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Changing jobs: worker mobility and wages in the UK labour market

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Abstract
We study the role of job-to-job transitions in shaping wage dynamics in the United Kingdom. We show that job moves have continued to generate substantial wage gains for movers even during a period of real wage stagnation and declining labour market mobility. Using an econometric model that accounts for worker, firm, and match heterogeneity, we decompose the job mobility premium and find a limited role for worker and firm effects, with most of the return explained by match-specific factors. We also examine the determinants of job mobility and show that much of its recent decline reflects compositional changes in the workforce, particularly ageing and increasing occupational professionalisation. We conclude by discussing the policy challenges of promoting job mobility as a driver of wage growth and more efficient labour market reallocation.

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1. Introduction

The drivers of workers' job moves and their consequences for pay have attracted renewed attention over the past decade, largely in response to the decline and stagnation in labour market dynamism. In both the UK and the US, the share of workers moving directly from one job to another – so-called job-to-job moves – fell sharply during the 1990s and early 2000s and has remained subdued since the Great Recession (Forth, Singleton, et al., 2025; Fujita et al., 2024) , with recent UK evidence pointing to an additional role for policy-induced changes, such as the minimum wage, in shaping mobility. This slowdown has raised concern because job moves are a key channel through which workers secure wage gains (Moscarini & Postel-Vinay, 2018)). In the UK, where weak pay growth has persisted since the Great Recession (Machin, 2025), the link between mobility and wage outcomes has become central to policy debate, with growing calls for measures to revitalise mobility and improve labour market fluidity. The current Government has justified both its planning and employment reforms to workplace rights in part on the basis that it will make workers more willing to change jobs[1].

This paper contributes to that debate by examining the recent evolution of job-to-job mobility and the associated wage premium in the UK. We develop an empirical framework to estimate the returns to job moves while accounting for match quality, firm and individual heterogeneity, and experience and tenure profiles. We explore which individual factors are most strongly associated with mobility, offering insights into how policy might better support workers in making beneficial job transitions.

The backdrop to our analysis is the persistent stagnation of real wages in the UK since 2007, illustrated in Figure 1. Average weekly pay, in 2024 prices, fell from £742 in 2007 to £715 in 2024—a decline of 3.6%. For the median worker, pay in 2024 (£613) remained just below its 2007 level (£615)[2]. This prolonged period of wage stagnation leaves the UK at the bottom of the OECD league tables (Machin, 2025). Importantly, weak wage growth has coincided with a decline in job-to-job mobility, raising the question of how lower mobility has contributed to poor pay performance.

To answer this question, we first set out to quantify the mobility premium for workers in the UK. Our descriptive findings indicate that workers who change employers experience, on average, an additional wage gain of around 5.6% compared to stayers. Although individual wage growth is strongly pro-cyclical (Moscarini & Postel-Vinay, 2018), the differential between movers and stayers remains stable, suggesting that job mobility provides consistent wage gains even through cyclical fluctuations. However, not all workers share the same propensity to move. Younger workers change job more frequently and we document significant differences in job mobility across occupation, sector, and type of work contract. Simple estimates of the mobility premium may therefore be biased. To address selection concerns, we estimate a model that incorporates observed human capital accumulation and unobserved heterogeneity at the individual, firm, and match level. The persistence of a significant premium

[1] See for example the 2025 Spring Statement by the UK Chancellor: "Giving more people access to higher-wage, higher-productivity jobs enhances labour mobility, which the OBR judges could add around another 0.1% to GDP by 2034-35." (HM Treasury, 2025).

[2] This was not due to a decline in the number of hours worked per week. Figure B1 in the Appendix plots the evolution of real hourly wages and shows similar patterns of wage stagnation since 2009.

after accounting for these factors provides robust evidence that mobility itself contributes to wage growth. Additionally, decomposing the movers' premium we find that improved residual match quality is the dominant driver, followed by the wage return from moving into higher-paying firms and, to a lesser extent, individual self-selection. These results highlight role of mobility in sustaining wage progression and the importance of policies that facilitate effective reallocation of labour in the economy.

Having established the wage gains associated with job moves, we examine the factors that shape mobility rates and explore their contribution to the recent mobility slowdown, as well as potential implications for policy. First, we follow a recent literature and characterise job moves based on jobs' task content (Poletaev & Robinson, 2008; Robinson, 2018; Deming, 2023). In line with previous evidence from the US (Robinson, 2018), we find that UK workers tend to move between occupations that are relatively similar in terms of task content. While, on average, occupational moves allow workers to switch to jobs that are more cognitively and less physically demanding (and thus better rewarded), this is not true of displaced workers. Second, we investigate patterns of occupational mobility across the life cycle. Unsurprisingly, the probability of moving to a new occupation when changing job declines with age (though it remains relatively common, never dropping below 50%). Similarly, the task distance covered by occupational moves shrinks in workers' prime age (45-55).

Therefore, an ageing workforce may partly explain the mobility slowdown affecting UK workers. Indeed, an Oaxaca-Blinder style decomposition in the footsteps of Firpo et al. (2018)reveals that compositional shifts explain two thirds of the mobility decline between the end the 2010s and the early 2000s, with age being the most important underlying factor.

These patterns of limited and declining mobility highlight serious challenges in the current context. An ageing workforce may be less likely to respond to job disruption at the hands of technological change (e.g. generative AI) by moving to different jobs requiring significant task adaptation, especially in the absence of adequate reskilling policies. This immobility may eventually expose them to job losses and skill downgrade.

Our paper contributes to two strands of the literature. We start by engaging with the literature on job mobility and its role in shaping earnings growth over the life cycle. While early studies highlighted the importance of job changes and search activity for young workers' wage progression (Topel & Ward, 1992; Keith & McWilliams, 1999), more recent research has focused on mechanisms such as firm sorting, poaching, and wage bargaining in explaining the patterns of wage inequality and wage gains from mobility (Card et al., 2018; Haltiwanger et al., 2018; Lochner & Schulz, 2024). We advance this literature by applying modern econometric methods that incorporate firm, individual, and match heterogeneity to revise the questions relating to the role of job moves in wage growth of workers and thereby offer a more comprehensive analysis of the impact of job mobility on individual earnings.

Second, we contribute to the literature on wage stagnation in advanced economies before and after the Great Recession. Prior work has pointed to the growing decoupling of productivity and wages (Eeckhout, 2022; Greenspon et al., 2021, for the US; Teichgräber & Reenen, 2021), for the UK) as well as to the rise of product and labour market power of firms in reducing the labour share and wages (Autor et al., 2020; Deb et al., 2022; Yeh et al., 2022). This study focuses more directly on the decline in job-to-job mobility, and its contribution to the weak

wage growth in the UK. In doing so, we also discuss the role of policy in reversing declining mobility improving labour market reallocation and potentially driven wage growth.

The remainder of the paper is structured as follows. Section 2 outlines the data sources and the methodology used to measure job moves. Section 3 documents recent trends in job-to-job mobility and the associated wage premium and sets out the empirical framework for estimating the returns to mobility and decomposing them into worker, firm, and match components. Section 4 examines how task content, age, and regional context shape mobility patterns and discusses their implications for policy design. Finally, Section 5 offers concluding remarks.

2. Data

In this Section we describe our two main data sources, and we discuss our approaches to measuring job moves before presenting some descriptive evidence on job mobility rates in the UK.

One of the main objectives of this paper is to provide estimates of the job changing premium in the UK. Our estimates of the premium are based on the Annual Survey of Hours and Earnings (ASHE), an annual survey conducted by the Office for National Statistics (ONS) covering a 1% sample of UK employees drawn from the HM Revenue and Customs Pay As You Earn system. The survey is administered to firms (on whose payroll the sampled employee is), which report information on employees' annual and weekly pay as well as hours worked. This information is based on employers' payroll systems and is therefore expected to be highly accurate. Once sampled, employees are followed annually, even as they change employer. This allows us to construct employment histories with detailed earnings information, which can be used to track job-to-job transitions and estimate the corresponding premia. However, the dataset also comes with important limitations, particularly when compared to comprehensive matched employer–employee data available in other countries. In particular, ASHE suffers from non-random attrition, with an employer response rate of around 55%, which creates frequent gaps in observed employment histories (Jewell et al., 2020) and may introduce selection bias. To address this concern, we implement the attrition-corrected longitudinal weights developed by (Forth, Bryson, et al., 2025) and re-estimate our main specifications using these weights. The results remain broadly unchanged, and we report them in Table B1 of the Appendix as a robustness check. We also discuss the implications of attrition in more detail in the empirical section.

Another limitation of the ASHE dataset is that it only reports limited information on employees' personal characteristics and job arrangements. Therefore, we extend our analysis by using the Labour Force Survey (LFS). The LFS is a quarterly survey representative of all adults in the UK with very detailed information on respondents' characteristics and their employment. The LFS also has a longitudinal element as respondents are interviewed for five consecutive quarterly waves. In our analysis, we leverage the two-quarter and five-quarter longitudinal series of the LFS to track individuals' employment histories over two and five quarters (one year) respectively. The longitudinal series of the LFS starts in 1993 but our main analysis

focuses on the period from 2001 to 2019[3]. Throughout our analysis of the LFS, we restrict the sample to individuals aged between 18 and 64 who are not in full-time education.

One limitation of the LFS is that it does not record information on employers' identities. This complicates the identification of job changes as we cannot simply track the identity of employers over time. To identify workers who have changed job, we follow a 'corrected tenure' approach whereby we consider workers' tenure in different waves of the panel. For example, in the five-quarter longitudinal series of the LFS, we would consider workers' tenure in the first and fifth wave of the panel, notionally one year apart. If in wave five the worker reports a tenure with their current employer of less than twelve months we would consider this as a potential job change as this would suggest they must have changed job at some point within the last year. However, the sampling scheme of the LFS means that in practice workers are not necessarily interviewed exactly twelve months apart (some individuals might be interviewed late in the interview window of the first wave but early in the fifth wave). It could therefore be technically possible to report having been in a job for less than eleven months in wave five while having been in a job for less than a month in wave one, which would be incorrectly classified as a job move. If uncorrected, this approach would overestimate the number of jobs moves. Fortunately, we can apply a simple correction to deal with this issue: we can require that a worker has been with their current employer for at least three months in the first wave they are interviewed. We apply this definition to both the two-quarter and five-quarter to consistently identify job moves.[4]

Descriptive evidence on job-changing rates

How mobile are British workers? To answer this question, Figure 2 plots the proportion of workers that are recorded as having changed job between two quarters in the two-quarter series of the LFS averaged annually between 1993 to 2021. First, the figure shows that the rate at which workers change job follows the business cycle, falling during recessions and bouncing back as the economy emerges from a downturn (as it did in the mid-90s and again in the aftermath of the Great Recession). Second, the figure reveals a secular slowdown in British workers' propensity to move: in 2000, 2.8% of workers moved jobs per quarter; in 2019, the rate of job mobility was down to 2.1%, 27% lower than in 2000[5].

This figure on overall workers' mobility hides important differences in propensity to change job across workers and jobs, which we turn to next. Figure 5 plots the (similarly defined) probability of changing job by the characteristics of workers and their jobs. Starting with sector of employment, we can see that workers in Hospitality and, to a lesser extent, 'Commerce' are much more likely to change job between quarters. More generally, workers in service-oriented sectors (with the clear exception of workers in Public Administration) change job more frequently on average than workers in Manufacturing, Utilities or the Primary Sector. Next, we turn our attention to differences by Occupation: in line with the evidence coming from sectors,

3 This is to avoid the Covid period and the ensuing issues related to low LFS response rates documented for example in Corlett (2024).

4 In practice, the job change rate as computed under the 'corrected tenure' approach tracks quite closely the uncorrected one. Importantly, both measures result in a significantly higher job change rate than if we were to use workers' self-reported job moves (which is probably afflicted by recall bias). Results are available upon request.

5 The same pattern of slowdown in worker mobility is found in ASHE. Figure B2 of the Appendix shows the yearly job-to-job mobility calculated using LFS and ASHE – both exhibiting a similar trend.

we find that workers in Sales and customer service or in Elementary occupations change job more frequently, whereas workers in Skilled trades or Professional and Managerial jobs are less likely to.

More intuitively, we find that workers in temporary jobs are around three times as likely to change job than their peers on permanent contracts and that part-time workers are slightly more likely to change job than their full-time counterparts. Turning to workers' characteristics, having a university degree does not seem to be associated with a higher propensity to change job, probably due to sorting into less mobile occupations (and sectors). Differences by gender are similarly unnoticeable. Interestingly, we see a strong mobility gradient emerge along the age distribution with the youngest workers – aged between 16-24 - much more likely to change job. This is despite the fact that we are not counting full-time students who may be switching from student to full-time jobs. Older workers become progressively less mobile with less than 2% of over-45 workers changing job. In Section 4, we will have more to add on workers' job mobility over the life cycle and on how the ageing of the British workforce might have contributed to the slowdown in mobility emerging from Figure 2.

