Immigrant Downgrading: New Evidence from UK Panel Data

Brian Bell* and Philip Johnson**

October 2023

*   *King's Business School & Centre for Economic Performance, London School of Economics*

**   *Migration Advisory Committee Secretariat*

Abstract

We examine the wage and occupation outcomes for cohorts of immigrants who arrived in the UK since 2002. Using the Annual Survey of Hours and Earnings (ASHE) with a matched migrant identifier, we can follow a 1% sample of all workers (native and migrant) within and across jobs. This also allows us to identify relative attrition rates between natives and migrants. The work focuses in particular on workers who arrived in the UK since 2004 as part of EU expansion. Consistent with prior work, we find substantial evidence of occupational downgrading for these migrants. Importantly, the panel data allows us to track these workers in subsequent years and we find very little evidence of substantial labour market improvement from initial entry. This result is robust to accounting for non-random attrition.

Acknowledgements: We are grateful to seminar participants at KCL, LSE, Strathclyde and UCL. This work was based on data from the Annual Survey of Hours and Earnings, produced by the Office for National Statistics (ONS), and Migrant Worker Scan (MWS) produced by His Majesty's Revenue and Customs (HMRC), and matched by Department for Pension and Works (DWP), and supplied to the Migration Advisory Committee. The data are Crown Copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the data in this work does not imply the endorsement of ONS in relation to the interpretation or analysis of the data. This work uses research datasets which may not exactly reproduce National Statistics aggregates. The views expressed do not represent the views of the Migration Advisory Committee or the Home Office.

1. INTRODUCTION

The first two decades of the twenty-first century witnessed a very rapid rise in the share of foreign-born in the United Kingdom. The 2001 Census showed that 8.9% of the population was foreign-born. The most recent 2021 Census reveals that this has risen to 16.8%, a rise of 7.9 percentage points in the share. By comparison, the share rose by only 2.4 percentage points in the two decades prior to 2001. There was also a notable change in the composition of the new arrivals. Most importantly, the EU expanded in 2004 (and again in 2007) to include East European countries following the collapse of the Soviet Union. The UK decided to allow the accession countries in 2004 (though not in 2007) to have immediate access to freedom of movement rights in contrast to other EU countries that maintained immigration controls, with their final removal across all EU countries only in 2011. To illustrate the effect of this decision, we can see that the number of Polish born in England and Wales rose from 58,000 (0.1% of population) in 2001 to 743,000 (1.2% of population) in 2021. At the same time however, there was also a substantial rise in the number of non-EU born. Those from outside the EU who came primarily for work generally needed to be high-skilled to obtain a work visa and so are likely to be quite different to the accession country migrants.

A natural question to ask is how these migrants have performed in the labour market – both at entry and as they remain in the country. There is of course a large literature that has explored the wages of migrants as their time in a host country increases. This literature on assimilation began with the classic Chiswick (1978) paper that showed that in a cross-section regression the earnings of recently arrived migrants in the US was significantly lower than migrants who had been in the country for a longer time, but that there was subsequent rapid wage growth as time in the US grew which led to an overtaking point where the earnings profiles of natives and immigrants crossed. Borjas (1985) pointed out that a cross-section regression could not separately identify returns to time in the host country from cohort quality differences. In other words, finding strong assimilation in a cross-section could also simply indicate that prior cohorts of migrants were of a higher "quality" than more recent cohorts. To resolve this, Borjas examined the same cohort over time from repeated cross-section data and found that within-cohort wage growth was significantly smaller than the growth predicted by cross-section regressions for most immigrant groups. Subsequent studies (Borjas (1995, 2015)) have shown that there are strong differences across migrant cohorts in their rate of assimilation and that many cohorts never achieve convergence. For example, Borjas (2015) shows that the 1995-99 arrival cohort of migrants in the US had a 27% wage disadvantage on arrival and that relative wage growth over the next ten years was only 2.5%.

It is important to note that the validity of following synthetic cohorts of migrants over time relies on the assumption that return migration is random. To see this, suppose we observe a cohort of migrant arrivals in year 0 and again at year 10. Assimilation is measured by comparing the wage growth of this cohort over the ten-year period with native (or another migrant cohort) wage growth over the same period. But suppose the lowest earning migrants in this cohort have returned to their home country by year 10. Then wage growth will look strong because of the compositional change of the cohort, and we will overestimate the extent of assimilation. Whilst one can examine observable characteristics of the cohort over time to infer changes in composition, only individual panel-data will suffice to address this problem. Rho and Sanders (2021) is one of the few studies to exploit high-quality panel data to address this.

We use a newly available panel dataset for the UK in this paper that follows a large number of migrants and natives each year and provides high quality data on wages and employment. The data allow us to observe job-to-job transitions and exit from the panel. Our focus is on the labour market performance of migrants since the start of the millennium with a particular focus on the group of migrants who arrived from the EU accession countries over the course of the 2000s. The paper is structured as follows. Section 2 discusses the data used in the results and provides descriptive statistics. As this is the first paper to utilise a large representative panel dataset for the UK to explore immigrant assimilation, we discuss evidence on attrition in Section 3. Section 4 presents evidence on wages of migrants and natives on entry into the UK labour market and Section 5 examines evidence on returns to tenure and experience and assimilation. We provide some interpretation of our results in Section 6 and conclude in Section 7.

2. DATA

2.1 DATASETS

Our analysis primarily uses the Annual Survey of Hours and Earnings (ASHE) – Migrant Worker Scan (MWS) matched dataset. ASHE is the premier source of earnings information in the UK and forms the basis for many official wage statistics. It is a 1% sample of all employees, with a panel structure which makes it possible to follow workers over time. The study has been used extensively for research on inequality, and due to its detailed earnings information also for studies on wage rigidities (Elsby, Shin, and Solon (2016), Bell, Bloom and Blundell (2022)). Firm identifiers have also led it to be used for studies on the role of within and between-firm inequality (Schaefer and Singleton (2020)).

The panel dataset for ASHE is available back to 1997 and is administered by the Office for National Statistics (ONS). Workers enter the sample frame by having a particular pair of digits at the end of their National Insurance Number (NINO), the UK equivalent of a Social Security Number, randomly assigned to all UK residents at age 16. Surveyors then identify the employer(s) of these individuals by Her Majesty's Revenue and Customs (HMRC) Pay As You Earn (PAYE) system, the UK government's income tax withholding system. This takes place each January.

Survey forms are then sent to employers requesting information on the worker(s) in the sampling frame who are identified as working for that employer in the PAYE records. It is a legal requirement for firms to complete the survey. Employers complete the forms using information from payroll records. For larger employers, much of the process is automated, with surveyors accessing payroll records and extracting information directly. The survey covers both the public and private sectors, and as it is administered via employers it excludes the self-employed, who constitute approximately 15% of UK employment as of 2019. The survey delivers useable information on 140,000 to 180,000 employees each year. Workers are followed throughout their entire working lives (as their NINO does not change), so years can be combined to form a panel dataset. Our sample uses data from 2002 to 2019, as 2002 was the first year that unique employer references were included in the data, and these are needed to identify employment spells (see below). We focus on those whose first employment spell begins after April 2001.[1] Our sample is therefore essentially all new entrants to the labour market from April 2001 onwards. Unless otherwise stated, our sample is restricted to those ages 18-64 when first observed.

The variables consistently available throughout the entire period include detailed wage and hours information for a snapshot period in April. Wages are broken down into standard and overtime pay. Studies using ASHE tend to use either weekly or hourly wages. From 1998, ASHE also provides a measure of annual earnings over the previous April-April tax year. This variable refers only to annual earnings at the worker's current employer, so needs to be used

[1] Although we use data from 2002 onwards, we use the data from 1997-2001 to identify all individuals already in the panel at some point in the five years prior to 2002. These individuals are then excluded since they must have had an employment spell prior to April 2001.

with caution as for workers who move employers, this will cover only part of their annual salary. Wages in ASHE are not top-coded. Our main wage outcome of interest is log hourly earnings. Earnings include overtime pay and any bonuses related to the surveyed work week. As is standard when using ASHE data, we exclude those whose pay is affected by absence in the reference week. Earnings are deflated by CPI and given in 2019 prices unless otherwise noted.

