The Great Resignation of the UK Labour Market

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Abstract

This paper investigates whether the United Kingdom experienced a Great Resignation (GR) in the aftermath of the Covid-19 pandemic. Using Labour Force Survey (LFS) microdata, I complement aggregate labour-market indicators with individual-level probability models to analyse quitting behaviour, job-to-job (J2J) mobility, and associated wage outcomes. The results show that the UK's post-pandemic labour market was marked by a pronounced rise in quits and job moves between 2021Q3 and 2022Q4, consistent with a Great Resignation or Great Reallocation driven by workers transitioning into new jobs rather than exiting the labour force. The increase in mobility is more pronounced among younger, more educated, female, non-White, full-time, and permanent-contract workers, although most within-group differences are statistically small. While J2J transitions are associated with higher probabilities of wage gains, this relationship does not significantly strengthen during the GR period, suggesting a limited role of the GR in shaping post-pandemic wage dynamics. Moreover, there is little evidence of substantial sectoral or occupational reallocation. This study provides the first systematic evidence on the Great Resignation in the UK and contributes to the broader literature on post-pandemic labour-market adjustment.

Keywords: Great Resignation, Covid-19, Reallocation, Wages.

JEL: J62, J23, J31, E24.

1. Introduction

The post-pandemic recovery of the UK labour market was marked by a robust increase in worker quitting behaviour, heightened job-to-job (J2J) mobility, and a persistently elevated stock of vacancies. Although the magnitude differed, the United States experienced a similar phenomenon: workers were leaving their jobs en masse even as the economy was still emerging from a severe recession. This trend drew the attention of economists and commentators alike, giving rise to the term "Great Resignation" (GR) to describe the period. Despite these parallels, the phenomenon remains relatively underexplored on the other side of the Atlantic.

The aim of this paper is to bridge this gap by examining whether the UK has experienced a Great Resignation (GR), and by analysing the key characteristics and implications of this phenomenon.

Specifically, the paper addresses the following research questions:

1. Did the UK labour market experience a Great Resignation?
2. What are the characteristics of the workers involved in this phenomenon?

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3. Is the Great Resignation associated with increases in pay?

There are several reasons why studying the Great Resignation (GR) of the UK labour market is important. From a labour economics perspective, it enhances our understanding of how the labour market responded to the pandemic shock. From a macroeconomic standpoint, the dynamics of job-to-job (J2J) transitions are particularly relevant. Empirical evidence shows that J2J movements are closely linked to rising vacancy rates (Bagger et al., 2022)—one of the two key variables typically examined in Beveridge Curve analysis. Furthermore, the Great Resignation in the United States was associated with a post-pandemic increase in wages (Faccini et al., 2022), making the phenomenon highly pertinent for inflation analysis as well.

This is the first paper documenting the GR in the UK. It also the first to study the characteristics of workers who quit or changed job. Finally this paper analyze the role of the GR in the post-pandemic earnings dynamics.

Most studies (e.g., Hobijn, 2022) analyze this phenomenon by visually inspecting aggregate time series, generally obtained from Labour Force Survey (LFS)–type data, and breaking them down by demographics. Although this approach is in line with a large body of literature in labour economics, it risks eclipsing relevant worker-level information and, more importantly, cannot capture conditional correlations. In this paper, I complement aggregate time series with individual-level analyses based on microdata from the UK LFS. In particular, I employ probability models to study how the likelihood of worker outcomes (such as quitting or switching jobs) is affected by worker characteristics during the Great Resignation. Furthermore, I test whether the probability of obtaining a pay increase is associated with J2J mobility and whether this relationship has changed during the Great Resignation.

First, the GR of the UK labour market is characterized by workers moving into new jobs rather than leaving the labour force. In fact, the individual-level analysis finds a significant increase in the probability of job moves and quits between 2021Q3 and 2022Q4, supporting the GR or Great Reallocation of the UK labour market in the post-pandemic recovery.

Second, the effect is greater for female, non-White, full-time, and permanent-contract workers who are younger and have higher levels of education. However, the within-group differences (such as male vs. female) are not significant for most groups.

Third, although J2J mobility has a positive effect on the probability of a wage increase, there is no significant change in this relationship during the GR. Hence, the GR does not appear to have significantly affected wage dynamics in the UK.

Lastly, in line with previous findings in the UK and with findings in the US, the GR does not exhibit significant sectoral or occupational reallocation.

