
$\triangle$ m above occupation	0.0420	0.0274	-0.217**	-0.160*
	(0.0974)	(0.0947)	(0.105)	(0.0953)
Observations	468	468	468	468

Entries are estimated regression coefficients of the yearly change in native log real hourly wages on the yearly change in the employed migrant to native ratio, $\triangle m_{ort}$ in the own, below and above occupations in High, Medium and Low occupations for years 2004-2016. There are 9 occupations in total ranked by ONS ordering where High Occupations are defined as the 2 highest ranked occupations, Medium Occupations are defined as the next two highest ranked occupations, and Low Occupations are the four lowest ranked and are estimated using 13 government office regions. Additional covariates are controls for migrants and natives separately and include the average age, the proportion with higher, high, intermediate and low education and year fixed effects. Clustered standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14: The impact of migration on native wages in high, medium and low occupations: Ordered by default SOC

Dependent Variable $\triangle lnW^N_{ort}$	(1) All	(2) High	(3) Medium	(4) Low
$\triangle Educ^L$ own	0.406	0.527	-0.437	0.558
	(0.265)	(0.575)	(0.362)	(0.332)
$\triangle Educ^I$ own	0.506*	0.712	-0.401	0.671**
	(0.264)	(0.547)	(0.340)	(0.322)
$\triangle Educ^H$ own	0.732**	1.050*	0.0116	0.703*
	(0.279)	(0.529)	(0.323)	(0.404)
$\triangle Educ^H$ below	0.154	0.254***	-0.168	0.261
	(0.113)	(0.0851)	(0.195)	(0.267)
$\triangle Educ^H$ above	0.0508	-0.0540	0.00237	0.245
	(0.0814)	(0.112)	(0.123)	(0.187)
Observations	1092	312	312	468

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Entries are estimated regression coefficients of the yearly change in native log real hourly wages on the yearly change in the overall proportion with high and higher education in the own, below and above occupations for All, High, Medium and Low occupations for years 2004-2016. There are 9 occupations in total ranked by ONS ordering where High Occupations are defined as the 2 highest ranked occupations, Medium Occupations are defined as the next two highest ranked occupations, and Low Occupations are the four lowest ranked and are estimated using 13 government office regions.. Additional covariates are controls for migrants and natives separately and include the average age, the proportion with intermediate and low education and year fixed effects. Clustered standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Correlation between education changes and wages: Ordered by default SOC

	(1)	(2)	(3)	(4)
	Train/Educ completed		Train/Educ offered	
mignat_change	0.0669**	0.0667**	0.000820	-0.0120
	(0.0322)	(0.0327)	(0.0561)	(0.0598)
mignat_change_below	0.0254	0.0230	0.0952**	0.0947**
	(0.0265)	(0.0276)	(0.0426)	(0.0424)
mignat_change_above	-0.0151	-0.0121	-0.00226	-0.000965
	(0.0393)	(0.0404)	(0.0543)	(0.0571)
Observations	1092	1092	1092	1092
Controls	N	Y	N	Y

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Entries are estimated regression coefficients of the yearly change in the proportion of natives who have taken or have been offered but rejected job related training or education on the yearly change in the employed migrant to native ratio, $\triangle m_{ort}$ in the own, below and above occupations for years 2004-2016. All estimations include 9 occupation groups ranked by ONS ordering and are estimated using 13 government office regions. Additional covariates are controls for migrants and natives separately and include the average age, the proportion with higher, high, intermediate and low education and year fixed effects. Clustered standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Correlation between migration and native training- Ordered by default SOC