The analysis in the paper also uses data on job tenure and job switches. ASHE contains an employment start date (empsta) that conceptually allows us to separately identify all employment spells of a worker. Inspection of the data shows however that this variable is often wrongly recorded – for example, a firm may report more than one start date for what is obviously a single employment spell, or the start date may be inadmissible e.g., wrong format or occurring after the survey date. We have performed an extensive cleaning exercise to correct the date. This involves using the employment start date in combination with the unique employer reference number and another variable that asks whether the worker is in the same job as the previous year. Combining these variables allows us to construct a cleaned indicator of employment spells. More details are provided in Appendix A. Our main results will use the cleaned employment spells, but we also report robustness tests that include only individuals that have no imputation of employment spells.

The MWS is a dataset produced by HMRC and identifies all NINOs that are issued by application from foreign nationals. Any person who wants to take paid employment in the UK must have a valid NINO. Those who enter the country after the age of 16 need to apply for a NINO and the application form records their date of arrival in the UK, date of NINO issuance and nationality at time of application. All NINOs issued though this procedure have the same random allocation of the last two digits as those issued automatically to UK residents at age 16, so 1% of all migrants will have the two digits making them part of the ASHE sample. The MWS is then simply matched onto ASHE using the unique NINO, which is then anonymised prior to release.

Finally, we also use the Labour Force Survey (LFS) both to compare the representativeness of the ASHE-MWS data (as this has not been used extensively for analysis of migrants) and to supplement the analysis where variables are not available in ASHE. Most importantly for our purposes, ASHE does not contain any measure of educational attainment.

2.2 DESCRIPTIVE STATISTICS

Table 1 explores how representative the ASHE-MWS data are for migrant samples. As this is a new dataset (though the core ASHE data has been used extensively), we compare tabulations with the LFS which has provided the main data for analysis of migration in the UK. We start in Panel A by examining the estimated stock of workers in 2019 by migrant nationality using both ASHE-MWS and LFS. We identify three migrant groups that we use throughout the paper – (i) A12 – nationals of the 12 Accession countries that joined the EU in 2004 and 2007, (ii) EU14 – nationals of the 14 EU countries prior to 2004 and (iii) ROW – the rest of the world. Note that Irish citizens are included in the UK native population as they are covered by the Common Travel Area. In both datasets, the sample are all those observed in 2019 aged 18-64 who are employees. The ASHE-MWS weights are derived by ONS to match the population totals in the LFS, so it is no surprise that the overall stock estimates are very close. However, the weights do not include nationality as a factor, so there is no automatic reason why ASHE-MWS and LFS should have the same stock estimates by nationality. In practice the stocks are very close for each migrant group. In Panel B we check whether the distribution of migrants by year of arrival is similar in the two datasets. We group migrants into five-year arrival cohorts and report the percentage of the stock in each cohort. It is clear that once again there is a very close match between ASHE-MWS and LFS.

Table 2 examines some basic demographics of the different groups. We report the median age (and share under age 30), the percentage male and percentage living in London for both datasets and separately for all migrants and for those recently arrived – defined as arriving in the UK within the last 2 years. For the LFS we can also report measures of education. The LFS provides two possible measures of educational attainment. First, respondents are asked the age at which they completed full-time education. We convert this to a years of schooling measure by assuming that all UK nationals started school at age 5, all EU14 and ROW started at age 6 and all A12 started at age 7 (see https://databank.worldbank.org/reports.aspx?source=2&series=SE.PRM.AGES). Second, respondents are asked to state their highest level of qualification. Prior to 2011, this question could not be used for migrants because almost all responses were coded as "other qualifications". Since 2011, the survey has aimed to convert foreign qualifications to the equivalent UK qualification. Overall, this has improved the value of this measure, but there is still a much larger fraction of "other qualifications" among migrants than natives. As a result, we use only the highest category of university degree and above which is unlikely to be mismeasured significantly. As this measure is only available from 2011, we use it simply to confirm that the years of schooling variable is effectively capturing the human capital of natives and migrants.

Migrants are generally younger than natives and this gap widens when we focus on those who have recently arrived. Almost 60% of newly arrived working migrants are aged under 30 compared to only 24% of working natives. Migrants are also more likely to work in London, though there is a clear difference between A12 and EU14/ROW migrants, with the latter group very heavily concentrated in the capital. This distinction between A12 and EU14/ROW migrants is again important when looking at educational attainment. A12 migrants have identical average schooling as natives, though they are less likely to either have a degree or less than 12 years of schooling relative to natives. In other words, they are more likely to be located in the middle of the educational distribution. By contrast, EU14/ROW migrants have much higher education levels than natives. They have an average of around 2 years of additional schooling, are almost 30 percentage points less likely to have under 12 years of schooling and around 25 percentage points more likely to have a degree.

3. Attrition

The longitudinal nature of our data allows us to explore relative attrition from the data by migrant status. This is an important issue in immigration economics that has predominantly relied of repeated cross-sectional data (e.g., census or labour force surveys) to generate migrant cohort data based on year of arrival to estimate returns over time spent in the host country. A key assumption with such data is that there is no important self-selection in return migration that would bias estimates of returns over time. For example, if the highest ability workers were most likely to return home, estimates of wage assimilation would underestimate the true returns.

Figure 1 shows the survival rate over a ten-year period for each nationality group and starting wage quartile. The data cover all individuals first observed in the data between 2002 and 2010 (so that we always have a full potential ten-year window after first observation) and we restrict attention to those aged under 40 at entry to avoid issues related to early retirement, though in the regression results below we remove this age restriction. Workers are assigned to a national wage quartile based on their reported wage in the first observation. There are two key observations to make.

First, attrition for UK nationals is reasonably smooth over duration and by the end of the ten-years amounts to around 20%. Recall that the data only covers those workers who are employees at each point in time. To get a sense as to whether this attrition rate is reasonable, we have examined data from the British Household Panel Survey (BHPS) that follows a representative sample of the UK population over time via traditional annual questionnaire. The key difference is that BHPS respondents can have any labour force status. If we select the cohort of BHPS respondents who were in paid employment in 2002, by 2012 we estimate that 15% of the cohort were in a different labour market state (5% self-employed and 10% unemployed/inactive). This group would of course also be missing in ASHE. So, the attrition rate looks broadly consistent with other longitudinal data given the nature of the ASHE sampling frame.

Second, migrants from all nationality groups have a substantially higher attrition rate. By the tenth year of observation, the attrition rate is roughly 30-45% - approximately 10-25 percentage points higher than for natives. There are two elements to this. There is notably large attrition in the first year i.e., a significant fraction is only observed for a single year and then never again. There is roughly a 5-10 percentage point difference between natives and migrants in year one attrition. We have no clear explanation for this. It is not explained by demographics such as age, sex, industry, occupation, or region. After accounting for this year one attrition, the gap between natives and migrants at year ten is around 5-15 percentage points. The most obvious explanation for this difference is return migration. To evaluate this, we have used the LFS to estimate how the size of a migrant cohort changes as time in the UK increases. Subject to measurement error, the size of the cohort should be largest at entry and decline as people leave the UK or die. Since we are focused on those aged under 40 at entry, the second effect will be very small. Our calculations from the LFS suggest that for those arriving between 2002 and 2010, the cohort size falls by around 15 percentage points over a ten-year period. So again, the attrition rates look consistent with alternative data sources.

The final observation from the figure is that there is little evidence of self-selected attrition based on starting wage quartile. To explore non-random attrition more formally, Table 3 estimates regressions of ten-year survival probabilities. Column (1) estimates the raw difference in survival probabilities between natives (the omitted group) and our three migrant nationality groupings. The A12 migrants have the lowest relative attrition of these groups (i.e., more likely to remain) whilst EU14 have the highest attrition. Across the next five specifications the models have an increasing set of demographics added to explore whether the attrition rates by migrant group are related to observable characteristics. The clear message of

Table 3 is that attrition rates remain remarkably stable suggesting that there is little evidence of selection - at least on observables, which include in the final column a full set of starting wage percentile dummies.