This paper is related to the emerging literature on the Great Resignation (GR). The Covid-19 pandemic was marked by unusually high quit rates. Hobijn (2022) underlines the cyclical nature of the phenomenon as he argues that elevated quit rates are typical of fast recoveries with strong employment growth. A similar conclusion is reached by Consolo and Petroulakis (2024), which argues that the wave of reallocation was driven by cyclical behavior of firms. However, other scholars suggest that the unique nature of the pandemic recession played a key role in mass resignations, as tight labour markets created ideal conditions for workers to leave their jobs en masse (Tessema et al., 2022, Liu-Lastres et al., 2023, Ng and Stanton, 2023). For example, Gittleman (2022) points out that the level of resignations is not unmatched by historical episodes but underlines that the pace of the phenomenon suggests the presence of factors beyond labour market tightness. In this regard, Tessema et al. (2022) highlight that the pandemic prompted employees to reassess their careers, increased job-related stress, and spurred appreciation for remote work. Consequently, many resigned when asked to return to physical workplaces. Other contributing factors include inadequate organizational support and management processes, which led to dissatisfaction and increased resignations (Tessema et al., 2022, Formica and Sfodera, 2022). Liu-Lastres et al. (2023) focus on the hospitality and tourism sectors, finding that high quit rates in these industries were driven by evolving work expectations, the growth of the gig economy, and the adoption of technological innovations. Finally, Bagga et al. (2023) formalize a shift in workers' preferences toward non-pecuniary job amenities.

2. Great Resignation or Great Reallocation?

Following the Covid-19 pandemic and associated restrictions, the UK economy began reopening in the spring of 2021. This reopening triggered a sharp increase in labour demand, particularly in hard-hit sectors such as hospitality, retail, and the arts, fuelled by pent-up demand for services. On the supply side, the period was marked by a notable rise in J2J mobility and heightened quitting behavior among workers. Worker reallocation during the pandemic was first documented by Carrillo-Tudela et al. (2023), who explain these flows as being driven primarily by sectoral rather than occupational shifts. However, their analysis does not cover the period of the GR.

The job-to-job (J2J) rate can be measured by observing changes in the employment tenures of employees between periods $t = 1$ and $t = 2$. The ONS computes the J2J rate using data from the longitudinal Two-Quarter Labour Force Survey (2QLFS), focusing on individuals who report being employed in two consecutive quarters and whose reported employment duration in the second quarter is less than three months.

Figure 1 presents the quarterly J2J rate alongside the reasons why workers change jobs. By the third quarter of 2021, the J2J rate had reached a historically high level of over 3%, remaining above this threshold for five consecutive quarters. At the same time, "resignations" rose to levels that were high by historical standards. in Figure 2, I plot the aggregate quit rates, i.e., the ratio of quits over employees, which is based on the QLFS. The figure shows how quits accelerated during 2021, recovering to and eventually surpassing pre-pandemic levels by the end of the year. Quitting contributes to both ongoing employment and overall separations; however, its role is particularly significant in facilitating J2J transitions, as reflected in the quit-to-hiring ratio shown in Figure 3. This pattern of elevated quitting and J2J movement persisted into 2023.

Therefore, the data suggest that workers started to quit in significant numbers, mostly to change their jobs. This is indicative of a phenomenon much discussed in the USA, but to a lesser extent in the UK, i.e., the "Great Resignation".

In fact in November of 2021 the United States recorded the highest level of people quitting their jobs since the early 2000's. However, additional research have pointed out that despite being sizable in recent decades, the Covid-19 GR is not unmatched by historical standards (Hobijn, 2022, Gittleman, 2022). According to Hobijn (2022) the increase in quit rates is driven by young and less-educated workers employed in the sectors severely hit by the pandemic. Also in the US, the majority of quitters seem to have switched employers rather than leaving the labour force. Consolo and Petroulakis (2024) find limited evidence or reallocation and mismatch in the US, attributing changes in employment to cyclical behavior of firms. In particular employment in smaller firms dropped at the onset of the pandemic and then quickly rebounded in the recovery. Similarly to the UK, they document a substantial increase in job-to-job moves. However, workers reallocated mainly with sectors and occupation

Therefore, The GR of UK labour market shares many similarity with what occured in the US, albeit of smaller magnitude. It is predominately characterized by workers reallocation, rather than leaving the labour force.

3. Switchers and Quitters in the Great Resignation?

In this section, I examine the characteristics of workers who switch jobs or resigned and how these may have shifted during the post-pandemic period.

To do this, I estimate a logistic regression to model the probability of switching job or quitting, $Y = 1$, as:

$$\Pr(Y = 1 \mid X) = \frac{1}{1 + e^{(-Z)}} \quad (1)$$

Where

$$Z = \beta_0 + \beta_1 x_1 + ... + \beta_n x_n \quad (2)$$

and X is a vector of individual-specific controls including gender, ethnicity, contract type, age group, education, sector and occupation of origin, region fixed effects and quarters fixed effects. Each regressor is associated with the values of coefficient β estimated by maximizing the log-likelihood function.