3. Measuring the Job mobility premium

3.1 Descriptive evidence on job mobility premium

After documenting the slowdown in job-to-job mobility and the individual characteristics associated with higher or lower mobility, we now turn to the wage returns from such labour market transitions. We begin by calculating inflation-adjusted yearly wage growth separately for movers and stayers, as shown in Figure 3. A first striking pattern is the substantial wage growth of movers: on average, workers who changed jobs experienced a 9.9% real wage increase over the period of analysis[6]. The fact that movers enjoy significantly higher wage growth than stayers suggests that wage gains are an important driver of mobility decisions. As discussed in the previous section, however, this also reflects selection, since movers differ systematically from those who remain with the same employer.

Looking more closely at the time variation, movers' wage growth fluctuates considerably, with lower gains concentrated during downturns in the early 1980s, the 1990s, and the Great Recession. This cyclicality is well established in the literature, where job mobility and associated returns are studied in the context of job ladder dynamics and their sensitivity to macroeconomic conditions (J. C. Haltiwanger et al., 2018; Moscarini & Postel-Vinay, 2016, 2018). The more interesting finding emerges when comparing movers' and stayers' wage growth to estimate the simple wage growth premium from mobility, presented in Figure 3. While movers' wage levels are consistently higher, the cyclical pattern of wage growth among stayers broadly mirrors that of movers. This shared cyclicality produces a relatively stable annual mobility premium, averaging 5.6% over the sample period, and displaying much less

[6] Figure 3 is based on a restricted ASHE sample (full-time workers observed in consecutive years), which excludes entrants and leavers and therefore yields a positively selected sample in terms of wage growth. In addition, mean wage growth is affected by outliers due to measurement error in earnings. When using median wage growth, we observe negative growth during periods of aggregate real wage decline (e.g. 2010–2013), consistent with Figure 1.

volatility than either movers' or stayers' wage growth. Even in the aftermath of the Great Recession, when real wage growth for stayers fell to nearly zero, movers still enjoyed a wage growth premium of 3.8 percentage points.

Having defined wage growth for movers and stayers separately, we can relate them to the overall wage growth experienced by workers annually through the following equation:

$$\Delta w_t = \underbrace{\Delta w_t^S\left(1 - J_{t,t-1}^M\right)}_{stayers} + \underbrace{\Delta w_t^M J_{t,t-1}^M}_{movers}$$

where Δw_t^S and Δw_t^M stand for wage growth among stayers (S) and mover (M) respectively and J^M is the share of workers who moved jobs between years $t-1$ and t. We can then track the contribution of movers to aggregate wage growth by computing the ratio $\Delta w_t^M J_{t,t-1}^M / \Delta w_t$ and plot the resulting time series in Figure 4. Despite some fluctuations, movers' wage growth has consistently accounted for close to one-fifth of total annualised wage growth in the UK. In the early 2010s, this share spiked above 30%. Notably, the sustained importance of movers to aggregate wage growth has occurred despite the slowdown in mobility ($J_{t,t-1}^M$) without a significant rise in movers' wage growth (Δw_t^M) highlights the anaemic performance of wage growth among stayers (Δw_t^S) in the UK labour market. The reliance on movers to sustain aggregate wage growth highlights the importance of understanding the drivers of mobility flows and the returns to job transitions, which we analyse in the remainder of the paper.

3.2 Estimation of job mobility premium

Econometric Framework

While the previous section provided descriptive evidence of wage gains from job moves, it has long been recognised that the decision to change jobs is not random. Job ladder models (Burdett & Mortensen, 1998; Moscarini & Postel-Vinay, 2018) emphasise that mobility is primarily driven by outside offers that exceed current pay, with the capacity to make such offers closely linked to firms' productivity and wage-setting ability, and shaped by broader macroeconomic conditions that influence labour market tightness. These mechanisms imply that mobility decisions are far from random and typically generate: (i) selection of movers, since higher-ability workers are more likely to receive attractive offers; (ii) firm selection, as more productive firms are better able to poach and retain workers, resulting in upward moves along the job ladder; and (iii), through their interaction, positive assortative matching, whereby high-productivity workers increasingly cluster in high-wage firms.

These selection and sorting effects motivate an empirical model that can account for such mechanisms in identifying and estimating the wage premium associated with job moves. We therefore adopt a modelling approach in the tradition of Abowd et al., (1999), extending the two-way fixed-effects framework with match effects (Addison et al., 2023; Woodcock, 2023) and controls for Mincerian experience and tenure.

We start by writing a baseline wage model equation stripped of unobserved worker, firm and match heterogeneity as follows:

$$w_{it} = \sum_{s=2}^{S} \gamma_0^s m_{it(s)} + f_0\left(T_{it(s)}, E_{it}\right) + X_{it}\beta_0 + \varepsilon_{it} \quad (1)$$

where w_{it} denotes the logarithm of i's wage at time t , $m_{it(s)}$ are indicator functions for each job spell s of worker i. Tenure in each job spell $T_{it(s)}$ and general experience E_{it} are included via the function $f_0\left(T_{it(s)}, E_{it}\right)$ and X_{it} includes the remaining individual level covariates. Finally, ε_{it} is the idiosyncratic error term.

Note that maintaining the definition used in the previous analysis we define a job move as an employer switch and therefore $m_{it(s)}$, *de facto*, captures worker's mobility in this modelling design – a change in employer implies a new job spell s. In this setting, γ_0^s are parameters of interest that identify the accumulated returns to consecutive job changes relative to the first job spell $s = 1$ (we normalize $\gamma_0^1 = 0$) assuming conditional exogeneity of mobility.

Considering the discussion on selection and sorting that are likely to result from job moving decisions, it is unlikely that Equation (1) would produce estimates of the returns to switching jobs that are isolated from individual selection, firm wage premia effects, and match heterogeneity. The estimated wage returns to job moves in Equation (1), γ_0^s, can hence be interpreted as the gross return to job moves which captures the selection and sorting effects previously described. Following these bias concerns and since we aim to assess the importance of individual, firm and match effects in explaining the mover's wage premium we augment the Equation (1) to explicitly account for such factors:

$$w_{it} = \sum_{s=2}^{S} \gamma_1^s m_{it(s)} + f_1\left(T_{it(s)}, E_{it}\right) + X_{it}\beta_1 + \theta_i + \psi_f + \phi_{if} + u_{it} \quad (2)$$

where θ_i is vector of individual effects, ψ_f is vector of firm effects and ϕ_{if} represents the job match fixed effect. In this model, γ_1^s can be understood as the net return to job moves holding the selection channels via worker, firm and match heterogeneity fixed.

Equation (2) is, however, overparameterized since worker and firm fixed effects are not separately identified in the presence of match fixed effects without further assumptions and that job mobility returns γ_1^s will be fully absorbed by the match fixed effects. To overcome the first underidentification challenge, we follow Woodcock (2015) and impose the additional assumption that match effects are orthogonal to worker and firm fixed effects[7]. This orthogonality condition does not restrict the relationship between worker (θ_i) and firm (ψ_f) heterogeneity and the explanatory variables ($m_{it(s)}$, $T_{it(s)}$, E_{it} and X_{it}) , but it remains a strong identifying assumption[8]. Under this framework, mobility is assumed exogenous conditional on worker, firm, and match effects, as well as other covariates.

Applying the match orthogonality assumption, one can get separate estimates of worker ($\hat{\theta}_i$), firm ($\hat{\psi}_f$) and match fixed effects ($\hat{\phi}_{if}$) by first estimating $\hat{\phi}_{if}$ from Equation (2) without the inclusion of worker and firm fixed effects and then estimating the orthogonal decomposition

[7] The orthogonal decomposition of match effects into firm and workers fixed effects has been widely used in the literature studying the importance of such heterogeneity in explain wage losses after displacement (Lachowska et al., 2020; Woodcock, 2023).

[8] See Woodcock (2015) for detailed discussion of the restrictions in mobility that the orthogonality assumption imposes.

$\phi_{if} = \sum_{s=2}^{S} \delta_{\phi}^{s} m_{it(s)} + f_{\phi}(T_{it(s)}, E_{it}) + X_{it}\beta_{\phi} + \theta_i + \psi_f + v_{if}$ to obtain estimates for $\hat{\theta}_i$ and $\hat{\psi}_f$ using OLS.

We then adapt Gelbach's (2016) omitted variable bias decomposition to express the difference between the gross returns to mobility from Equation (1) and the net returns from Equation (2) as:

$$\hat{\gamma}_0^s - \hat{\gamma}_1^s = \hat{\delta}_{\theta}^s + \hat{\delta}_{\psi}^s + \hat{\delta}_{\phi}^s \qquad (3)$$

where $\hat{\delta}_{\theta}^s$, $\hat{\delta}_{\psi}^s$ and $\hat{\delta}_{\phi}^s$ measure, respectively, the contribution of worker selection, firm sorting and match quality to explain the difference between estimated gross and net returns to mobility, $\hat{\gamma}_0^s - \hat{\gamma}_1^s$. As pointed out previously, since variation across job spells ($m_{it(s)}$) can fully be explained by match effects, Equation (3) ends up reflecting the decomposition of gross return to job switches ($\hat{\gamma}_0^s$) into each of the components $\hat{\delta}_{\theta}^s$, $\hat{\delta}_{\psi}^s$ and $\hat{\delta}_{\phi}^s$. These contributions are estimated by projecting the fixed effects onto the covariates included in Equations (1) and (2) via the auxiliary regressions:

$$\hat{\phi}_{if} = \sum_{s=2}^{S} \hat{\delta}_{\phi}^s m_{it(s)} + \hat{f}_{\phi}(T_{it(s)}, E_{it}) + X_{it}\hat{\beta}_{\phi} + \hat{\theta}_i + \hat{\psi}_f \quad (4)$$

$$\hat{\theta}_i = \sum_{s=2}^{S} \hat{\delta}_{\theta}^s m_{it(s)} + \hat{f}_{\theta}(T_{it(s)}, E_{it}) + X_{it}\hat{\beta}_{\theta} \quad (5)$$

$$\hat{\psi}_f = \sum_{s=2}^{S} \hat{\delta}_{\psi}^s m_{it(s)} + \hat{f}_{\psi}(T_{it(s)}, E_{it}) + X_{it}\hat{\beta}_{\psi} \qquad (6)$$

Finally, consistent with the identification conditions of the econometric model proposed by Abowd, Kramarz and Margolis, henceforth AKM, (Abowd et al., 2002; Kline, 2024), estimation is restricted to the largest connected set of firms—those linked directly or indirectly by observed worker moves. Since our focus is on the returns to job mobility, restricting to the connected set approximates the relevant sub-population of interest: firms and workers where mobility is actually observed[9]. Nonetheless, because connected sets tend to overrepresent larger employers, sample restrictions introduce potential limitations that we discuss in the next section.

Sample Selection

When we restrict our sample to private-sector firms and working-age individuals (16–64) within the largest connected set, the resulting dataset contains 675,400 observations—68.4% of the total sample prior to applying the restriction.[10] Table 1 presents descriptive statistics for both the full sample and the connected set. Workers in the analysis sample exhibit slightly higher hourly wages—around £0.80 more on average—than those in the full sample. However, it is encouraging that hours worked and worker characteristics such as sex, age, tenure, and

[9] Other studies using this family of models aim to study the role of firms in explaining different dimensions of wage inequality in the whole of the labour market (Card et al., 2013, 2016; Song et al., 2019) and therefore representativeness of their sample relative to the average worker assumes a higher importance.

[10] Following the literature, we restrict the baseline AKM analysis to private-sector workers, as centrally determined pay scales and more limited informative mobility in the public sector make firm effects harder to interpret and weaken identification. Including public sector workers leaves the qualitative results unchanged, though the worker component becomes more negative, consistent with a combination of negative selection and wage compression in that sector (see Appendix Table B4).

skill level remain well balanced across the two samples. More notable differences emerge when comparing firm characteristics. Firms in the largest connected set are, on average, more than twice the size of those in the full sample (535 vs. 200 employees) and are somewhat more concentrated in sectors such as manufacturing and financial services. The contrast between the relatively small differences in worker characteristics and the much larger gaps in employer characteristics is evident in the sample sizes: while moving to the connected set reduces the number of workers by about one-third (166,159 vs. 106,524), the number of firms falls far more sharply (77,472 vs. 22,950).