4. ENTRY DOWNGRADING

Previous work (Eckstein and Weiss (2004) and Dustmann et al (2013)) has highlighted the substantial downgrading of new immigrants in the labour market. To explore this for our sample, we document the occupational distribution of natives and migrants in Table 4. The table uses LFS data so that we can provide a breakdown by education, but Appendix Table A2 shows the same patterns using the ASHE-MWS data.

Reflecting the descriptive demographics discussed above, there is a clear distinction between the A12 and EU14/ROW migrants. Recent EU14/ROW migrants are somewhat less likely to be in the managerial occupational group but more likely to be in the professional group than natives. However even though this group of migrants has significantly higher education levels than natives, they are more likely to be in lowest skilled grouping of routine occupations, though this downgrading weakens as time in the UK increases. By contrast, the A12 group exhibit very substantial downgrading. 65% of newly arrived A12 migrants work in routine occupations compared to only 17% of natives, even though education levels are broadly similar and there are fewer A12 migrants with less than 12 years of schooling. Earlier arrivals have somewhat lower shares in the routine occupations (48%) but still much higher than natives – suggesting that this downgrading is persistent for this migrant group. Appendix Table A2 shows the same patterns using the ASHE-MWS data.

In the lower two panels of Table 4 we break down the occupational distribution by educational attainment. We group years of schooling into 3 categories: 0-11 years, 12-15 years and 16+ years. The high education category broadly corresponds to university-level education whilst the low education level corresponds to leaving school at the compulsory leaving age. The same broad patterns of downgrading are reflected within each educational category. Perhaps most notably, 41% of recent A12 migrants with a high education level start work in a routine occupation, whilst only 3% of high education natives work in these occupations.

The analysis in Table 4 would suggest that migrants are likely to experience a wage penalty upon entry into the UK labour market as a result of this occupational downgrading, and that the penalty is likely to be higher for A12 migrants than those from EU14/ROW. To examine this, Table 5 estimates a set of entry wage regressions. The sample is any worker who has started a new employment spell within the last twelve months, and for migrants they must also have arrived in the UK within the last two years. The dependent variable in these regressions is therefore the starting log real hourly wage in a job. The first four columns use the ASHE-MWS data, whilst the final four columns use LFS. All the regressions include a full set of age, time, sex and region dummies. Column (1) shows that A12 migrants experience a 24% (1- exp (-0.27)) entry wage disadvantage relative to natives, whilst the gap is around 13% for EU14/ROW migrants. Column (5) is the exact equivalent using LFS data and shows the identical picture. In Column (2) we simply add a set of 9 1-digit occupation dummies to explore the extent to which the occupational downgrading observed in Table 4 can account for these wage gaps. There is very substantial attenuation when occupation dummies are included, with the wage gap for all three migrant groups falling to around 6%. In other words, for the A12 migrants around three-quarters of the entry wage disadvantage can be explained by the occupational 'choice' of the migrant. The same results using LFS data are shown in Column (6). We cannot control for education in the ASHE-MWS data. However, columns (7) and (8) of the table do so for the LFS data. Comparing the base regression with and without education shows a small fall in the entry wage gap for A12 migrants but a very substantial rise for EU14/ROW. This is to be expected given the significantly higher levels of education of these latter migrant groups. Once again, controlling for occupational downgrading explains much, though not all, of the entry wage gap.

One might be concerned by the comparison that is being made in these regressions. We are comparing newly arrived migrants in their first employment with any native worker who starts a new employment spell. Many of these natives will have had prior experience and so it may not be that surprising that there is a large wage gap relative to migrants. One approach to dealing with this is to restrict the native sample in the regression to only their first observed job in the panel. Columns (3) and (4) use this approach for the ASHE-MWS data. As expected, the entry wage gaps fall substantially. For EU14/ROW workers the gap vanishes, suggesting that they suffer no entry wage penalty relative to more similarly experienced natives – though of course they are more highly educated so we would expect a wage premium. For A12 migrants the entry wage penalty drops by around one-half but is still substantial. Controlling for occupation almost entirely eliminates the entry wage gap for all migrant groups.

The results of Table 5 paint a fairly clear picture. A12 migrants experience a substantial wage penalty at entry compared to natives and this is substantially due to their much higher probability of being located at the bottom of the occupation distribution. There is no strong evidence to suggest that they get paid less than new native employees *within* an occupation. EU14/ROW migrants have a much smaller penalty at entry – though given their higher education levels they should experience a wage premium.

Part of the reason for a wage penalty may also be related to the minimum wage. Jobs in the routine occupational grouping are much more likely to be paid the national minimum wage and so occupational downgrading is likely to be associated with a higher probability of being paid the minimum wage. This raises an interesting question as to whether we are really observing occupational downgrading for migrants or whether migrants are only offered minimum wage jobs which will disproportionately also be in the routine occupations. To explore this, Table A3 shows the share of workers in each occupation grouping that are paid the minimum wage (or within 5p per hour). The minimum wage is year- and age-specific. As expected, around 10% of UK workers in routine occupations are paid the minimum wage, compared to 1% in managerial and professional occupations. The share of minimum wage workers is higher for migrants in routine occupations, with 19% of earlier-arriving migrants and 28% for the newly arrived. Interestingly there is no difference between A12 and EU14/ROW in terms of minimum wage incidence. In Table A4, we estimate the probability of receiving the minimum wage at entry. Column (1) gives the raw percentages by migrant group and shows that the A12 have a 17 percentage-point higher incidence than natives, whilst it is closer to 7 percentage points for EU14/ROW. Standard demographic controls do not alter this picture (Column (2)). Finally in Column (3) we add a set of 1-digit occupation dummies. The A12 incidence almost halves relative to natives and the difference with the EU14/ROW is significantly eliminated.

We take two things from this analysis. First, migrant workers are more likely to be minimum wage workers than natives. Second, much of this is explained by which occupation group the worker is in, and there are always a majority of migrant workers even in the routine occupations who are paid more than the minimum wage. Of course, for our analysis of wage progression it does not matter particularly whether the worker starts in a minimum wage job or not.

To provide further evidence on entry wages, we can use the methods of Dustmann, Frattini and Preston (2013) to estimate where newly arrived migrants are located relative to the native wage distribution, and where we would have predicted they would be massed based on their education and age. Figures 2A and 2B show these estimates for the A12 and EU14 & ROW separately. Two key points emerge. First, newly arrived migrants of all nationalities are more likely to be located toward the bottom of the native wage distribution than natives, with a particularly large density for A12 migrants. Second, whilst EU14 & ROW migrants would be predicted to be distributed much further up the native wage distribution, the A12 predicted distribution lies almost exactly on the horizontal line i.e., we would predict that A12 migrants would be distributed across the wage distribution like natives. This again highlights the key distinction between the A12 migrants and those from the rest of the EU and ROW. A12 migrants are as educated as natives, and so have predicted wages that are broadly similar, though there is a higher mass at the very bottom of the expected distribution because A12 migrants are younger than natives.

5. Persistence of Downgrading

To explore the subsequent labour market performance of migrants, we begin by examining the mobility of workers. Figure 3 shows the number of jobs that individuals have held as time since labour market entry increases. By definition all groups begin with one job – their entry job. Over the next five years, the average worker will have worked for 2 employers. Interestingly there is no evidence of substantial differences across the different migrant groups and natives in this statistic – job mobility appears to be similar. However, Figure 3 also looks at job mobility of those who start in routine occupations and shows that both UK workers and EU/ROW migrants are more likely to change employers than A12 migrants who start in routine occupations. We know from the previous section that more migrants start in routine occupations. So, an alternative measure of mobility is to examine the probability that a worker who starts in a routine occupation moves into one of the better-paid occupational groups over time. Figure 4 shows this for the first five years for each group. By the fifth year, 35% of UK workers have moved out of routine occupations into a higher grouping. In contrast, this is lower for all the migrant groups and in particular for the A12 migrants who have only a 16% chance of exiting routine occupations. This combination of high occupational downgrading at entry and low occupational exit over time suggests that these migrants may exhibit weak wage assimilation to natives as time in the UK increases. We now formally examine this.