The data are taken from the longitudinal 2QLFS, which allows to capture transitions between employment states in two consecutive quarters. The sample spans from 2015 Q1 to 2023 Q2. All regressions are estimated using a survey-weighted logistic model. Specifically, I apply the longitudinal population weights provided in the LFS. These weights adjust for differential probabilities of selection, non-response, and post-stratification to ensure national representativeness.

Lastly, it is important to notice that my main objective is not prediction, i.e., to provide the probability of switching job of a worker, but to study which factors influence the probability of switching in the context of the GR. Therefore, I do not perform the sensitivity and specificity analysis typical of model evaluation for predicting purposes.

This logistic specification can equivalently be written in log-odds form as:

$$\ln\left(\frac{P(Y_i = 1)}{1 - P(Y_i = 1)}\right) = \beta_0 + \delta_t + \delta_r + \gamma' X_i + \varepsilon_i, \quad (3)$$

where δ_t denotes quarter fixed effects , δ_r regional fixed effects and $\gamma' X_i$ the vector of individual covariates.

To statistically test the relevance of the Great Resignation, Fig. 4 displays the marginal effects of the quarterly time fixed effects, obtained by running Eq. 1. There is a clear increase in the probability of switching and quitting, compared to the baseline, demonstrated by a cluster of positive and significant coefficients in the period spanning 2021Q3 and 2022Q4. While modest, the size effect is comparable to those of the other covariates. This suggests that this window of time — which roughly corresponds to the five consecutive quarters in which the aggregate J2J remains above the level of 3%, as shown in Fig. 1 — is historically important for workers quitting and reallocation.

To evaluate whether the GR affected certain demographic groups differently, I augment the baseline model ass:

$$\ln\left(\frac{P(Y_i=1)}{1-P(Y_i=1)}\right) = \beta_0 + \beta_1 GR_t + \gamma' X_i + \beta_3 (GR_t \times X_i) + \delta_r + \varepsilon_i, \tag{4}$$

where GR_t is an indicator variable equal to one for observations between the third quarter of 2021 and the fourth quarter of 2022. This period, identified based on the significant marginal effects of the quarterly time fixed effects shown in Fig. 4, captures the phase associated with the GR.

I exclude sector and occupation variables — which are analyzed in more detail below — and interact all remaining controls with the GR dummy. These interactions are captured by the set of coefficient β_3. Quarters fixed effects are dropped because of collinearity with the interaction terms and the GR dummy.

Figure 5 reports the with-in group Average Marginal Effects (AME) of the GR dummy for each subgroup. These AMEs represent the average change in the predicted probability of the outcome (switching or quitting) when $GR_t = 1$ versus $GR_t = 0$ computed separately within each subgroup (e.g. males, females, etc.) while keeping all other covariates at their observed values.

Note that these are not the interaction effects recommended by Ai and Norton (2003), which quantify the difference-in-differences of predicted probabilities for nonlinear models. Because my interest is in whether the GR increased the probability of job mobility within specific groups, not in comparing the change in GR effects between groups, the within-group AMEs are the most appropriate measure here. Moreover, for multi-values categorical characteristics such as age group or education, interaction effects yield not a single number but a set of values or contrasts across groups (for instance, changes in the probability of the outcome between young and old individuals). Hence for the sake of this exercise it is reasonable to employ the simple with-in group marginal effects, reported in Fig. 5.

In other words, for each subgroup defined by a categorical covariate, the reported AME of the GR dummy reflects the average predicted change in the probability of switching (or quitting) during the GR period relative to the period outside the GR, holding all other characteristics constant at their observed values.

Overall the GR seems to significantly increase the probability of both switching and quitting across covariates. It positively impacts the probability of switching in females more than males, in non-whites more than whites, in full-time contracts more than part-time contracts and in permanent contracts more than in non-permanent ones. However, the interactions computed according to Ai and Norton (2003) are mostly not significant, indicating that there is not a significant change in probability across these characteristics (say male vs female) during the GR. Age appears to have a declining effect on J2J transitions; being in a younger age group increases the probability of switching. This is broadly consistent with findings based on aggregated data in the US by Hobijn (2022). Finally, higher levels of education are associated with higher likelihood of switching. This appears to be somewhat in contrast to pre-pandemic literature like Haltiwanger et al. (2018) that finds that J2J moves are more relevant in reallocation of less-educated workers. To conclude the analysis of Fig. 5, by focusing on quits the findings broadly reflect those of switching, although some estimates are not significant.

4. Earnings, Job-to-job mobility and the Great Resignation

The analysis so far has focused on workers' characteristics but has not yet revealed the potential drivers of the Great Resignation. One would expect that voluntary J2J transitions are motivated by more favourable working conditions. These may include higher wages, better relationships with management and colleagues, shorter commuting distances, opportunities for career progression, the availability of remote work, reduced working hours, improved work–life balance, or a change in career path.