Although the overrepresentation of larger employers in the largest connected set is consistent with other empirical studies using AKM models, the degree of imbalance is particularly pronounced in our data. Higher non-response rates among small firms and the 1% random sampling design of ASHE mean that many moves, especially those involving smaller employers, as well as transitions into and out of the labour force are not observed. As a result, the connected set disproportionately captures mobility among larger firms and more stable employment relationships. This has two implications. First, the effective mobility network underpinning identification is thinner than in a fully observed employer–employee panel, which may limit the precision of the estimated worker and firm effects. Second, the resulting sample is skewed towards workers who are, or have been, employed by larger firms. Together, these features suggest that our estimates may understate the role of firm sorting relative to match quality, a point we revisit in the discussion of the results.

Estimation Results

We start our analysis by estimating the benchmark model in Equation (1). Column (1) of Table 2 shows that the wage premium follows a monotonic pattern along the successive job moves order. The second job (the first employer move) is associated with a 7.2% wage uplift relative to the first job, while higher-order moves accumulate these gains: the third and fourth or higher jobs yield 10.4% and 10.6% gains, respectively, relative to the first job[11]. The weighted average accumulated wage gain from moving jobs is estimated to be approximately 9.8%. Since the model includes a flexible function of age and tenure to capture general and firm-specific human capital accumulation, the estimated coefficient can be interpreted as the average accumulated wage return to switching jobs, over and above the gradual returns to human capital that typically shape earnings profiles over the life cycle for both movers and stayers. To provide context for the magnitude of this premium, we estimate the incremental wage return from each additional move by differencing the coefficients across move orders ($\gamma_1^{s+1} - \gamma_1^s$) and then computing a weighted average based on the proportion of workers making each move. This yields an estimate of 2.5% which represents roughly half the unconditional mover premium reported in Figure 3.

The estimated movers' premium inevitably incorporates selection. For instance, higher-ability workers with greater earnings potential are more likely to be poached, while more productive firms are better positioned to make attractive offers. We therefore turn to decomposing the

[11] It is important to note that, to avoid small-sample bias, job moves of order 4 represent fourth or higher moves – workers who move more than four times across employers are aggregated in this category. Estimates allowing for a finer discretisation of higher-order job moves deliver qualitatively identical results, but with increased imprecision in the corresponding coefficients; these are visible in Table B3 in the Appendix.

contribution of worker, firm, and match-specific wage premia to these returns, as different weights on each component have distinct policy implications.

Following Equations (4) to (6), the estimated contributions of worker, firm, and match heterogeneity to the gross return are presented in Columns (2) to (4) of Table 2. Worker fixed effects contribute negatively - by about 1.4 percentage points on average - indicating negative selection of movers along worker heterogeneity. Although surprising at first glance, this finding is consistent with Haltiwanger et al. (2018b), who show that lower-paid and lower-skilled workers are more likely to move up the job ladder through job-to-job transitions, while highly educated workers typically match to higher-paying firms earlier in their careers and are less likely to separate from them and hence experience large wage gains from mobility. By contrast, moving into better firms contributes positively, though modestly, to job mobility returns. The 0.9 percentage point impact of firm sorting accounts for about 10% of the mobility premium and falls short of offsetting the negative contribution from worker heterogeneity. The result of both these counteracting effects is that the residual match component is estimated to explain the largest share of the wage mobility return.

While the relatively small contributions of worker and firm effects are consistent with Addison et al. (2023), who rely on a longer and more representative employer–employee panel, it is important to recognise potential biases. Limited mobility in AKM-type estimators (Andrews et al., 2008; Bonhomme et al., 2023) can attenuate both worker and firm components due to noisy fixed-effect estimates, and the fact that our analysis sample is biased towards larger employers mechanically compresses the variance of firm effects even in the absence of limited mobility concerns. These forces jointly imply that the contributions of both worker and firm heterogeneity may be understated.

Nevertheless, only a strongly asymmetric downward bias would be sufficient to overturn the result that the residual, interpreted here as match quality net of worker and firm heterogeneity, accounts for most of the mobility return. Importantly, unlike studies that decompose the variance of wages to assess the role of worker and firm heterogeneity in inequality (Card et al., 2013, 2016; Song et al., 2019), our focus is on decomposing the mean mobility premium, which is less sensitive to limited mobility bias, as attenuation primarily affects variance shares rather than mean differences. That said, some of what we attribute to match quality could reflect residual measurement error, though absent strong asymmetries this is unlikely to drive the main result. Moreover, a growing literature on worker, firm, and match heterogeneity in contexts such as post-displacement earnings losses (Helm et al., 2023; Lachowska et al., 2020; Woodcock, 2023) similarly highlights the important role of match quality in shaping wage trajectories after shocks.

The fact that better worker–employer matches play such a dominant role in movers' wage gains is also consistent with structural models emphasizing complementarities between worker skills and firm productivity in the production function (Bagger & Lentz, 2019; Lise et al., 2016) as well as frameworks where bargaining over match surplus occurs under competition for hiring and retention (Postel–Vinay & Robin, 2002).

Given the importance of understanding what determinants drive match quality, namely other forms of specific human capital and its complementarity with firms' productivity, we proceed to analyse the role of occupation and its task contents in shaping job mobility decisions.

4. Heterogeneity in job mobility patterns and implications

The analysis so far has shown that changing job rewards workers with additional wage growth of 2.5% they would not otherwise experience. Another way of characterising job moves is by considering the *type* of jobs workers move across. While not all job moves necessarily imply a change in occupation, for many workers, changing jobs may represent an opportunity for an occupational upgrade, as they may move to an occupation that commands higher wages, offers better growth prospects or whose content is simply better aligned with their own skills. On the other hand, changing occupation may require learning to perform unfamiliar tasks, which may restrict workers' ability to move in the first place. In this section, we document how common it is for British workers to change occupation and we describe how 'big' these moves are by considering the task content of the occupations they move between. This analysis can not only tell us how occupationally mobile British workers are but also help us better understand the underlying nature of job changes, and how this differs across workers and over time.

Some related literature

Our analysis is descriptive in nature and does not adopt any specific theoretical viewpoint. At the same time, it speaks to a growing literature that emphasises the importance of jobs' task content in explaining cross sectional wage differences as well as wage differences over the life cycle. Seminal work by Acemoglu & Autor (2011) inaugurated a successful strand of literature that characterizes jobs in terms of the tasks workers are expected to perform as part of the production process. A key distinction introduced in the paper is between *routine* tasks that are to be performed repetitively (and can be thus easily automatised) and *non-routine* tasks that cannot be broken down in a sequence of predictable steps but require workers to exert a higher degree of discretion.

This framework has been successively deployed to study the impact of job mobility on wages through the lenses of human capital accumulation and depreciation. While an earlier literature had postulated that any industry- or occupation-specific human capital would be lost when switching to a different industry or occupation (Kambourov & Manovskii, 2009; Neal, 1995), under a task-content framework, workers develop *task-oriented skills* that can be carried across occupations. How much of the accumulated task-specific human capital can be used after changing job will depend on how similar the two occupations are in terms of their task content. To answer this question, Poletaev & Robinson (2008) developed measures of distance between occupations based on the composition of their task content. Furthermore, under an assumption that workers find their way into occupations whose task-requirements are best aligned with their own skill mix, Yamaguchi (2012) establishes a direct link between the task-content of the occupation a worker is employed in and their (unobserved) specific human capital. Invoking this relationship, (Robinson, 2018) anticipates that workers would normally move to jobs with higher task intensity and treats these moves as evidence of human capital accumulation. Displaced workers would instead experience a task downgrade which mirrors a loss of specific human capital.

In the analysis that follows, we adopt the toolkit introduced by Poletaev & Robinson (2008) and Robinson (2018) to characterise occupational moves. At the same time, we reject some of the assumptions they implicitly use and we refrain from interpreting changes in the task content

of occupations as direct evidence of human accumulations or loss. Changes in the task content associated to job moves can simply give us a better idea of the implications of job mobility for workers.

Measuring task-content and occupational distance

To characterise jobs in terms of their underlying task requirements, we initially depart from the approach used by Robinson (2018) and based on the DOT. We instead borrow the conceptualization of tasks introduced by Acemoglu & Autor (2011). Drawing on the distinction between routine and non-routine tasks and whether tasks are cognitive or manual in nature, they identify five components that can be used to describe each occupation: non-routine cognitive analytical, non-routine cognitive personal, non-routine physical, routine cognitive, and routine manual tasks. They rely on the US-based O*NET dictionary of occupation attributes to rate the importance of each of these tasks in every occupation[12]. We adapt this approach to the UK context by mapping the 2009 version of O*NET into the UK occupational classifications (SOC 2000 and SOC 2010) allowing us to construct equivalent measures of task-importance for UK occupations at the 4-digit level[13]. Since the task-importance measures have no cardinal interpretation, we standardise them across occupations. Next, we follow Robinson (2018) and define how different any two 4-digit occupations are by computing the Euclidian distance between the vectors of their respective standardised task-importance measures. In particular, we define task distance between occupations k and k' as:

$$\text{Dist}_{kk'} = \sqrt{\sum_{t \in T} \omega_t \Delta_t^2}$$

Where Δ_t is the difference between the t^{th} component of the task importance measures in occupation k and k' and ω_t are weights summing to one. We follow Robinson (2018) in weighting all task components equally.

Figure 6 shows the distribution of the distance associated with workers' job moves as measured in the five-quarter LFS between 2002 and 2020. We can see that around 35% are moves within the same (4-digit) occupation. As task requirements are measured at the occupation level, these moves are naturally associated with a distance of zero. Remaining job moves are to a different occupation, generally implying a positive distance as task requirements between two occupations differ. We can see there is quite a lot of dispersion in the distance associated to job moves, but most moves that are to a different occupation (66%) cover a distance between 1.5 and 3 (for reference, a distance of 1 would be equivalent to moving from being a nursing auxiliary to a care worker whereas an example of a move covering a distance of 3 would be all the way from nursing auxiliary to a solicitor). Generally, this shows that job-movers who do change occupation are quite mobile, even if, unsurprisingly, they tend to move to occupations that are more similar (i.e. closer in distance) to their original employment than if

[12] A new prototype skill taxonomy was launched in 2025 by Skills England (UK Standard Skills Classification) promising a more accurate description of UK´s occupations´ task content based on the more recent and detailed UK SOC 2020 classification. For the purpose of this study, we prefer to keep relying on the more established O*NET taxonomy as it allows us to use measures of task content that have been widely used in the previous literature.

[13] The mapping is based on an employment-weighted many-to-many crosswalk between O*NET and UK SOC 2010 with the employment figures reflecting the relative importance of occupations in the US and the UK.

they were to pick an occupation randomly. This is clearly visible in Figure 7 where we overlay the distribution of task-requirement distance covered by observed occupational moves with the distribution we would see if workers picked a random occupation whenever they change occupation[14].

Changes in task-requirements associated with job moves

Next, we consider how job moves affect the type of tasks workers perform in their jobs. We do this by computing the difference in the importance of each of the five tasks in the two occupations workers move between when they change job. The results are presented in Figure 8. We first focus on the overall period considered in our analysis (2002-2020) where we observe that, as workers change job, they tend to move to occupations where, on average, non-routine tasks are more prominent. In particular, they move to jobs where non-routine cognitive analytical skills are nearly 0.1 SD more important, although they also experience a slight increase in the importance of routine cognitive tasks. This is mostly at the expense of routine manual and, to a lesser extent, non-routine personal tasks, both less prominent in the occupations workers move into.

Separately, we consider job-moves that occurred in the period up to and including the financial crisis (2002-2010) and after the crisis (2013-2020). In doing so, interesting differences between the two periods emerge. Notably, post-crisis job-movers have started moving into jobs with higher intensity of non-routine physical tasks and routine cognitive tasks. In addition, workers were moving into jobs with much lower intensity of routine manual tasks in the run up to the financial crisis, but this trend has disappeared in more recent years. While the task changes associated with job moves are not very large in magnitude, they appear to be positive for British workers. Moving into jobs where analytical tasks are more predominant should be welcomed as these tend to be associated with stronger wage growth (Deming, 2023). More problematically, a shift towards occupations that require more routine cognitive tasks could be worrying to the extent that ongoing diffusion of AI technologies can increasingly automate this type of task (Acemoglu and Restrepo, 2024; Eloundou et al., 2023).

Clear differences also emerge as we consider the cause behind job moves. In Appendix Figure A1, we plot the differences in task importance by whether workers left the previous job voluntarily (due to a resignation) or involuntarily (following a dismissal or redundancy). Workers who lose their job are typically re-employed in jobs with less emphasis on analytical and personal tasks, and more emphasis on non-routine physical tasks. On the contrary, workers who change their job voluntarily typically move to jobs where analytical tasks are more important (although routine cognitive tasks are also more prominent). These findings are in line with evidence from the US, where Robinson (2018) finds that while occupational switchers on average tend to move to jobs requiring higher analytical skills, displaced workers end up in jobs with weaker analytical skill or non-routine physical skills requirements but that require more strength.