We follow the standard approach in the literature to estimate wages as a function of time with a particular employer (tenure) and time spent working for all employers (experience). This gives rise to a standard wage equation of the form:

$$w_{it} = \beta T_{it} + \gamma E_{it} + X_{it}\Pi + \varepsilon_{it}$$

where w_{it} is the log real hourly wage of individual i in period t, T_{it} is tenure with the current employer, E_{it} is total labour market experience accumulated with the current and all former employers, and X_{it} are a set of additional controls. The error term, $\varepsilon_{it} = A_i + \theta_{ij} + \nu_{it}$, includes an individual fixed-effect (A_i) capturing unmeasured ability, a job-match effect (θ_{ij}) capturing heterogeneity in the quality of the job-match, and a transitory error (ν_{it}).

As first noted by Altonji and Shakotko (1987) and Topel (1991), OLS estimates of β and γ will be biased if the unobserved individual and job-match effects are correlated with tenure, experience, or both. A common approach to addressing this issue is to use the deviation of tenure from its job mean as an instrument for tenure. This is valid because it is orthogonal to the fixed unobservable individual and job match error components, A_i and θ_{ij}. IV estimates using this instrument may still be biased due to the potential correlation between experience and job-match heterogeneity.

Table 6 estimates standard tenure and experience return regressions for the full sample which can be compared with other estimates from the literature. Columns (1) – (6) are cross-sectional regressions, whilst (7) and (8) are worker fixed-effect panel regressions. In all except the first column, wages are adjusted each year by aggregate real wage growth. Returns are estimated using either non-parametric individual experience and tenure dummies or using a quartic in experience and tenure (denoted by Polynomials in the table). Experience is measured as age minus 18 as we do not completely observe all labour market spells, whilst tenure is measured as time with current employer. The cross-section estimates suggest a 15-20% return for ten years of tenure, and 45-55% return for ten years of experience. These estimates are broadly the same for OLS and IV (Column (6)) and where we restrict the sample to workers that have had no imputation of tenure (Column (4)). These estimates are broadly in line with the literature. For example, Williams (2009) estimates returns for the UK using the BHPS. He estimates ten-year returns at 14% for tenure and 54% for experience, which are remarkably close to our estimates. Dustmann and Pereira (2008) also using the BHPS has slightly lower returns to tenure (9%) and higher returns to experience (79%). Our results also show that switching to panel regressions does not substantively change the estimates, again highlighting that non-random attrition does not seem to be biasing the results.

To explore assimilation, we supplement the wage regression above with a quadratic in year since arrival which by definition is zero for UK workers. A positive return to years since arrival would then imply assimilation. The first column of Table 7 reports the estimated cross-sectional returns to time in the UK for A12 and EU14/ROW migrants respectively. These are quite low. A12 migrants gain 5% relative to natives over a ten-year period which is small relative to the large wage penalty at entry. The estimate is higher for EU14/ROW at 7.2%. However, these estimates may be biased as we know that there is a 30-45%% attrition rate for migrants over ten years. Column (2) therefore estimates the fixed-effect panel regression. There is no strong evidence that this affects the A12 estimates which are now 6%, but there is a notable difference for EU14/ROW assimilation estimates that now rise to 13%. This is roughly equivalent to the raw wage differential at entry and suggests that any wage disadvantage is eliminated during the first ten years in the UK. In the final two columns of Table 7 we estimate the assimilation returns separately for migrants who start in routine occupations (Column (4)) and those starting in the other occupation groups (Column (5)). In both cases, returns for A12 migrants are lower than for other migrants and the returns are also lower for those starting in the routine occupations. This helps explain the underperformance of A12 migrants relative to EU14/ROW migrants – they are more likely to start work in routine occupations and these occupations provide lower assimilation returns.

6. INTERPRETATION

Borjas (2015) presents a simple two-period model to understand immigrant assimilation in the presence of human capital accumulation. Let K be the number of efficiency units an immigrant acquired in their home country, with a fraction δ of these units being specific to the home country labour market. This implies a post-migration human capital of $E = (1 - \delta)K$. Clearly δ = 1 for natives and 0 < δ < 1 for migrants. In the first period, the migrant can invest a fraction π of their human capital in acquiring additional human capital and this investment has a payoff of g percent in the second period. With a discount rate of ρ, the present value of the postmigration income stream is simply:

$$PV = (1 - \delta)K(1 - \pi) + \rho[(1 - \delta)K(1 + g)]$$

The key decision for a migrant is simply to choose the value of π that maximises the present value of post migration earnings. Whilst Borjas provides closed-form solutions by specifying a functional form for g, we focus here on a number of predictions that flow from the model which can help interpret our results. First, migrants have a wage disadvantage at entry relative to similar natives because δ is less than one. Second, migrants who discount their future earnings in the UK more heavily (a lower ρ) will invest less. Investment will therefore be higher for migrants who plan to permanently remain in the UK. Third, migrants should invest more than similar natives. This is because the foregone earnings when investing are lower for migrants (because δ is less than one). Finally, investment will be lower if the worker is in a job that does not provide strong returns to human capital and where mobility out of the job is weak. Imagine an extreme case in which human capital above a minimum (e.g. school leaving certificate) was not valued at all. Then no worker would invest in any additional human capital accumulation and natives and migrants would earn the same as the value of δ would be one for both groups.

These simple predictions help us understand our results and the differences across migrant groups. The wage disadvantage at entry for all migrant groups suggests that δ is indeed less than one. However, the EU14/ROW migrants have a notably lower wage penalty than the A12. This is consistent with the former group having a smaller discount for foreign human capital which is understandable in a context in which at least a fraction of these workers will have needed to obtain employment prior to receiving a visa and are therefore more likely to have been selected as having human capital that is valued by UK employers. The returns to time in the UK are larger for EU14/ROW migrants than A12 despite the initially smaller wage disadvantage. This is consistent with the latter group either having lower expected time in the UK or having jobs that do not significantly reward experience and human capital. The heavy concentration of A12 migrants at entry into the lowest occupational grouping is likely to militate against significant human capital accumulation given the well-known low returns to such investment in these occupations.

7. CONCLUSION

Using newly available panel data for the UK that includes an identifier for migrant workers, we show that workers from those countries that joined the EU in 2004 and 2007 – the A12 – have substantially lower wages at labour market entry in the UK than other similarly qualified workers. The evidence shows that this is a result of occupational downgrading. Utilising the panel aspect of the data allows us to explore subsequent wage progression for these workers. We show that these workers remain toward the bottom of the wage distribution as their time in the UK increases, with only marginally faster wage growth than natives. Given the size of the initial downgrading wage penalty, these workers are on average unlikely to reach the wages of similarly qualified natives.

REFERENCES

Abramitzky, Ran., and Leah Boustan (2017) "Immigration in American Economic History", *Journal of Economic Literature,* 55(4), 1311-45.

Altonji, Joseph, and Robert Shakotko (1987) "Do wages rise with seniority?", *Review of Economic Studies,* 54(3), 437-59.

Bell, Brian, Nicholas Bloom, and Jack Blundell (2022) "Income dynamics in the United Kingdom and the impact of the Covid-19 recession", *Quantitative Economics,* 13(4), 1849-78.

Borjas, George (1985) "Assimilation, Changes in Cohort Quality, and the Earnings of Immigrants", *Journal of Labor Economics,* 3(4), 463-489.

Borjas, George (1995) "Assimilation and Changes in Cohort Quality Revisited: What Happened to Immigrant Earnings in the 1980s?", *Journal of Labor Economics*, 13(2), 201-45.

Borjas, George (2015) "The Slowdown in the Economic Assimilation of Immigrants: Aging and Cohort Effects Revisted Again", *Journal of Human Capital,* 9(4), 483-517.

Chiswick, Barry (1978) "The Effect of Americanization on the Earnings of Foreign-Born Men", *Journal of Political Economy,* 86, 897-921.