Unfortunately, many variables capturing these aspects are not reported in the two-quarter Labour Force Survey (2QLFS) longitudinal data. For instance, earning variables are only observed in waves 1 and 5 of the survey. This would suggest that the analysis should instead draw on the five-quarter LFS (5QLFS). However, the latter suffers from sample size limitations: the number of respondents completing all five waves has historically been small compared with the standard QLFS datasets, and sample sizes have declined further since the pandemic. In fact, the ONS suspended dissemination of the 5QLFS in June 2023 due to these issues.

To overcome this limitation, I turn to the two-year Annual Population Survey longitudinal dataset (2YAPS). The 2YAPS is based on responses to waves 1 and 5 of the LFS, with an additional sample boost designed to improve estimates at the sub-regional level. As a result, the dataset includes information on respondents' earnings, such as hourly pay. In this section, I explore the relationship between employees' earnings and within-employment reallocation in the context of the GR. In particular, I aim to assess whether J2J mobility is associated with higher earnings and whether this relationship has changed during the GR period, which also coincides with elevated and persistent inflation.

Before outlining the method, it is important to highlight key features and limitations of the data. First, earnings and wage information from the LFS are self-reported and are generally known to be underestimated. Therefore, while wage levels should be interpreted with caution, the variable remains useful for cross-sectional analysis.

Second, estimating J2J transitions using the 2YAPS is more challenging than with the 2QLFS. In the 2YAPS, variables are reported at an annual frequency, and the longitudinal dimension spans five quarters. Thus, J2J transitions can be inferred for individuals who are employed in both years and report an employment duration of less than 12 months in the second year. However, it is more difficult to rule out the possibility that some of these individuals experienced short spells out of employment between jobs.

To improve the identification of true J2J transitions, I estimate different J2J rates based on reported employment duration and then compare these series with the J2J rate derived from the 2QLFS, averaged by year.

Figure 6 plot the time series. There is a level difference between the series obtained from respondents with employment duration of less than 6 months and less than 3 months and the J2J rate computed from the 2QLFS. However, despite some difference in trend for some data points during the pre-pandemic period, the APS series closely track the 2QLFS. The series obtained from respondents with employment duration of less than a year deviates considerably in many years and is therefore ignored thereafter.

Table 1: Average Marginal Effects on Pay Increase

	(1)	(2)	(3)	(4)	(5)	(6)
J2J	0.085***	0.057***	0.059***	0.050***	0.058***	0.067***
	(0.008)	(0.010)	(0.014)	(0.010)	(0.010)	(0.009)
GR	0.023***	0.022***	0.023***	0.027***		0.022***
	(0.004)	(0.004)	(0.005)	(0.004)		(0.004)
J2J $\times$ **GR**	0.012	0.016	0.008	0.019		0.004
	(0.020)	(0.025)	(0.035)	(0.024)		(0.023)
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	341,844	212,924	133,056	212,924	212,924	212,924

Notes: dy/dx for factor levels is the discrete change from the base level.
Controls include gender, age, education, a dummy for white, full-time employment, permanent contract, health issues, working more hours, and region fixed effects. Column (3) excludes proxy responses. Column (4) includes hourly pay at time $t = 1$. Column (5) excludes the GR variable and includes time fixed effects. Column (6) uses the six-month J2J definition.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In this section, I examine the relationship between earnings, J2J mobility, and the Great Resignation (GR). In particular, I test whether moving into a new job has a positive effect on pay and whether this effect changed during the GR period.

I calculate longitudinal changes in earnings for respondents reporting their hourly pay in the two-wave Annual Population Survey (2YAPS). The sample includes individuals aged 18–65 and excludes observations with hourly pay below the national minimum wage in each year and each age bracket Francis-Devine (2025). I compute the change in hourly pay between $t = 1$ and $t = 2$, and define an indicator for an *earnings (or wage) increase* when this difference exceeds £1.

I estimate a logistic regression model of the form:

$$\ln\left(\frac{P(Y_i = 1)}{1 - P(Y_i = 1)}\right) = \beta_0 + \beta_1 \text{J2J}_i + \beta_2 \text{GR}_t + \beta_3 (\text{J2J}_i \times \text{GR}_t) + \gamma' X + \varepsilon_i, \tag{5}$$

where $Y_i = 1$ if individual i reports a wage increase between $t = 1$ and $t = 2$, and X is a set of controls.

The J2J indicator equals one for individuals employed in both periods with an employment duration of less than three months at time $t = 2$. I also employ the definition of J2J based on six months employment duration. GR_t is a dummy equal to one for the years 2021–2022, capturing the effect of the Great Resignation. Controls include standard demographic and job characteristics—age, gender, education, ethnicity, contract type, health status, region fixed effects, and an indicator for working additional hours at $t = 2$. As in the previous section, I apply the longitudinal population weights provided in the LFS. For robustness, I also test alternative assumptions about the standard errors.