While these findings may not be too surprising, they are nonetheless concerning for displaced workers. Intuitively, voluntary job movers have had more time to search for their next job and have better outside options (the possibility to stay in their current employment) so that they would only switch when they find a better match, leading to more common occupational

[14] The random moves distribution is simply based on the idea that a worker's probability to move to a given occupation is proportional to the employment share in that occupation.

'upgrades'. Displaced workers, instead, often go through a period of non-employment when they normally face a weaker outside option as well as an elevated risk of skill depreciation[15]. In these circumstances, they would be prepared to accept any job offer, including in more routine-intensive occupations with lower wages and weaker prospects.

Occupational mobility over the life cycle

Given that occupational moves require adapting to different job content, which comes at a cost, one may wonder how British workers' propensity to change occupation varies with age, as the time horizon over which any gain from moving to a better occupation shortens. In Figure 5, we have already seen how job mobility rates decline with age. In Figure 9, we focus instead on the probability of changing occupation (conditional on having changed job), which is plotted in blue against the left axis. We can see that at the beginning of workers' careers, nearly 75% of job changes result in a change of occupation. The proportion declines consistently with age (save for a short uptick in late 30s) but never drops below 50 percent, indicating that occupational moves remain relatively frequent (conditional on changing job in the first place). On the right axis, we plot the average task requirement distance associated with these occupational moves. The average distance rises until workers reach their late twenties and slightly falls afterwards before rising again when workers reach their mid-fifties. The overall difference is not large (at most around 40% of a standard deviation), but it is interesting to see how older workers who change occupation cover occupational distances that are as high as for younger workers. Of course, given that older workers are less likely to move in the first place, those who move may be a particularly selected sample of individuals who are either particularly adaptable or motivated, or may have lost their job and been forced to relocate to very different occupations. Without additional information it is unclear whether this pattern has desirable implications or not.

Spatial differences in mobility

When it comes to workers' propensity to change job, another important dimension of heterogeneity may come from geography. Figure 10, plots the probability of changing job between two quarters across the devolved nations and the nine English regions. While differences are not as striking as they are at times across sectors and occupations (See Figure 5), we can see that the Northern English regions (especially the North East) and the Midlands lag behind when it comes to workers' mobility, whereas workers in Northern Ireland, Scotland, Wales but also the South of England are slightly more mobile.

What explains the decline in job mobility?

A primary concern emerging from our analysis is the slowdown in workers' job mobility in Britain since the turn of the century (see Figure 2). So far, we have only had a very limited understanding of what might lie behind this decline. Analysis in Section 2 and Section 4, showed that job mobility tends to decline with age as workers become less likely to change job more likely to stay in the same occupation when changing. An ageing workforce may therefore translate into less job turnover. Figure 5 also points to substantial differences in job mobility across sectors and occupations, as well as depending on the type of working arrangement. We have also seen how workers' mobility differs significantly across regions (see Figure 10). Changes in job mobility rates could therefore mask changes in the employment structure, with

[15] See Pissarides (1992) for a theoretical discussion on skills depreciation as a result of unemployment. For some empirical results, see Edin & Gustavsson (2008).

workers increasingly employed in lower-mobility jobs. Alternatively, it could be that workers' propensity to change job, conditional on their characteristics, has shifted. For example, it could be that 30-year-olds are less likely to change job today than they were up to twenty years ago.

To solve this puzzle and shed light on the nature of this secular decline in job mobility, we follow Firpo et al. (2018) and decompose differences in job mobility rate over time into a first component reflecting changes in the observed workforce composition and one reflecting changes in workers' conditional probability to move. We focus on changes between two periods: the four-year pre-Covid period between 2016 and 2019 and the 2001-2004 period, when job mobility was close to its (recent) peak. In this way, we exclude the period affected by the Great Recession when job mobility would have been affected by the business cycle. We consider changes in workforce composition along dimensions related to both workers' and jobs' characteristics, including workers' age, gender, education as well as the sector, occupation and region of employment and whether they are on part-time hours or on a temporary contract. Results are shown in Figure 11. In the top panel we can see that nearly 60% of the 0.23 percentage point decline in job mobility between these two periods can be attributed to changes in workforce composition. The remaining is instead explained by the fact that, conditional on their characteristics, workers have become less mobile over time. The lower panel breaks down the contribution of different characteristics. As anticipated, changes in workers' age are by far the most important factor behind the composition-driven decline in mobility. The share of workers aged 45 or above raised over time from 34% to 40%[16]. Changes in the occupational composition of the workforce also played a non-negligible negative role. In particular, the fifteen-year period saw a marked increase in the share of workers employed in Professional occupations (from 13% to 24%) at the expense of lower-skilled occupations that typically exhibit higher job-changing rates (everything else equal). The slowdown in workers' propensity to move was partly mitigated by the sharp increase in graduates joining the workforce (more than doubling from 15% to nearly 40% of the workforce over this time frame) as graduates are more likely to change job. Other workers' and jobs' characteristics did not play a significant role in driving down the job-mobility rate. Similarly, despite differences in mobility across regions, changes in the geographical composition of the labour force had virtually no impact on the mobility rate.

5. Conclusion and Policy Discussion

In the face of prolonged wage stagnation since the Great Recession, job-to-job mobility represents a way of stimulating wage growth as workers who change job typically experience larger wage increases than workers who stay put. At the same time, who changes job is not random and one wonders whether these mobility gains are simply driven by selection, rendering policies aimed at increasing mobility a blunt instrument to encourage wage growth.

Our analysis reveals this is unlikely to be the case. After controlling extensively for experience and tenure across different job spells, ensuring we compare workers with similar earnings growth profiles, we document a wage gain of around 2.5% per additional job move. We further decompose the mobility premium into the separate contribution of firm, worker and match

[16] Appendix Table A1 reports changes in the workforce composition between 2001-04 and 2016-20

fixed effects and find that most of the premium is attributed to better realized matches between workers and firms, consistent with job moves incorporating forms of dynamic wage bargaining Postel–Vinay & Robin (2002) and strategic complementarities between worker skills and firm productivity Bagger & Lentz (2019). Worker and firm fixed effects instead play a more limited role.

The finding that job mobility premium is mostly the result of better worker-firm matches carries important implications for policy. If the premium entirely stemmed from moves to better firms, policies to improve *all* workers' mobility (e.g. by reducing general search and hiring costs) would be beneficial for workers regardless of their own level of productivity as they would become more likely to move to better-paid firms and see their wages increase. Similarly, keeping search frictions constant, policies that encourage the entry and growth of more productive firms would increase the pool of better-paying firms workers could move to, resulting in more chances to move to better firms and experience wage gains. But when gains primarily stem from match quality, simply increasing the frequency of job moves would not in itself guarantee stronger wage growth. The way to stimulate wage growth through mobility would be to reduce information frictions and better align workers' skills with job requirements by ensuring skills' portability and creating more training opportunities, both on- and off-the-job.

These results are echoed by our analysis of the changes in jobs' task content associated with job changes where we find that job moves broadly lead to improvements in the tasks workers are expected to perform, with cognitive tasks becoming more important, especially non-routine ones. At the same time, the opposite happens among workers who change occupation as a result of being laid-off in their previous job. These workers are more likely to end up in jobs with lower task requirements likely resulting in a poorer match with a job they are overqualified for. This is in line with recent empirical findings in the job displacements literature where the dissolution of better matches is identified as a primary cause of wage loss Helm et al. (2023). Part of this misallocation could be solved by designing a better system of unemployment protection that supports workers in finding a better match by reducing information frictions and giving workers more time to look for a job (See discussion in Brewer & Murphy, 2023).

Overall, our findings confirm job-to-job mobility to be a reliable source of wage growth among workers with the benefits being surprisingly stable over time and across the business cycle. Problematically, job mobility has slowed down in the UK over the last years, meaning that fewer workers get to benefit from this bonus, partly explaining the negative overall performance of wages.

Our analysis identified some of the main factors driving this slowdown. We found that around two thirds of the decrease in mobility can be attributed to compositional changes due to the ageing and professionalization of the workforce – as older workers and those employed in Professional are typically less likely to change job. Whether the weaker mobility of a more professionalised and educated workforce is detrimental remains an open question. On one hand, the lower mobility of this category may be a by-product of greater skill specialization, which could result in higher productivity and wages. On the other hand, labour markets for highly specialised workers may be thinner (especially in some regions), reducing workers´ outside options at the advantage of their employers, who could capture a greater share of the potential productivity surplus. This may be particularly relevant in a context of rising

monopsony power, especially among firms employing high-skilled workers (Deb et al., 2022). At the same time, we do not document noticeable changes in Professionals´ propensity to change job between the early 2000s and late 2010s, suggesting that, at least on the surface, rising labour market concentration would have not had any visible effect on mobility among high-skilled workers.

Another possibility is that Professional workers´ lower mobility may have to do with non-monetary aspects. For example, qualitative evidence from Handscomb et al. (2022) suggests that high-skilled workers may be less prone to change job for fear of losing perks they enjoy in the current job, such as flexible work arrangements. Improving statutory employment rights could therefore be a way of avoiding these lock-in effects that deter mobility – and this is part of the Government's justification for its wide-ranging employment reforms. These include, for example, giving workers on zero hour contracts a right to a contract with regular guaranteed hours, and making it harder for employers to reject workers' requests to move to a flexible work arrangement (Department for Business and Trade, 2024). These changes may mean that workers who have gained arrangements which offer security and flexibility after bargaining on the job may feel more confident of being able to gain similar arrangements in a new job.

Regarding ageing, this is of course part of a broader challenge facing most advanced economies. At the same time, an older workforce does not necessarily need to translate into a less mobile one. Many of the policies discussed above could reduce the cost for older people to change job or occupation, particularly adult learning and training. Understanding how the returns to mobility vary across age groups remains an important question for future research, particularly given differences in job search opportunities over the life cycle.

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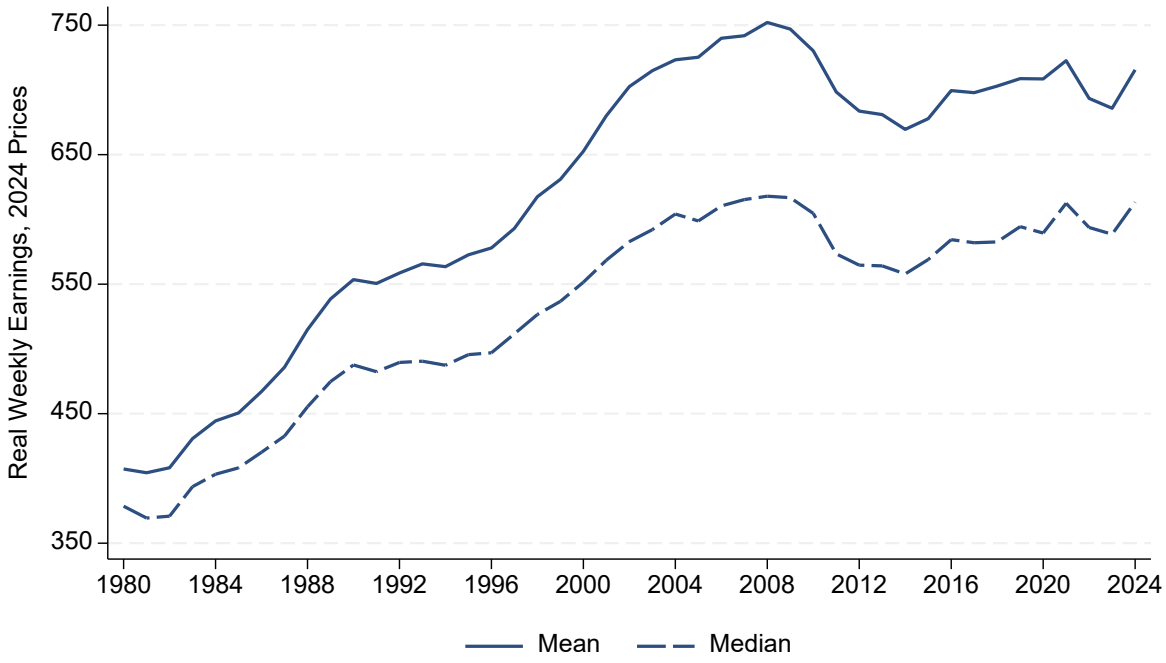
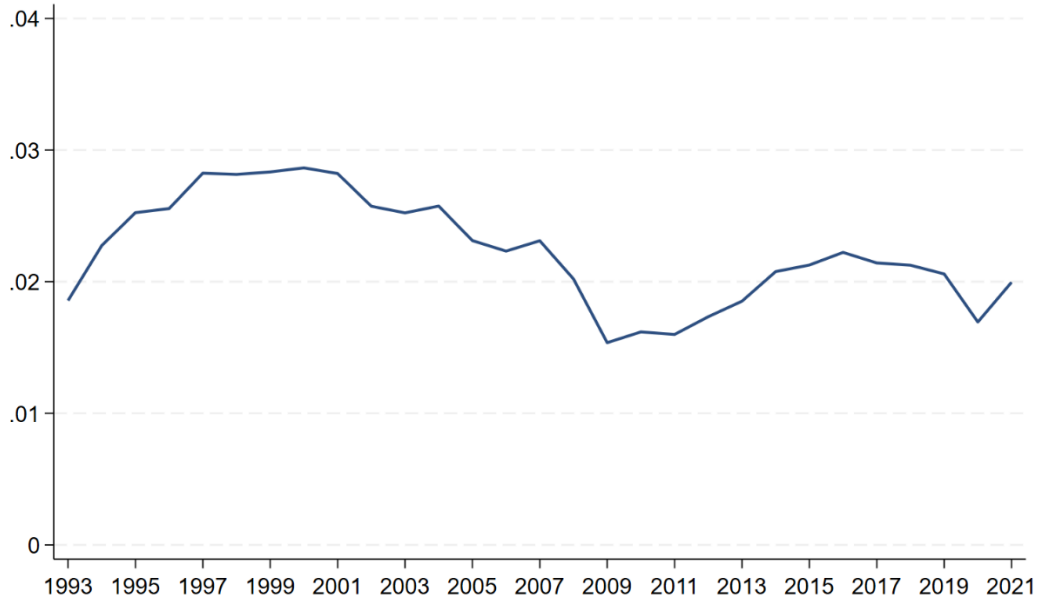
Figures and Tables