Chiswick, Barry., Y. Lee, and Paul Miller (2005) "A Longitudinal Analysis of Immigrant Occupational Mobility: A Test of the Immigrant Assimilation Hypothesis", *International Migration Review,* 39(2), 332-53.

Dustmann, Christian, Tommaso Frattini, and Ian Preston (2013) "The Effect of Immigration along the Distribution of Wages", *Review of Economic Studies*, 80, 145-73.

Dustmann, Christian, and Sonia Pereira (2008) "Wage Growth and Job Mobility in the United Kingdom and Germany", *Industrial and Labor Relations Review*, 61(3), 374-93.

Eckstein, Z., and Yoram Weiss (2004) "On the Wage Growth of Immigrants: Israel 1990-2000", *Journal of the European Economic Association,* 2(4), 665-95.

Gibson, John, David McKenzie, Halahingano Rohorua, and Steven Stillman (2018) "The Long-term Impacts of International Migration: Evidence from a Lottery", *The World Bank Economic Review,* 32(1), 127-47.

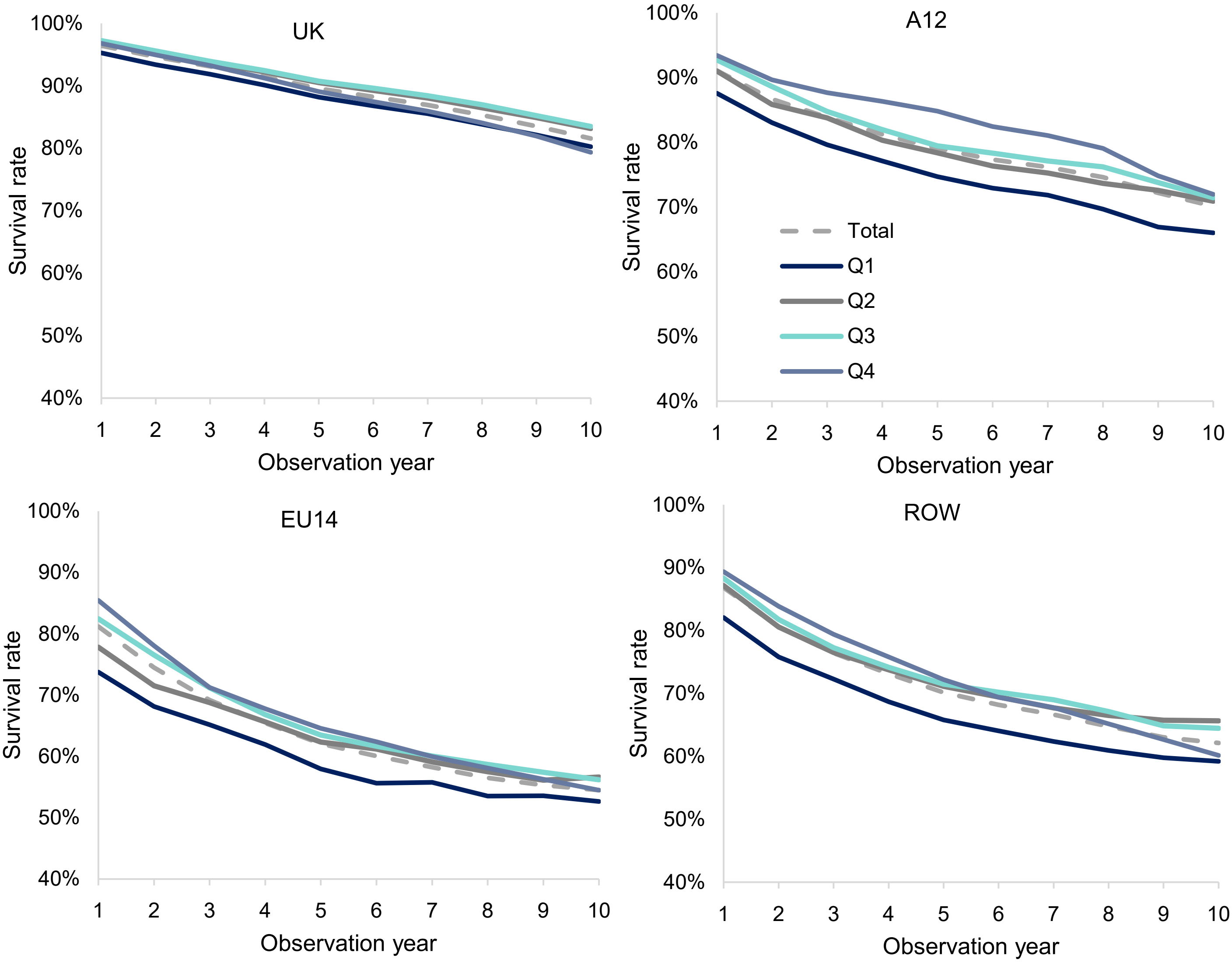
Mattoo, A., I Neagu, and C Özden (2008) "Brain Waste? Educated Immigrants in the US Labor Market", *Journal of Development Economics,* 87(2), 255-69.

Rho, Deborah, and Seth Sanders (2021) "Immigrant Earnings Assimilation in the United States: A Panel Analysis", *Journal of Labor Economics,* 39(1),

Topel, Robert (1991) "Specific capital, mobility, and wages: wages rise with job seniority", *Journal of Political Economy,* 99(1), 145-76.

Williams, Nicolas (2009) "Seniority, experience, and wages in the UK", *Labour Economics,* 16, 272-83.