I report the odds ratios in the Appendix, while Table 1 presents the average marginal effects (AMEs) of J2J, GR, and their interaction. The AMEs for the interaction term are computed following Ai and Norton (2003). Column (1) shows results without controls: switching jobs increases the likelihood of a pay increase by 8.5 percentage points, while during the GR the likelihood increases by 2.3 percentage points. The AME of the interaction term—capturing how the effect of job changes on pay increases differed during the GR—suggests an additional 1.2 percentage point increase, though this effect is not statistically significant. Overall these results are robust across a number of specifications. By including controls in column (2), the change in probability following a J2J move decrease but the overall results are unchanged. In column (3) I exclude proxy responses, which are reported not by the individual but by another member of the household, and therefore are more likely to be subject to measurement error. The are no significant changes also if I control for earnings at time $t = 1$ as in column (4). Column (5) confirms the importance of switching job for earnings dynamics, by dropping the GR dummy and including year fixed effects. In column (6) I replicate column (2) employing a different definition of J2J moves using individuals with a duration of less than six months at time $t = 2$, and the results are unaltered.

Hence, the results suggest that:

i changing jobs increases the likelihood of experiencing a pay increase by approximately 6–8 percentage points;

ii the period of the Great Resignation (GR) is associated with an increase in the likelihood of a pay increase of around 2 percentage points;

iii switching jobs during the GR does not appear to have a statistically significant additional effect on the probability of a wage increase.

5. Additional Results

5.1. Sectoral and Occupation mobility during the Great Resignation

Given the peculiar sectoral dynamics of the pandemic—marked by a pronounced asymmetry between the sectors and occupations most affected and those largely shielded from its impacts—occupational and sectoral transitions are an important element to analyze during the Great Resignation.

In Table 2, I report the proportion of switchers and quitters who change industry and occupation, before and after the GR period in the entire sample. Among workers who changed employers, the share who changed industry during the Great Resignation was about 3 percentage which is significant at 10%. Instead, the share of workers who changed occupation was 5 pp lower, significant at 5%. Thus, conditional on making a job-to-job move, the Great Resignation is not associated with greater sectoral or occupational reallocation; if anything, moves shifted more within the same occupation and within the same industry compared with earlier periods. This result is unchanged if we look at Quits. The lack of occupational mobility was already documented by Carrillo-Tudela et al. in the early phases on the GR, and is consistent with findings in the US (Consolo and Petroulakis, 2024).

Table 2: Industry/Occupation Change Shares Outside vs During the Great Resignation

	J2J		**Quit**	
	Outside GR	During GR	Outside GR	During GR
Change industry				
No	0.47	0.50	0.50	0.54
Yes	0.53	0.50	0.50	0.46
Change occupation				
No	0.52	0.56	0.57	0.70
Yes	0.48	0.43	0.43	0.30

Notes: Shares by period; columns within each block sum to 1 (rounding may cause slight discrepancies). "During GR" is 2021Q3–2022Q4.

Nevertheless, it is still possible that specific sectoral or occupational transitions were relevant during this phase. To this end, I run a series of regressions where the dependent variable is an indicator of transitioning from one sector to another. The key independent variable is the GR dummy, with demographic controls and regional fixed effects included. The same procedure is applied for occupations. I then estimate the average marginal effects of the GR dummy and construct transition matrices for sectors and occupations. Rows represent the origin, while columns represent the destination. The cells indicate whether the probability of a given transition changed during the GR.

To facilitate the exposition, sectors are grouped into three categories reflecting the underlying labour market dynamics of the pandemic. Manufacturing and construction compose the *mildly hit* group, as these sectors were shut down during the first wave of infections but were less constrained in the subsequent waves. The *hard-hit* group, instead, is composed of retail, hospitality, and the arts—sectors most severely affected and those that recorded the highest take-up rates in government support measures. At the opposite side of the spectrum, we find those sectors shielded by remote work, which include IT, financial, real estate, professional, administrative activities, public administration, education, and other services, which I label as *laptop sectors*. Transport, health, and primary sectors are excluded due to their limited relevance and data availability.

Figure 7 shows the transition matrix for these broad sectors, colour-coded to indicate magnitude. Not surprisingly, the only significant results are on the main diagonal. These coefficients, although small in magnitude, are the largest and suggest a lower probability of remaining in hard-hit sectors and a higher probability of remaining in less affected sectors.