Figure 1*:* Real Weekly Earnings, 1980-2024



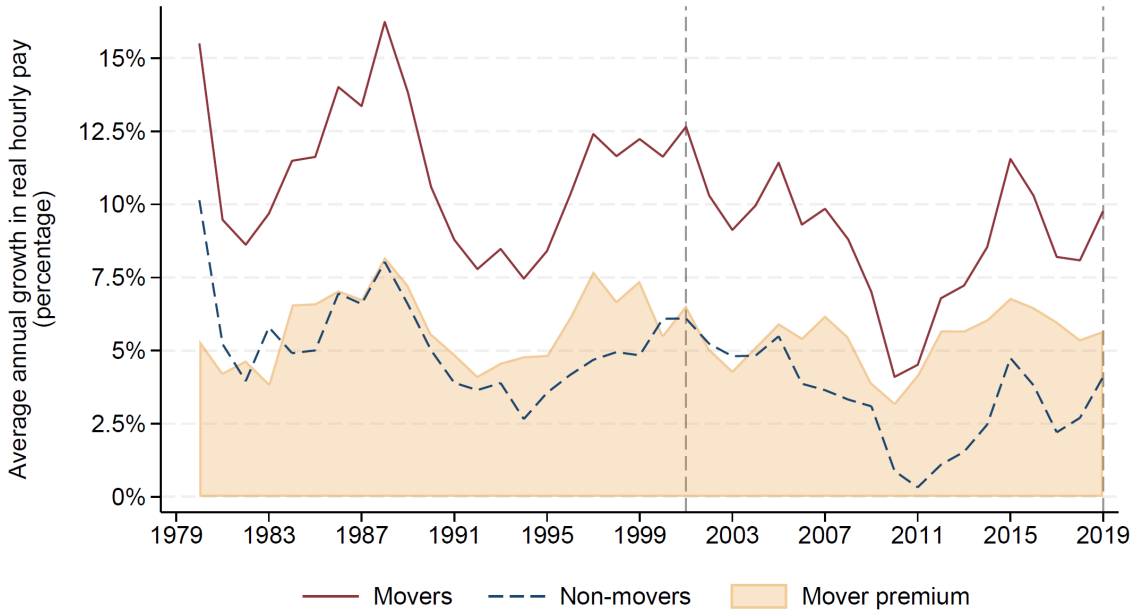
Notes: Mean and median total weekly earnings of all workers, expressed in 2024 consumer prices (CPI). Source: New Earnings Survey/Annual Survey of Hours and Earnings.

Figure 2*:* Proportion of workers moving to a new job per quarter



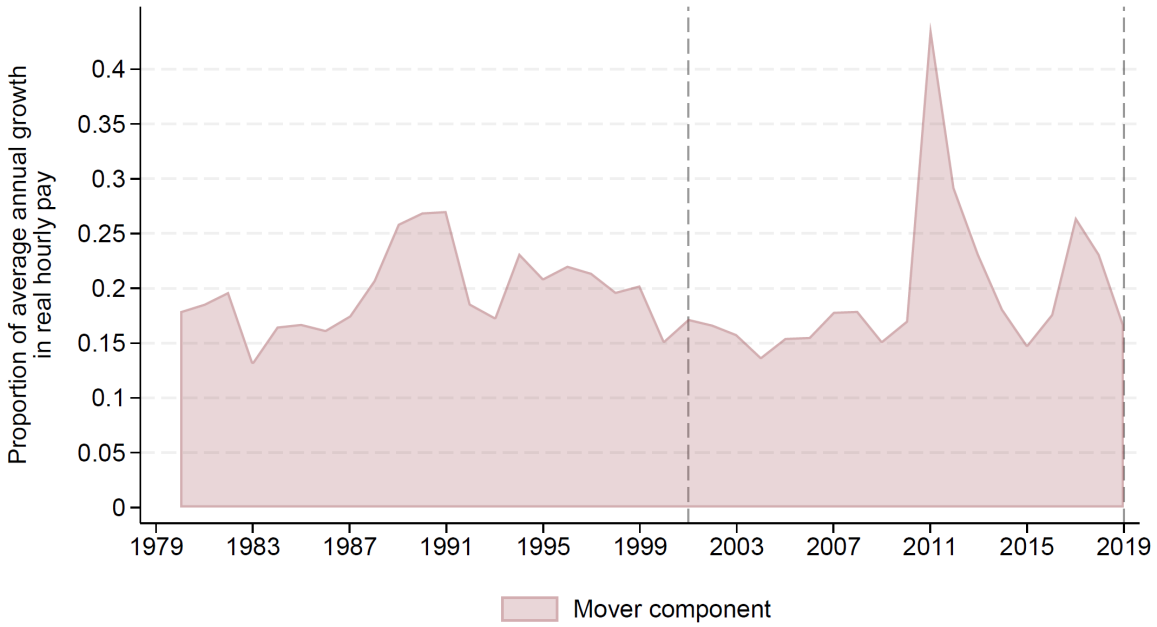
Notes: The figure shows the proportion of workers who move to a new job between two consecutive quarters over time in the UK (1993-2021). A worker is considered as having changed job if reported in employment in two consecutive quarters, and with a tenure in the second quarter not exceeding three months and strictly lower than the tenure in the first quarter (see definition in Section 2). The sample is based on workers between 16 and 64 years of age, who are not in full-time education. Source: Two-quarter longitudinal Labour Force Survey.

Figure 3: Wage growth of movers and non-movers, 1980-2019



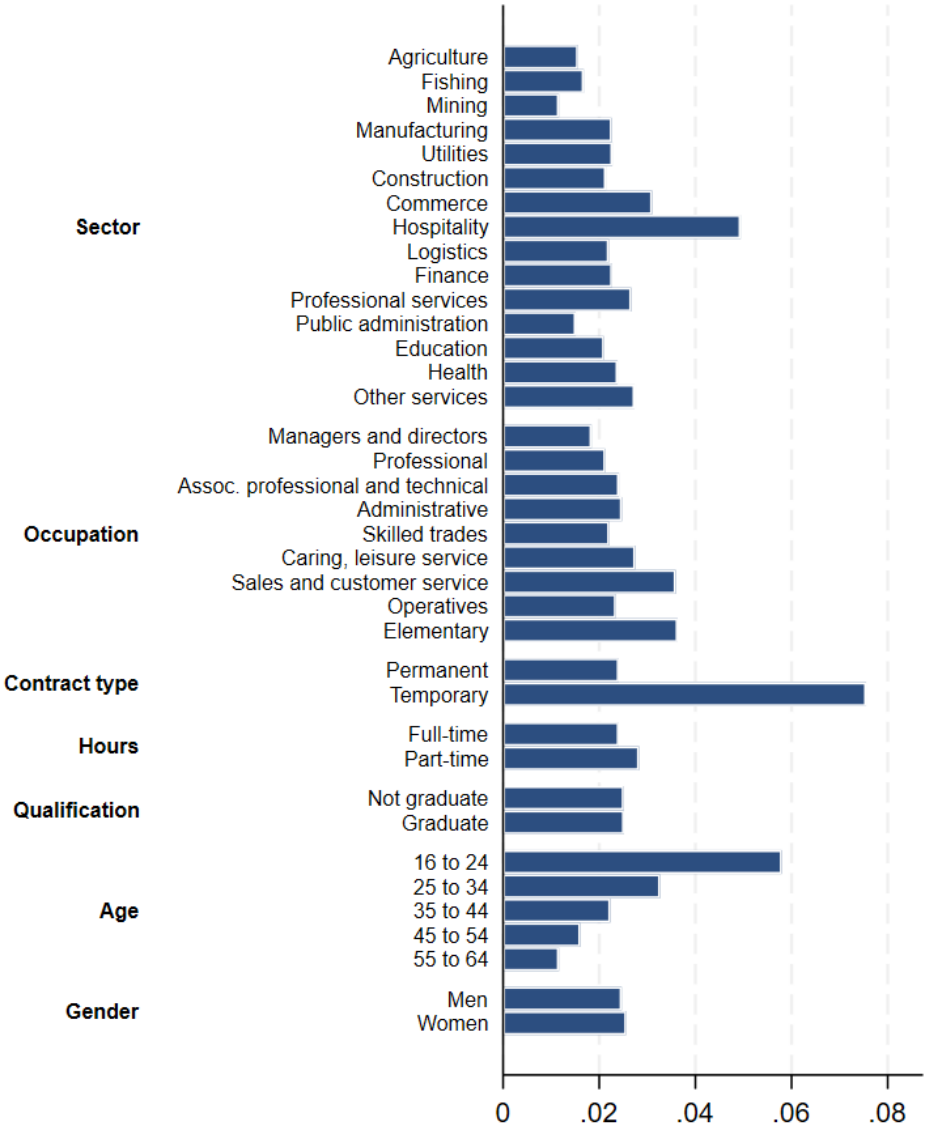
Notes: The figure shows the year-on-year wage growth in real hourly wages for movers and non-movers. Worker is considered to have moved jobs if reporting not to be in the same job and employer firm has changed. Sample is based on workers in fulltime jobs, aged 16 to 64 and without loss of pay due to absences. Annual wage growth is trimmed at 99.5th and 0.5th percentiles.

Figure 4: Contribution of movers wage growth to total annual wage growth



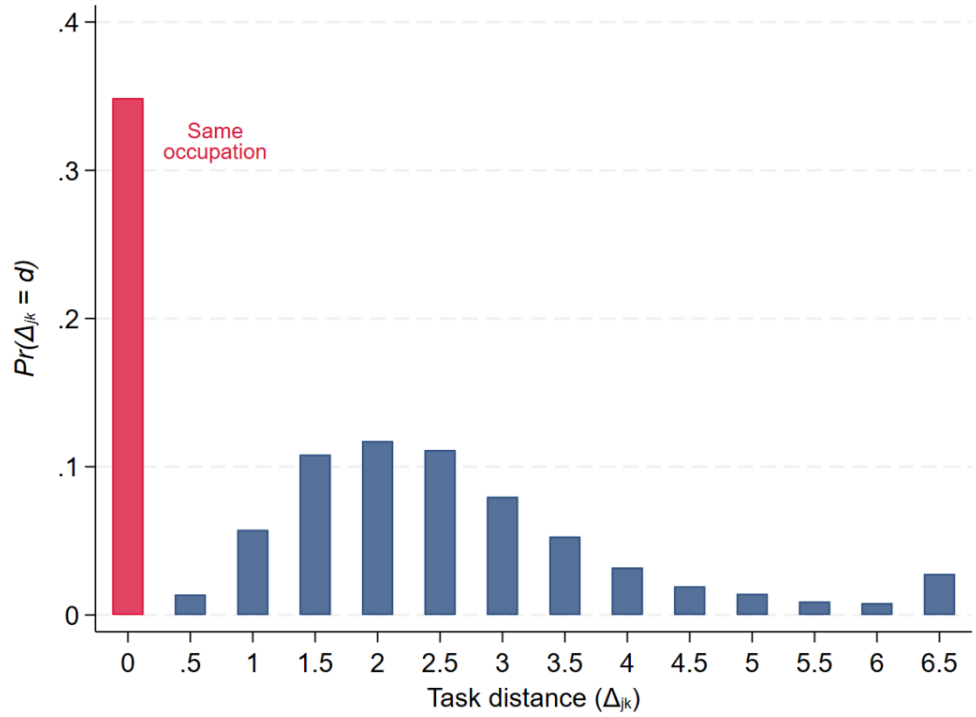
Notes: The figure shows the share of average annual growth in real hourly pay corresponding to movers wage growth ($\Delta w_t^M J_{t,t-1}^M / \Delta w_t$). Worker is considered to have moved jobs if reporting not to be in the same job and employer firm has changed. Sample is based on workers in fulltime jobs, aged 16 to 64 and without loss of pay due to absences. Annual wage growth is trimmed at 99.5th and 0.5th percentiles.