FIGURE 1: SURVIVAL PROBABILITIES BY NATIONALITY AND WAGE QUARTILE



Source: ONS, ASHE MWS

FIGURE 2A: A12 ENTRY WAGE DISTRIBUTION

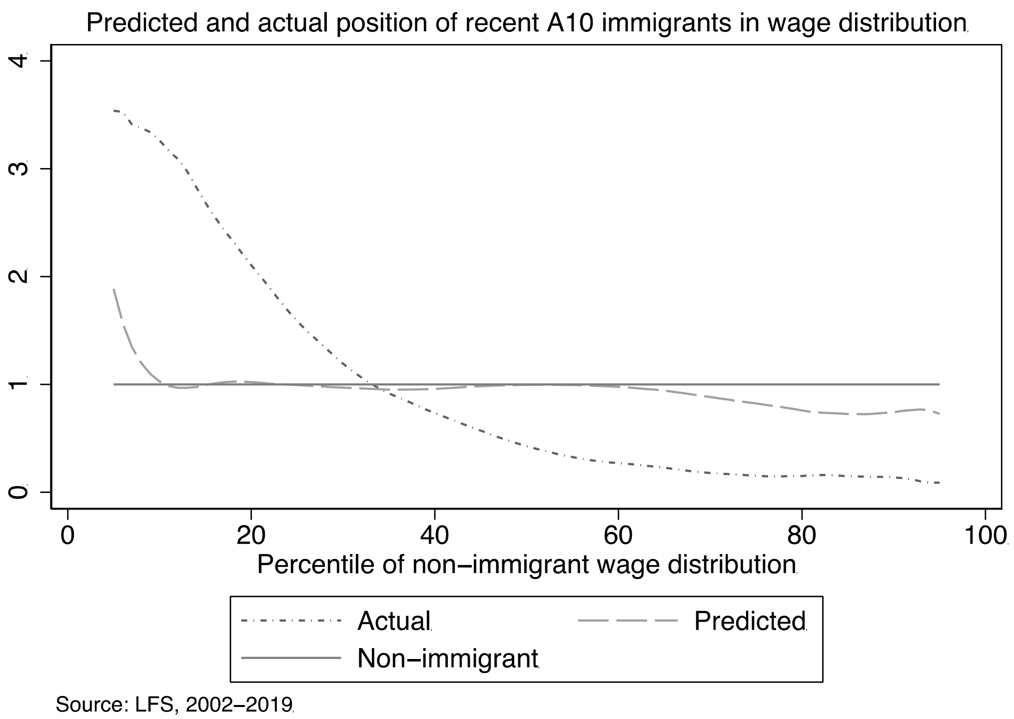


FIGURE 2B: EU14 & ROW ENTRY WAGE DISTRIBUTION

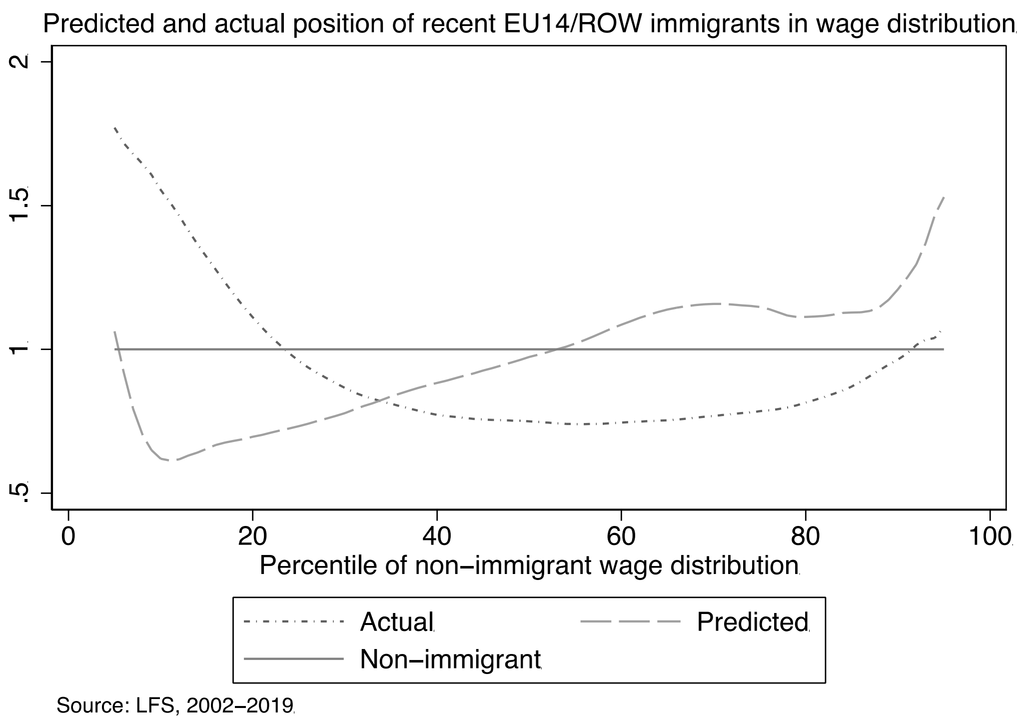


FIGURE 3. AVERAGE NUMBER OF JOBS

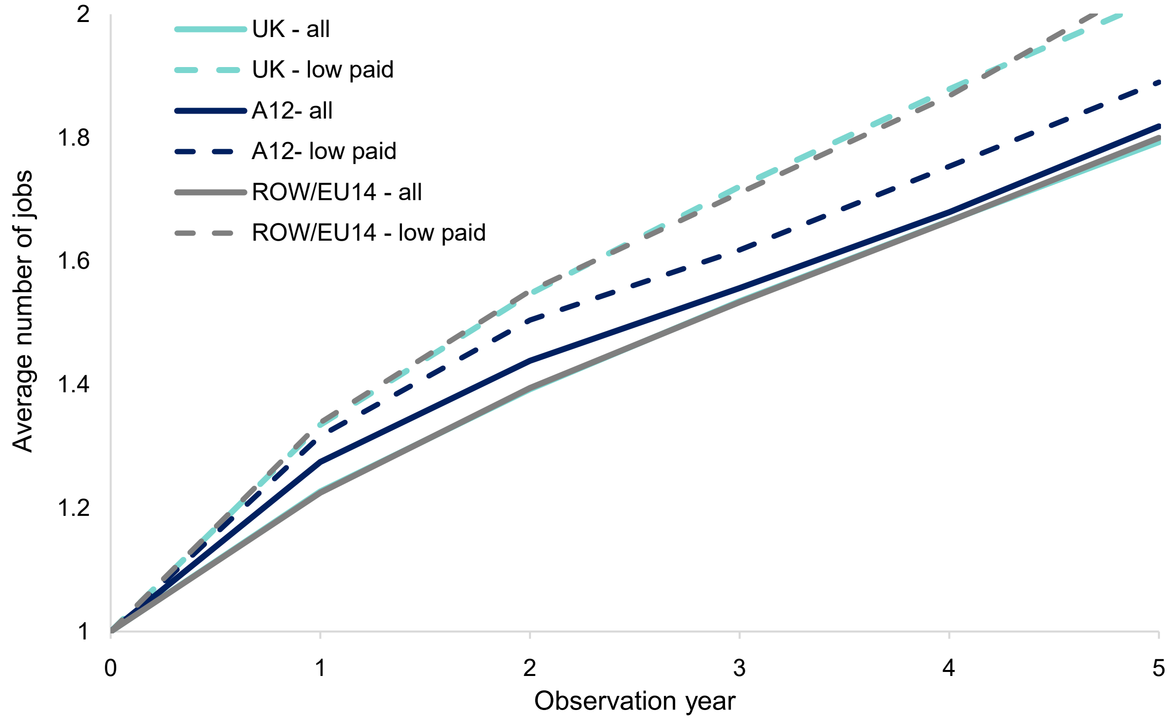


FIGURE 4. PROBABILITY OF SWITCHING OUT OF ROUTINE JOB

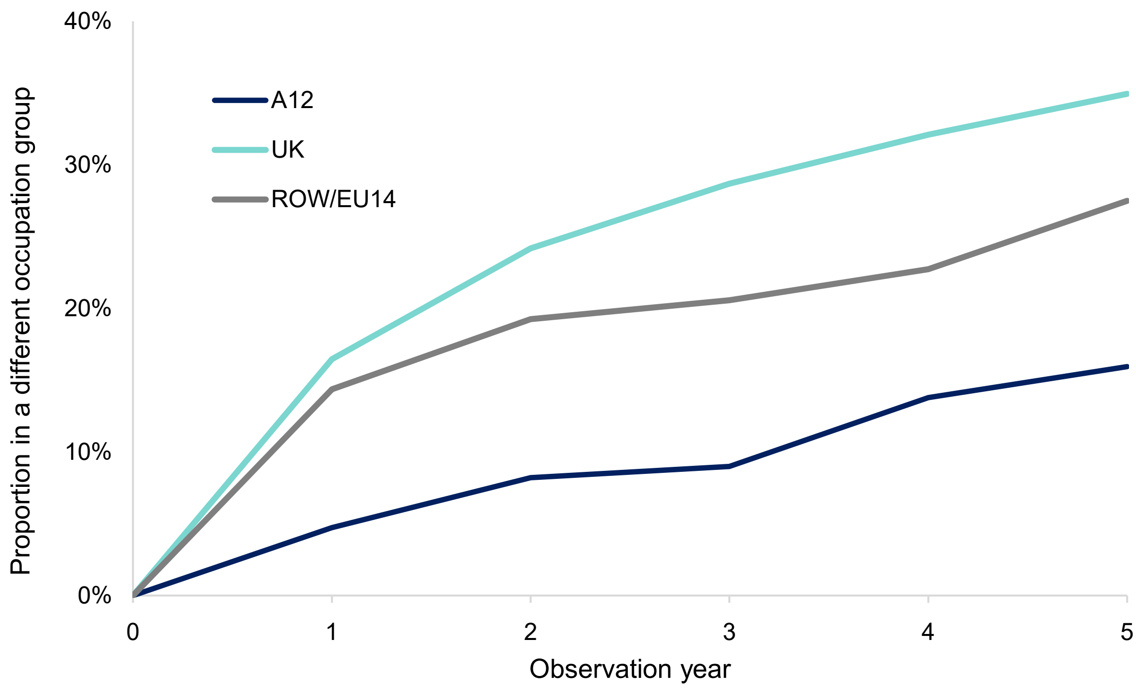


TABLE 1: DESCRIPTIVE STATISTICS

Migrant Group	Total	UK	A12	EU14	ROW
Panel A: Stock of Workers, 2019					
ASHE-MWS	26,275,398	22,826,471 (86.9%)	1,118,034 (4.3%)	749,077 (2.9%)	1,581,816 (6.0%)
LFS	26,493,087	22,788,800 (86.0%)	1,066,156 (4.0%)	881,460 (3.3%)	1,756,671 (6.6%)
Panel B: Migrant Distribution by Cohort					
ASHE-MWS					
2000-2004			14.5%	27.6%	48.6%
2005-2009			50.9%	27.6%	33.9%
2010-2014			24.8%	30.8%	13.2%
2015-2019			9.8%	14.1%	4.3%
LFS					
2000-2004			18.4%	32.1%	43.2%
2005-2009			49.7%	26.6%	33.4%
2010-2014			23.1%	28.9%	16.9%
2015-2019			8.8%	12.4%	6.6%

Notes: Panel A sample are all employees aged 18-64 in 2019. Panel B sample are all employees aged 18-64 over the 2002-2019 sample period. Migrant group is identified in ASHE-MWS based on self-reported nationality at time of NINO application and in LFS using self-reported nationality at time of interview.