A similar exercise is carried out for occupation. The groups are clustered into five categories based on the SOC20 classification: *Managers* (Group 1); *Professionals* (including Professional and Associate Professional groups, Groups 2 and 3); *Sales/Admin* (including Administrative and Service occupations, Groups 4 and 7); *Skilled Blue Collar* (Group 5); and *Blue Collar* (including Other Services, Operators, and Elementary occupations, Groups 6, 8, and 9).

Figure 8 shows the results. The largest effect is observed for the probability of remaining in the Professional group, while Blue Collar and Sales/Admin workers appear less likely to leave their respective positions.

6. Conclusion

Despite the similarities between post-pandemic labour market dynamics in the UK and the US—particularly high quit rates and increased job-to-job mobility—research on the UK remains limited.

This paper documents the phenomenon of the so-called "Great Resignation" in the British labour market. I complement aggregate time-series analysis with a probability model based on Labour Force Survey microdata.

I find that workers primarily resigned to move into new positions rather than to leave the labour force. The likelihood of changing jobs is higher among female, non-White, full-time, and permanent-contract workers who are younger and have higher levels of education. However, within-group differences are not significant for most categories. I also find that switching jobs during the post-pandemic labour market recovery did not significantly increase the likelihood of receiving a pay rise compared with other periods. Lastly, I find that the Great Resignation did not provoke substantial sectoral or occupational reallocation.

It is important to acknowledge some limitations of the datasets employed. The 2QLFS lacks key variables relevant to the drivers of the Great Resignation—such as earnings, working conditions, and job satisfaction—because earnings are recorded only in waves 1 and 5. The 2YAPS provides earnings data and a larger sample but relies on self-reported wages. Moreover, identifying job-to-job transitions in the 2YAPS is more complex, as variables are annual and the longitudinal span covers five quarters, making it difficult to rule out brief periods of non-employment. The reliability of the findings could be enhanced by using firm-level data, such as the Annual Survey of Hours and Earnings (ASHE), particularly its longitudinal microdata containing detailed information on wages and firm characteristics. Furthermore, I cannot observe firm or productivity dynamics underlying job mobility.

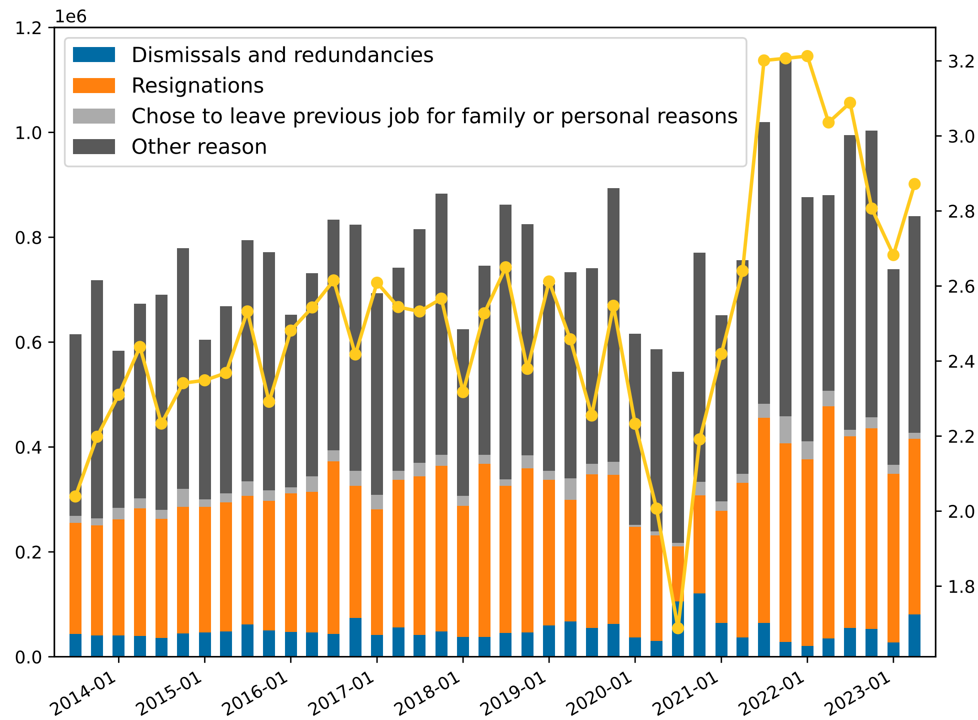

Figure 1: The yellow line represents the job-to-job rate - the percentage of job-to-job moves over the aggregate number of people still in employment between two consecutive quarters - plotted on the right hand vertical axis. The stacked bars are the number of workers moving job-to-job by reasons of moving, expressed in thousands on the left hand vertical axis. The series are all not seasonally adjusted, computed by the ONS.