Figure 5: Proportion of workers who moved job since previous job by jobs' and workers' characteristics



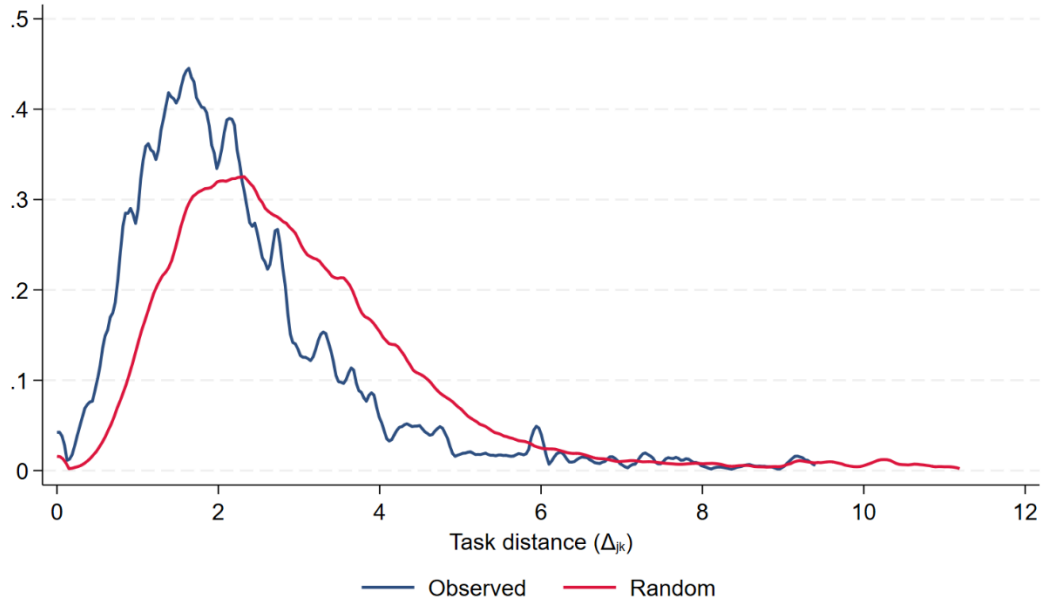
Notes: This figure shows the proportion of workers who move job between two consecutive quarters by their original job's characteristics and workers' individual characteristics. A worker is considered as having changed job if reported in employment in two consecutive quarters, and with a tenure in the second quarter not exceeding three months and strictly lower than the tenure in the first quarter (see definition in Section 2). The sample is based on workers between 16 and 64 years of age who are not in full-time education in the period 2001 to 2019 who are not enrolled in education. Source: Two-quarter longitudinal Labour Force Survey.

Figure 6: Distribution of task requirements distance involved in workers' job moves



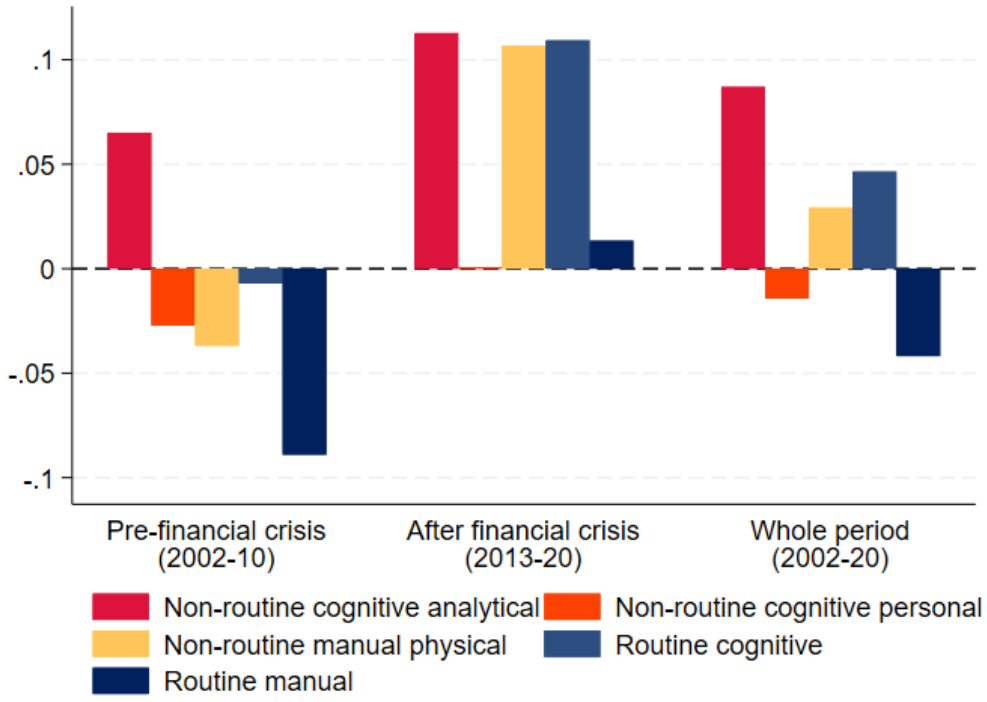
Notes: The figure shows the distribution of task requirements distance (Δ_{jk}) covered by workers moving job from occupation *j* to occupation *k* between two consecutive quarters. Task requirement distance is the average of the Euclidian distance across the standardised measures of the importance of the following five domains: (a) non-routine cognitive; (b) non-routine personal; (c) non-routine physical; (d) routine cognitive; (e) routine manual. A task distance of zero reflects workers changing job but staying in the same occupation. The sample is based on workers between 16 and 64 years of age who are observed in employment in the first and fifth quarters of the five-quarter longitudinal Labour Force Survey between 2002 and 2019; we exclude observations in 2011 as occupational coding is not consistent in that period. Individuals in full-time education are excluded. Source: Five-quarter longitudinal Labour Force Survey and O*NET.

Figure 7: Distribution of task requirement distance involved in occupational changes – observed vs. random moves



Notes: This figure shows the distribution of task requirement distance (Δ_{jk}) for observed occupational moves overlaid with the distribution that would emerge if workers moved at random across 4-digit occupations. The observed distribution is based on occupational moves as recorded in the five-quarter Labour Force Survey between 2002 and 2020. The random distribution assumes that the probability of moving to occupation k is proportional to the share of people employed in that 4-digit occupation (in 2004). The sample is based on workers between 16 and 64 years of age who are observed in employment in the first and fifth quarters of the five-quarter longitudinal Labour Force Survey between 2002 and 2019; we exclude observations in 2011 as occupational coding is not consistent in that period. Individuals in full-time education are excluded. Source: Five-quarter longitudinal Labour Force Survey and O*NET.

Figure 8: Differences in tasks requirements across job moves by period

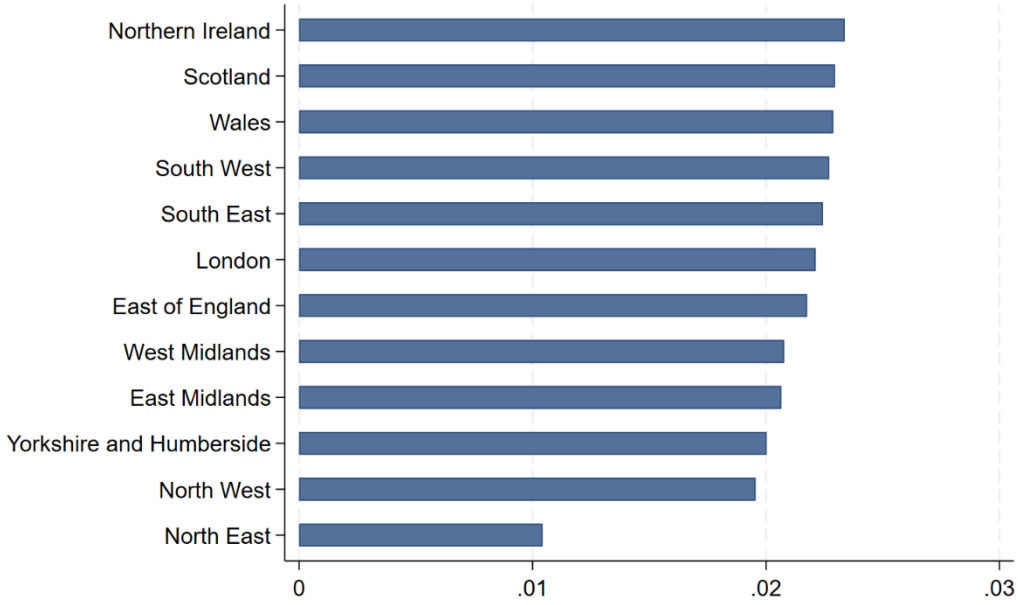


Notes: This figure shows how the importance of different types of tasks changes across occupational moves in the full-period (2002-2020) and separately for each period before and after the financial crisis. Job moves pertain to workers who changed occupation between the first and fifth quarter of the five-quarter Longitudinal Labour Force Survey; respondents who were not in employment in either quarter are not considered. The period up to the financial crisis incudes job moves whose last quarter falls between 2002 and 2010. The post-financial-crisis period includes job-moves between 2014 and the first quarter of 2020. Job-moves for which the last quarter falls between 2011 and 2013 are excluded because of missing data. Task requirement components of each occupation are defined using O*NET mapped into the UK SOC 2000 and 2010 occupational classifications and standardised across all classified occupations. Accordingly, the scale refers to changes in the importance of a task where 1 corresponds to a one standard deviation change. *Source:* Five-quarter longitudinal Labour Force Survey and O*NET.

Figure 9: Proportion of job moves to different occupation and average task requirement distance by age

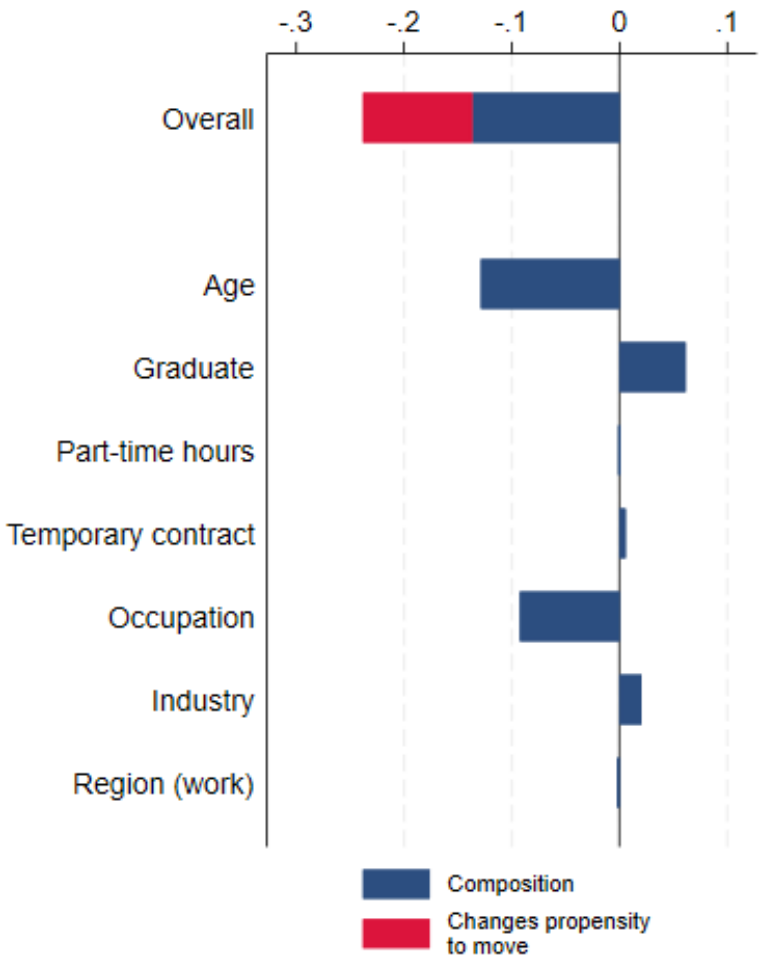
Notes: This figure shows the proportion of workers who move to a different 4-digit occupation upon changing job from the age of 16 to 64 (left axis) alongside the task requirements distance involved in the occupational move (right axis). Job moves are defined using the five-quarter Labour Force Survey and considering the occupation individuals are employed in the first and fifth quarter respectively. Task-requirement distance is measured as the Euclidian distance between the task requirements vectors that characterise the two occupations. Sample includes individuals who are observed in employment in bot the first and fifth quarter between 2002 Q2 and 2020 Q1 and is restricted to 16-64 year olds who are not in full-time education.
Source: Five-quarter Labour Force Survey and O*NET.