TABLE 2: DEMOGRAPHIC CHARACTERISTICS

Migrant Group	UK	A12	EU14	ROW
ASHE-MWS - ALL				
Median Age	41	32	32	34
% Under 30	24.0%	39.1%	36.4%	27.0%
% Male	51.3%	50.1%	53.8%	54.3%
% London	13.2%	20.8%	45.5%	39.3%
ASHE-MWS – RECENT ARRIVALS				
Median Age		27	28	28
% Under 30		63.8%	59.4%	58.3%
% Male		53.6%	54.9%	56.2%
% London		18.8%	46.4%	41.9%
LFS - ALL				
Median Age	40	31	33	33
% Under 30	25.1%	43.4%	34.5%	34.2%
% Male	50.7%	50.5%	53.5%	57.1%
% London	11.0%	21.0%	46.7%	39.9%
Years of Schooling	13.0	13.0	15.3	14.8
% Less than 12 YoS	44.0%	36.9%	15.7%	17.2%
% Degree	32.4%	27.1%	57.8%	55.3%
LFS – RECENT ARRIVALS				
Median Age		27	29	29
% Under 30		65.3%	51.6%	50.7%
% Male		55.2%	55.7%	60.4%
% London		18.9%	48.9%	41.1%
Years of Schooling		12.9	15.4	15.0
% Less than 12 YoS		39.2%	13.3%	13.9%
% Degree		23.7%	58.5%	63.0%

Notes: Sample are all employees aged 18-64. Migrant group is identified in ASHE-MWS based on self-reported nationality at time of NINO application and in LFS using self-reported nationality at time of interview. Migrant group data are restricted to those who arrived in the UK from 2000 onwards. Recent arrivals are those observed within two years of arrival.

TABLE 3: TEN-YEAR SURVIVAL IN PANEL

	(1)	(2)	(3)	(4)	(5)	(6)
A12	-0.074	-0.090	-0.087	-0.072	-0.073	-0.072
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
EU14	-0.211	-0.231	-0.205	-0.200	-0.197	-0.194
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
ROW	-0.136	-0.151	-0.128	-0.125	-0.123	-0.121
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
WAGE QUARTILE 2					0.024	
					(0.003)	
WAGE QUARTILE 3					0.044	
					(0.004)	
WAGE QUARTILE 4					-0.010	
					(0.005)	
Entry-Year	X	X	X	X	X	X
Age		X	X	X	X	X
Region			X	X	X	X
Job Characteristics				X	X	X
Wage Percentiles						X
# Obs	152,412	152,412	152,372	151,000	151,000	151,000
Mean UK Workers						

Notes: Dependent variable equals 1 if individual is observed at year 10 or after in panel, 0 otherwise. Sample is restricted to individuals first observed between 2002 and 2009, aged between 18-64, and whose first employment occurred after April 2001. Standard errors in parentheses.

TABLE 4: OCCUPATIONAL DISTRIBUTION, 2002-2019

	UK	A12		EU14 & ROW		Average wage
		Earlier	Recent	Earlier	Recent	
ALL						
Manager	12.6	4.9	1.7	10.6	8.9	19.55
Professional	31.8	14.1	8.1	37.6	38.6	17.83
Skilled & Semi-Skilled	38.6	32.8	25.4	32.3	28.0	9.80
Routine	17.1	48.3	64.8	19.6	24.5	8.68
HIGH EDUCATION						
Manager	16.1	7.6	3.6	12.8	11.9	
Professional	62.7	31.3	26.8	55.3	54.5	
Skilled & Semi-Skilled	17.9	31.9	29.0	20.5	21.4	
Routine	3.3	29.2	40.5	11.4	12.3	
LOW EDUCATION						
Manager	10.5	3.2	0.8	6.3	3.7	
Professional	16.3	5.1	1.6	13.2	11.6	
Skilled & Semi-Skilled	45.9	33.2	22.6	42.1	35.3	
Routine	27.2	58.5	75.0	38.4	49.4	

Notes: LFS sample are all employees aged 18-64. Migrant group data are restricted to those who arrived in the UK from 2000 onwards. Recent arrivals are those observed within two years of arrival. Education is defined using years of schooling, with high education being 16 or more years, and low education being 11 years or less. Occupation categories are defined by grouping 1-digit SOC codes: Manager (1), Professional (2 & 3), Skilled & Semi-Skilled (4-7) and Routine (8 & 9).

TABLE 5: ENTRY WAGE REGRESSIONS

	ASHE-MWS				LFS			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
A12	-0.270	-0.065	-0.157	-0.024	-0.285	-0.076	-0.246	-0.081
	(0.004)	(0.003)	(0.004)	(0.003)	(0.012)	(0.010)	(0.011)	(0.010)
EU14	-0.135	-0.062	0.005	0.010	-0.109	-0.054	-0.173	-0.084
	(0.006)	(0.004)	(0.005)	(0.004)	(0.015)	(0.012)	(0.015)	(0.013)
ROW	-0.127	-0.052	0.012	0.017	-0.108	-0.044	-0.149	-0.067
	(0.005)	(0.004)	(0.004)	(0.004)	(0.009)	(0.007)	(0.009)	(0.008)
Occupation		X		X		X		X
Education							X	X
# Obs	472,707	472,707	119,471	119,471	116,836	116,787	110,573	110,527

Notes: Dependent variable is the log real hourly wage, and all regressions include a full set of time, age, sex and region dummies. Columns (1) - (4) use the ASHE-MWS data, while columns (5) – (8) use the LFS data. Sample is restricted to 2002-2019, within twelve months of job start and within two years of arrival for migrants. Columns (3) and (4) further restrict the sample to be the first job recorded for each worker. Standard errors in parentheses.

TABLE 6: TENURE & EXPERIENCE REGRESSIONS

	CROSS-SECTION						PANEL	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
5 YRS TENURE	0.133	0.129	0.123	0.148	0.135	0.081	0.078	0.074
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
10 YRS TENURE	0.197	0.198	0.200	0.222	0.159	0.156	0.117	0.118
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
15 YRS TENURE	0.259	0.259	0.256	0.288	0.170	0.225	0.149	0.148
	(0.002)	(0.002)	(0.001)	(0.004)	(0.003)	(0.001)	(0.002)	(0.001)
5 YRS EXPERIENCE	0.286	0.291	0.339	0.278	0.137	0.349	0.334	0.341
	(0.003)	(0.003)	(0.001)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
10 YRS EXPERIENCE	0.483	0.487	0.524	0.462	0.243	0.540	0.555	0.554
	(0.003)	(0.003)	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
15 YRS EXPERIENCE	0.569	0.572	0.607	0.544	0.304	0.627	0.676	0.681
	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)
Adjusted Wage		X	X	X	X	X	X	X
Polynomials			X			X		X
Measured Experience					X			
Spell Quality = 1				X				
IV						X		
# Obs	2,673,130	2,673,130	2,673,130	1,205,745	2,673,130	2,673,130	2,430,047	2,430,047

Notes: Dependent variable is the log real hourly wage, and all regressions include a full set of sex and region dummies. Columns (1) - (6) are cross-section regressions, while columns (7) – (8) are panel fixed-effect. Sample is restricted to 2002-2019, and for migrants arriving from 2000 onwards. Standard errors in parentheses are clustered at the individual-level.