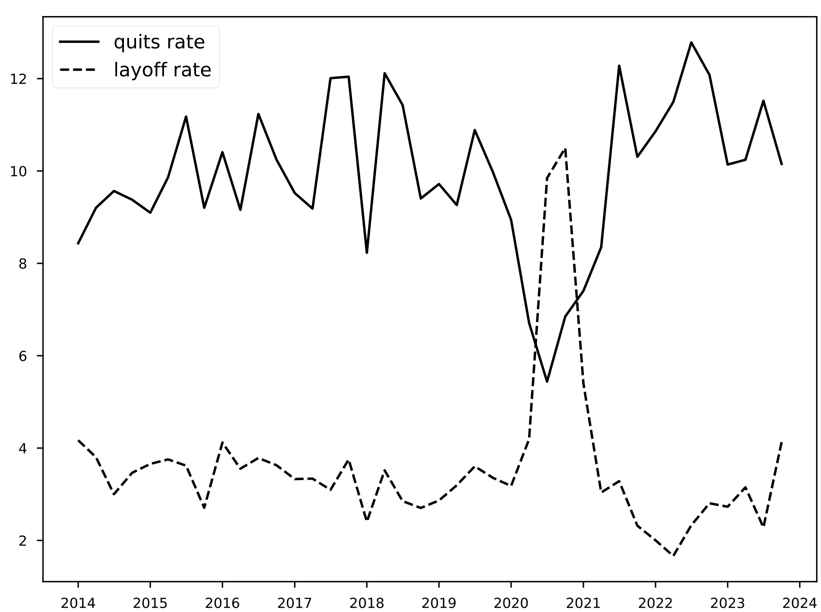

Figure 2: The black line is the quit rate - the number of quits per 1000 employees. The dashed line is the layoff rate - the number of redundancies per 1000 employees.

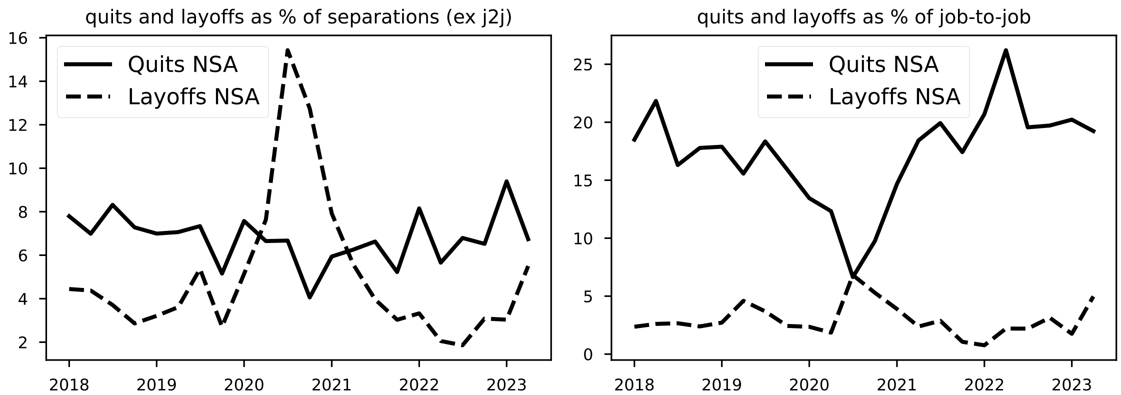

Figure 3: The left hand panel shows the percentage of quits and redundancies over separations excluding job-to-job moves. The right hand panel shows the percentage of quits and redundancies over job-to-job moves. The sample spans from 2018 Q1 to 2023 Q2. All series not seasonally adjusted.