Figure 10: Proportion of workers changing job by employment region



Notes: This figure shows the proportion of workers who move job between two consecutive quarter by their original job's region. A worker is considered as having changed job if reported in employment in two consecutive quarters, and with a tenure in the second quarter not exceeding three months and strictly lower than the tenure in the first quarter (see definition in Section 2). The sample is based on workers between 16 and 64 years of age who are not in full-time education in the period 2001 to 2019.
Source: Two-quarter longitudinal Labour Force Survey.

Figure 11: Decomposition of change in job mobility rate (between 2016-19 and 2001-04)



Notes: The top panel of this figure shows the decomposition of the overall change in job mobility rates between 2001-04 and 2016-19 into the component explained by changes in workers' and jobs' characteristics and the component explained by changes in mobility rates conditional on characteristics. The bottom panel plots the contribution of different groups of characteristics to the change in mobility rates explained by compositional shifts. The decomposition is based on Firpo, Fortin and Lemieux (2018)´s adaptation of a classical Oaxaca-Blinder decomposition. Workers' characteristics include five age groups, gender, an indicator for having a university degree, indicators for working part-time hours or being a temporary contract and indicators for each major occupation group, industrial section and 13 regions. The sample is based on workers between 16 and 64 years of age who are not in full-time education.
Source: Two-quarter Labour Force Survey.

Table 1: Sample Descriptive Statistics (2004-2019)

	Full Sample	Connected Set Sample
	(1)	(2)
Wages and Hours:		
Hourly Wages (prices 2019)	21.5	22.7
Hours Worked	38.6	38.3
Workers Characteristics		
Sex	0.324	0.322
Age (Years)	40.6	40.3
Current Tenure (Months)	103.1	104.2
Job Order	3.6	3.7
High Skilled	0.338	0.347
Medium Skilled	0.247	0.226
Low Skilled	0.415	0.427
Firm Characteristics		
Firm Size	200	535
Industry		
Agriculture & Minning	0.029	0.021
Manufacturing	0.186	0.202
Energy & Recycling	0.006	0.008
Construction	0.080	0.055
Retail & Hospitality	0.229	0.230
Transport & Communications	0.053	0.066
Financial Services	0.030	0.053
Other Services	0.387	0.365
Number of workers	166,159	106,524
Number of firms	77,472	22,950
Observations	986,953	675,400

Notes: Sample of full-time workers in the private sector of working age (16-64). Column (1) includes the full sample of workers. Column (2) restricts the sample to firm in the largest connected set. Hourly wages exclude overtime pay. Hours worked exclude overtime hours. Skill level are defined based on the first occupation observed for each worker.
Source: Annual Survey of Hours and Earnings

Table 2: Returns to job moves – worker, firm and match heterogeneity

Log Real Hourly Wages	(1)	(2)	(3)	(4)
		Decomposition		
	Baseline	Worker $\hat{\delta}_{\theta}^{s}$	Firm $\hat{\delta}_{\psi}^{s}$	Match $\hat{\delta}_{\phi}^{s}$
Job Move (Employer Spell)				
2	0.072	-0.002	0.009	0.064
	(0.005)	(0.005)	(0.003)	(0.003)
3	0.104	-0.019	0.006	0.117
	(0.006)	(0.006)	(0.003)	(0.011)
4	0.106	-0.017	0.010	0.114
	(0.0059)	(0.006)	(0.003)	(0.012)
Average Effect				
	0.098	-0.014	0.009	0.103
	(0.005)	(0.005)	(0.003)	(0.011)
Number of workers	105,293	105,293	105,293	105,293
Number of firms	22,641	22,641	22,641	22,641
Observations	665,057	665,057	665,057	665,057

Notes: Sample of full-time workers in the private sector of working age (16-64) within the largest connected set. Column (1) reports OLS estimates of Equation (1). Columns (2) to (4) reports OLS estimates of Equations (4) to (6) respectively. All models include a) a quadratic function of current tenure interacted with employer spell order; b) quadratic terms of past tenure by employer spell; c) third order polynomial of age centred at 40 years of age following Card et al (2018) interacted with sex and skill level; d) year fixed effects interacted with sex and skill level; and e) log employer size. Standard errors are clustered at worker level and reported in parenthesis.
Source: Annual Survey of Hours and Earnings

Appendix A: Data Description and Cleaning

Matched employer-employee panel construction. We follow Jewell et al. (2020) in constructing a panel from the yearly ASHE cross-sections for period 2004-2019. For workers with multiple jobs, we keep only their main job, identified by an indicator variable in the raw data. In a few cases with a missing main-job indicator, we impute it by selecting the job with the highest working hours. Panel units are defined by the workers' unique personal identifiers. Workers can be matched with their employers through ASHE's enterprise reference number, a unique firm identifier. Firm IDs are missing for some observations, however, so we impute them from a "same job" dummy variable that indicates the worker is in the same job as in the previous reference period. If the employer identifier for worker i is missing in year t and we know the worker is in the same job from year $t-1$, then we can safely impute the missing year-t employer ID with the corresponding value from year $t-1$. ASHE cross-sectional datasets also include a local unit identifier that identifies establishments within the cross-section, although it is not consistent across years. We use this local unit identifier to impute missing firm ID's with the modal firm ID of workers with the same local unit ID in the same year. Finally, the recorded starting date of employment allows us to impute a few more missing firm IDs backwards when it remains constant over a period with some missing employer IDs.

Sample selection. Our estimation sample comprises full-time workers employed in the private sector, earning at least 80% of the minimum wage, and aged 16-64 during the sample period. We define a private-sector employer as a firm with the legal status of a private company, sole proprietor, or partnership as per the Inter-Departmental Business Register (IDBR), a variable ASHE includes. We code every other legal status as public and drop the employment relation from the sample. We drop observations that identify a worker as having incurred a loss of pay in the reference period. Similarly, we drop trainees and apprenticeships by filtering on an "adult rate of pay" indicator. We keep observations with non-missing information on gross weekly earnings, hourly wages, and basic hours. We further restrict basic hours to the interval $[1, 100]$ by dropping any observations reporting basic hours outside that range. Finally, we restrict the estimation sample to the largest component of the graph connecting workers and firms through job-to-job moves.

Job histories. Following Addison et al. (2023), we construct workers' job histories along a sequence of up to 10 jobs. We define a job as an uninterrupted spell with the same employer over consecutive observations, which do not necessarily correspond to consecutive years due to non-cumulative attrition that generates time gaps when workers are absent from the panel in some reference periods.[17] For each panel unit, we identify job moves as changes in the employer ID from one observation to the next. Importantly, we encode within-worker job-order IDs before filtering observations as described in the previous paragraph. This generates some gaps in job histories in our final sample, but better represents the accumulation of experience and tenure, which are key regressors in our analysis. We measure tenure in months, defined as the difference between the monthly date corresponding to the reference period (April 1) and the monthly date corresponding to the reported start of the employment relation. For each job (within worker), we measure accumulated past experience as the sum of our tenure variable over every observed previous job. For example, for worker i in job 3, we sum worker i's tenure in their first and second job. Therefore, since we follow histories up to 10 jobs and there is no past history at the first job, we generate 9 past-experience variables. We detail our cleaning procedure for the underlying "starting date of employment" variable below.

[17] The Employers' response rate is 55% (66% for employee work) and any absent worker in a given year remains in the sampling frame for the following period (Jewell et al., 2020).

Data cleaning. While full-time work is defined as more than 30 weekly basic hours of work, the ONS applies a lower threshold for teaching contracts. In such cases, we recode the full-time indicator based on the 30-hour threshold. We drop a very small proportion of workers who have inconsistent age time series, with some becoming younger over time and others aging more than twice the time gap between consecutive observations. Similarly, a few observations record unrealistic employment start dates, with some implying the job starts in the future, or the employee started working at an implausibly young age. There are also some inconsistencies over time within a panel unit, where some observations record different starting dates for the same employment relation. We impute the modal job starting date in such cases when it is unique, or the earliest among the multiple modes. We resolve inconsistencies in firm size as measured by the number of employees listed in the IDBR and IDBR legal status in a similar fashion: When there is within firm-year variation in the reported number of employees or legal status, we impute the (smallest if not unique) modal value at the firm level.[18] Finally, we follow a similar mode-selection procedure to resolve within-job-match variation in occupation and industry codes as measured by the 2-digit SOC and SIC classifications, respectively, which we harmonise over the sample period through crosswalks. Given the limited information on employees' personal characteristics provided in ASHE, in particular the absence of any education measures, we construct a proxy based on our harmonised 1-digit SOC occupations grouping: high skilled (SOC = 1-3), medium skilled (SOC = 4-6) and low skilled (SOC = 7-9).

References

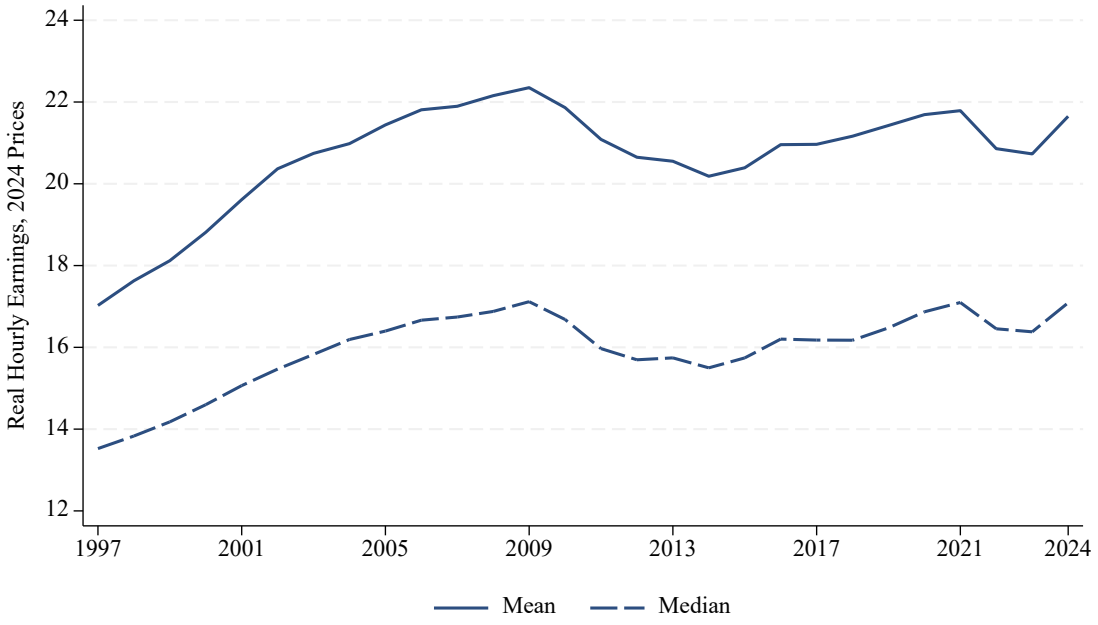
Addison, J. T., P. Portugal, and P. Raposo (2023): "Retrieving the Returns to Experience, Tenure, and Job Mobility from Work Histories," IZA DP No. 15977, IZA Institute of Labor Economics.

Jewell, S. L., G. Razzu, and C. Singleton (2020): "Who Works for Whom and the UK Gender Pay Gap," *British Journal of Industrial Relations*, 58, 50-81.

[18] In the case of legal status, the lower categories correspond to those we code as private, as discussed in our sample selection criteria.