TABLE 7: RETURNS TO TIME IN THE UK

	(1)	(2)	(3)	(4)	(5)
A: A12 MIGRANTS					
5 YEARS IN UK	0.013	0.031	0.034	0.025	0.050
	(0.004)	(0.005)	(0.007)	(0.005)	(0.009)
10 YEARS IN UK	0.050	0.060	0.061	0.046	0.095
	(0.006)	(0.007)	(0.008)	(0.007)	(0.012)
B: EU14 & ROW MIGRANTS					
5 YEARS IN UK	0.040	0.068	0.077	0.042	0.078
	(0.002)	(0.003)	(0.004)	(0.005)	(0.004)
10 YEARS IN UK	0.069	0.122	0.137	0.078	0.139
	(0.003)	(0.005)	(0.007)	(0.009)	(0.006)
# Obs	2,673,130	2,430,047	1,135,235	2,430,047	2,430,047

Notes: Dependent variable is the log real hourly wage, and all regressions include a quartic in tenure and experience and region dummies. Columns (1) is a cross-section regression and includes sex and nationality dummies, while columns (2) – (5) are panel fixed-effect. Sample is restricted to 2002-2019, and for migrants arriving from 2000 onwards. Column (3) is restricted to individuals with a spell quality=1, Column (4) reports estimates for those starting in routine occupations, and Column (5) reports estimates for those starting in non-routine occupations. Standard errors in parentheses are clustered at the individual-level.

APPENDIX A

Employment Spells

Employment spells are identified using employment start date (empsta), firm identifier (entref), and worker identifier (piden). To create a cleaned set of employment spells we proceed with the following steps:

1. Generate a cleaned empsta_revised variable that is missing for any empsta that does not have the correct MMYYYY format, where MM is greater than 12, where YYYY is before 1940 or after 2019 or where MMYYYY is after the current survey month.
2. Create a potential employment spell indicator (unique_job) that is unique for each worker with a given employer i.e., a piden-entref match identifier.
3. An employment spell is accepted if every observation in unique_job has the same empsta_revised (and is not missing) and the number of empsta_revised entries is the same as the number of reported years in the job. So, for example, if a particular unique_job has 9 years of observations, the employment spell is accepted if there are 9 entries for empsta_revised and they are all the same. An employment spell that satisfies this criterion is marked spell_quality=1.
4. If there are some missing empsta_revised within an employment spell but those that are reported in the spell are the same, replace the missing empsta_revised with the reported one provided the reported empsta_revised is before the first observed date in the spell. So, for example, suppose a particular unique_job has 7 years of observations starting in 2007, and has an empsta_revised of 102006 for 4 entries and is missing for the other 3. Since the reported start date (Oct 2006) is prior to the first observation of the job (April 2007) and there is only one reported employment start date, we replace the 3 missing empsta_revised values with 102006. An employment spell that satisfies this criterion is marked spell_quality=2.
5. If there is variation in empsta_revised within an employment spell, replace all empsta_revised with the modal empsta_revised provided it is before the first observed date in the spell. So, for example, suppose a particular unique_job has 7 years of observations starting in 2007, and has an empsta_revised of 102006 for 4 entries and an empsta_revised of 032006 for the other 3. Since the modal reported start date (Oct

2006) is prior to the first observation of the spell (April 2007), we replace the 3 divergent empsta_revised values with 102006. An employment spell that satisfies this criterion is marked spell_quality=3.

6. If there are no valid empsta_revised within an employment spell, we keep the employment spell and set the employment start date as the survey date of the first observation of the spell. An employment spell that satisfies this criterion is marked spell_quality=4.
7. If an employment spell has multiple valid empsta_revised this may indicate a broken employment spell i.e., the worker previously worked for the same firm. We generate a new_unique_job identifier that identifies a piden-entref-empsta_revised match. By construction, each new_unique_job is a subset of a unique_job. Any unique_job where each new_unique_jobs within it have the same empsta_revised (and is not missing) and the number of empsta_revised entries is the same as the number of reported years in the new_unique_job will be a set of valid employment spells. An employment spell that satisfies this criterion is marked spell_quality=5.

TABLE A1: EMPLOYMENT SPELL QUALITY DISTRIBUTION

	Number of Observations	Number of Individuals
Total Sample	3,005,422	429,801
Spell Quality = 1	1,885,797 (62.7%)	248,723 (57.9%)
Spell Quality = 2	235,178 (7.8%)	28,871 (6.7%)
Spell Quality = 3	504,257 (16.8%)	56,932 (13.2%)
Spell Quality = 4	53,505 (1.8%)	42,694 (9.9%)
Spell Quality = 5	275,707 (9.2%)	47,387 (11.0%)
Unallocated	50,978 (1.7%)	5,194 (1.2%)

Notes: Number of observations are totals within each employment spell quality categorization. Number of individuals reports totals that have the relevant spell quality as the highest in their entire record.

TABLE A2: OCCUPATIONAL DISTRIBUTION, 2002-2019

	UK	A12		EU14 & ROW		Average wage
		Earlier	Recent	Earlier	Recent	
ALL						
Manager	12.8	5.1	1.4	10.6	6.9	21.89
Professional	31.3	14.8	6.9	38.4	35.6	19.53
Skilled & Semi-Skilled	38.6	31.7	24.8	30.9	30.5	10.34
Routine	17.4	48.4	66.9	20.1	27.0	9.16
ONE-DIGIT GROUPS						
Managers & Directors	12.8	5.1	1.4	10.6	6.9	21.89
Professional	16.4	8.4	4.2	26.6	23.7	22.26
Associate Professional & Technical	14.8	6.4	2.6	11.9	11.9	16.77
Admin & Secretarial	13.1	8.3	5.9	8.4	7.4	11.38
Skilled Trades	8.4	9.8	7.9	5.6	5.1	12.56
Caring, Leisure & Other Service	8.6	8.1	5.9	10.0	7.9	9.45
Sales & Customer Service	8.5	5.5	5.1	7.0	10.1	8.37
Process, Plant & Machine Operatives	6.5	16.2	15.6	5.0	3.2	11.00
Elementary	10.9	32.2	51.3	15.2	23.9	8.37

Notes: ASHE-MWS sample are all employees aged 18-64. Migrant group data are restricted to those who arrived in the UK from 2000 onwards. Recent arrivals are those observed within two years of arrival.

TABLE A3: OCCUPATIONAL DISTRIBUTION & MINIMUM WAGE, 2002-2019

	UK	A12		EU14 & ROW	
		Earlier	**Recent**	**Earlier**	**Recent**
MINIMUM WAGE SHARE					
Manager	1.0	2.9	8.4	1.6	0.9
Professional	0.8	1.7	2.3	0.8	0.7
Skilled & Semi-Skilled	5.6	9.5	16.9	9.4	12.3
Routine	10.4	19.3	27.8	18.7	28.7

Notes: ASHE-MWS sample are all employees aged 18-64. Migrant group data are restricted to those who arrived in the UK from 2000 onwards. Recent arrivals are those observed within two years of arrival. Cells give the share of workers that earn within 5p of the minimum wage at the time.

TABLE A4: MINIMUM WAGE INCIDENCE REGRESSIONS

	(1)	(2)	(3)
A12	0.174	0.168	0.100
	(0.003)	(0.003)	(0.003)
EU14	0.069	0.076	0.044
	(0.004)	(0.004)	(0.004)
ROW	0.068	0.089	0.061
	(0.003)	(0.004)	(0.003)
Controls		x	x
Occupation			x
# Obs	477,034	476,991	476,991

Notes: ASHE-MWS sample are all employees aged 18-64. Sample is restricted to 2002-2019, within twelve months of job start and within two years of arrival for migrants. Dependent variable is a binary indicator equal to 1 if the worker earns within 5p of the minimum wage at entry. Controls include a full set of time, age, sex and region dummies. Occupation controls are 1-digit dummies.
Standard errors in parentheses.