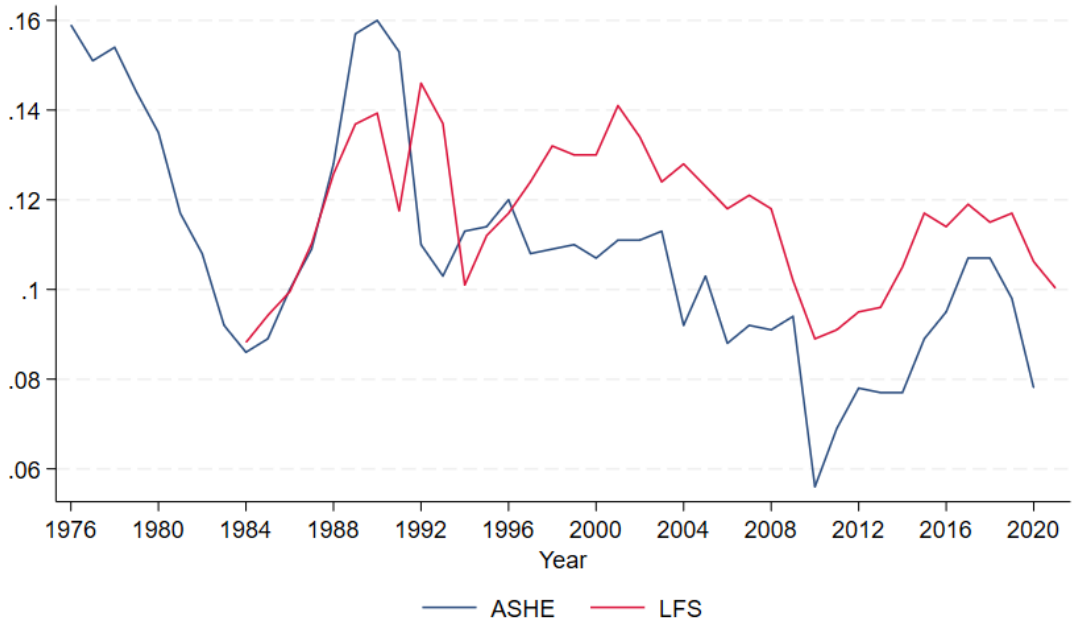
Appendix B: Additional Figures and Tables

Figure B1: Real Hourly Earnings, 1997-2024



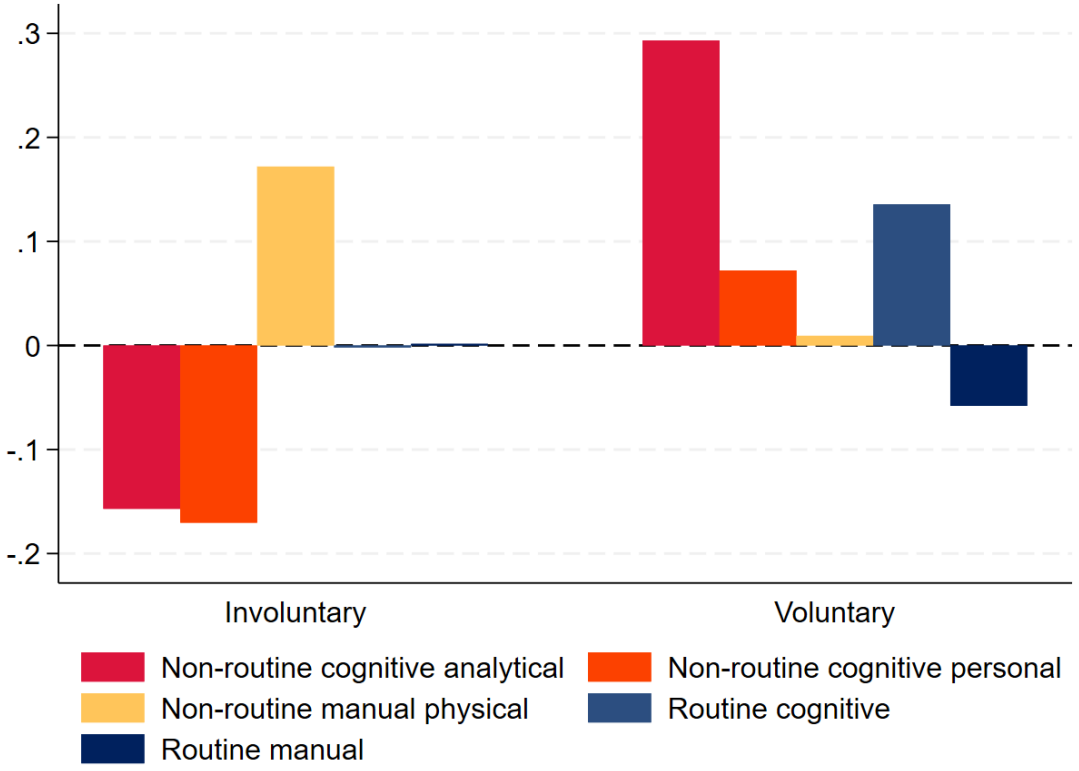
Notes: Mean and median total hourly earnings of all workers, expressed in 2024 consumer prices (CPI).
Source: New Earnings Survey/Annual Survey of Hours and Earnings

Figure B2: Difference in year-on-year job changing rates in different datasets



Notes: This figure plots the probability of a worker changing job with respect to the previous year as measured in ASHE/New earnings survey panel dataset (1976-2003) and LFS.

Figure B3: Differences in tasks requirements across job moves by reason for leaving previous job



Notes: This figure shows how the importance of different types of tasks changes across occupational moves, separately by whether workers left the original job voluntarily or not. Job moves pertain to workers who changed occupation between the first and fifth quarter of the five-quarter Longitudinal Labour Force Survey in the 2002-2020 period; respondents who were not in employment in either quarter are not considered. Involuntary job moves refer to workers who reported to have been dismissed or made redundant (including voluntary redundancies) in their last job. Voluntary job moves refer to workers who report to have resigned from their previous job Job-moves for which the last quarter falls between 2011 and 2013 are excluded because of missing data. Task requirement components of each occupation are defined using O*NET mapped into the UK SOC 2000 and 2010 occupational classifications and standardised across all classified occupations. Accordingly, the scale refers to changes in the importance of a task where 1 corresponds to a one standard deviation change. *Source:* Five-quarter longitudinal Labour Force Survey and O*NET.

Table B1: Workforce composition (2001-04 and 2016-19)

	Workforce Composition	
	2001-04	2016-19
Sector		
Agriculture	0.01	0.01
Fishing	0.00	0.00
Mining	0.00	0.00
Manufacturing	0.17	0.11
Utilities	0.01	0.01
Construction	0.06	0.05
Commerce	0.14	0.13
Hospitality	0.03	0.05
Logistics	0.07	0.06
Finance	0.05	0.05
Professional services	0.10	0.14
Public administration	0.08	0.08
Education	0.10	0.12
Health	0.12	0.15
Other services	0.05	0.05
Occupation		
Managers and directors	0.14	0.10
Professional	0.13	0.24
Assoc. professional and technical	0.14	0.15
Administrative	0.15	0.11
Skilled trades	0.10	0.08
Caring, leisure service	0.08	0.09
Sales and customer service	0.07	0.08
Operatives	0.08	0.06
Elementary	0.11	0.10
Job characteristics		
Permanent	0.95	0.95
Temporary	0.05	0.05
Full-time	0.78	0.77
Part-time	0.22	0.23
Age group		
16 to 24	0.12	0.11
25 to 34	0.25	0.26
35 to 44	0.28	0.23
45 to 54	0.23	0.25
55 to 64	0.11	0.15
Personal characteristics		
Men	0.53	0.51
Women	0.47	0.49
Non-graduate	0.85	0.61
Graduate	0.15	0.39

Notes: This Table reports average characteristics of the workforce in the periods 2001-2004 and 2016-2019 as reported in the Two-quarter Longitudinal Labour Force Survey. The sample is restricted to workers between the age of 18 and 64 who are not in full-time education. Source: Five-quarter longitudinal Labour Force Survey and O*NET.

Table B2: Returns to job moves using attrition weights

Log Real Hourly Wages	(1)	(2)	(3)	(4)
		Decomposition		
	Baseline	Worker $\hat{\delta}_{\theta}^{s}$	Firm $\hat{\delta}_{\psi}^{s}$	Match $\hat{\delta}_{\phi}^{s}$
Job Move (Employer Spell)				
2	0.077	0.001	0.010	0.066
	(0.005)	(0.005)	(0.003)	(0.010)
3	0.113	-0.009	0.006	0.116
	(0.006)	(0.006)	(0.003)	(0.011)
≥ 4	0.117	-0.008	0.009	0.115
	(0.006)	(0.006)	(0.003)	(0.013)
Average Effect				
	0.107	-0.006	0.008	0.104
	(0.005)	(0.005)	(0.003)	(0.011)
Number of workers	106,433	106,433	106,433	106,433
Number of firms	22,923	22,923	22,923	22,923
Observations	674,784	674,784	674,784	674,784

Notes: Sample of full-time workers in the private sector of working age (16-64) within the largest connected set. Column (1) reports OLS estimates of Equation (1). Columns (2) to (4) reports OLS estimates of Equations (4) to (6) respectively. All models include a) a quadratic function of current tenure interacted with employer spell order; b) quadratic terms of past tenure by employer spell; c) third order polynomial of age centred at 40 years of age following Card et al (2018) interacted with sex and skill level; d) year fixed effects interacted with sex and skill level; and e) log employer size. Attrition corrected weights used in all models. Standard errors are clustered at worker level and reported in parenthesis.
Source: Annual Survey of Hours and Earnings

Table B3: Returns to job moves – worker, firm and match heterogeneity (8th order moves)

Log Real Hourly Wages	(1)	(2)	(3)	(4)
		Decomposition		
	Baseline	Worker $\hat{\delta}_{\theta}^{s}$	Firm $\hat{\delta}_{\psi}^{s}$	Match $\hat{\delta}_{\phi}^{s}$
Job Move (Employer Spell)				
2	0.072	0.001	0.009	0.063
	(0.005)	(0.005)	(0.003)	(0.009)
3	0.099	-0.020	0.005	0.114
	(0.006)	(0.006)	(0.003)	(0.011)
4	0.108	-0.028	0.008	0.129
	(0.007)	(0.007)	(0.003)	(0.013)
5	0.115	-0.037	0.001	0.151
	(0.008)	(0.008)	(0.004)	(0.014)
6	0.121	-0.046	0.009	0.158
	(0.009)	(0.009)	(0.004)	(0.016)
7	0.159	0.011	0.005	0.142
	(0.011)	(0.010)	(0.005)	(0.018)
≥ 8	0.151	0.055	0.015	0.081
	(0.013)	(0.013)	(0.006)	(0.021)
Average Effect				
	0.106	-0.015	0.007	0.103
	(0.005)	(0.005)	(0.002)	(0.011)
Number of workers	106,433	106,433	106,433	106,433
Number of firms	22,923	22,923	22,923	22,923
Observations	674,784	674,784	674,784	674,784

Notes: Sample of full-time workers in the private sector of working age (16-64) within the largest connected set. Column (1) reports OLS estimates of Equation (1). Columns (2) to (4) reports OLS estimates of Equations (4) to (6) respectively. All models include a) a quadratic function of current tenure interacted with employer spell order; b) quadratic terms of past tenure by employer spell; c) third order polynomial of age centred at 40 years of age following Card et al (2018) interacted with sex and skill level; d) year fixed effects interacted with sex and skill level; and e) log employer size. Attrition corrected weights used in all models. Standard errors are clustered at worker level and reported in parenthesis.
Source: Annual Survey of Hours and Earnings

Table B4: Returns to job moves including public sector

Log Real Hourly Wages	(1)	(2)	(3)	(4)
		Decomposition		
	Baseline	Worker $\hat{\delta}_{\theta}^{s}$	Firm $\hat{\delta}_{\psi}^{s}$	Match $\hat{\delta}_{\phi}^{s}$
Job Move (Employer Spell)				
2	0.075	-0.020	0.012	0.082
	(0.004)	(0.005)	(0.002)	(0.007)
3	0.111	-0.047	0.014	0.145
	(0.005)	(0.005)	(0.003)	(0.009)
≥ 4	0.113	-0.056	0.014	0.155
	(0.005)	(0.005)	(0.003)	(0.010)
Average Effect				
	0.104	-0.046	0.014	0.137
	(0.004)	(0.004)	(0.002)	(0.008)
Number of workers	167,092	167,092	167,092	167,092
Number of firms	31,837	31,837	31,837	31,837
Observations	1,148,625	1,148,625	1,148,625	1,148,625

Notes: Sample of full-time workers in the private and public sectors of working age (16-64) within the largest connected set. Column (1) reports OLS estimates of Equation (1). Columns (2) to (4) reports OLS estimates of Equations (4) to (6) respectively. All models include a) a quadratic function of current tenure interacted with employer spell order; b) quadratic terms of past tenure by employer spell; c) third order polynomial of age centred at 40 years of age following Card et al (2018) interacted with sex and skill level; d) year fixed effects interacted with sex and skill level; and e) log employer size. Standard errors are clustered at worker level and reported in parenthesis. Source: Annual Survey of Hours and Earnings