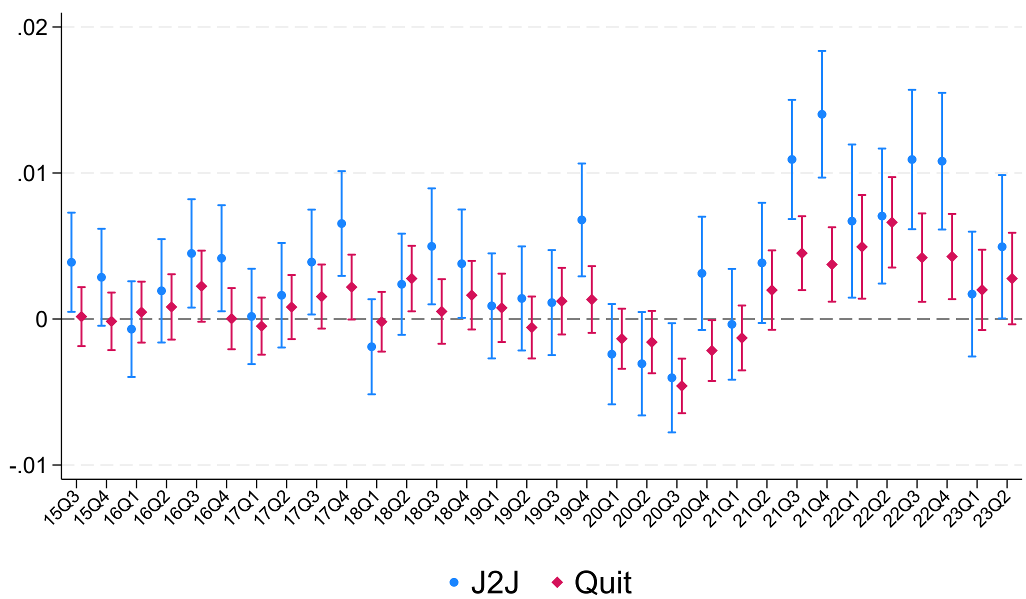

Figure 4: AVerage Marginal effects of time fixed effects from estimating logit model on the likelihood of switching job or quitting.

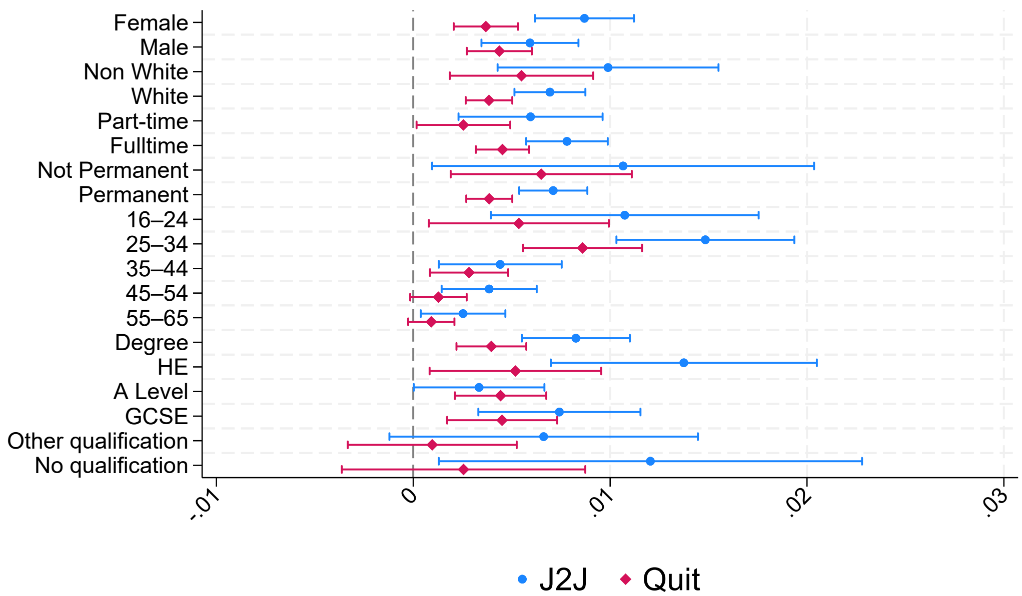

Figure 5: Average Marginal Effects of demographics variables on the likelihood of switching and quitting.

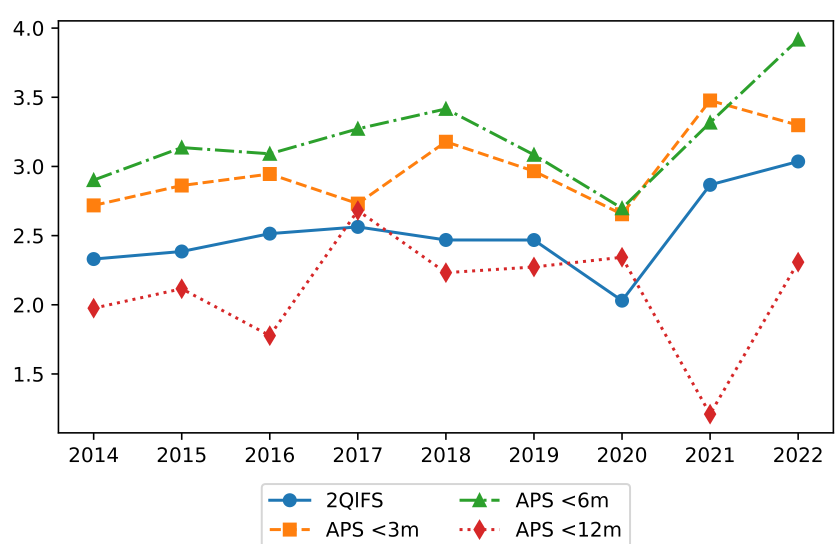

Figure 6: The 2QLFS represents the J2J rate obtained from the Longitudinal Two-Quarter Labour Force Survey, averaged over years. The APS series are obtained from the Longitudinal Two-Year Annual Population Survey, based on employment durations of less than 12 months, less than 6 months, and less than 3 months.

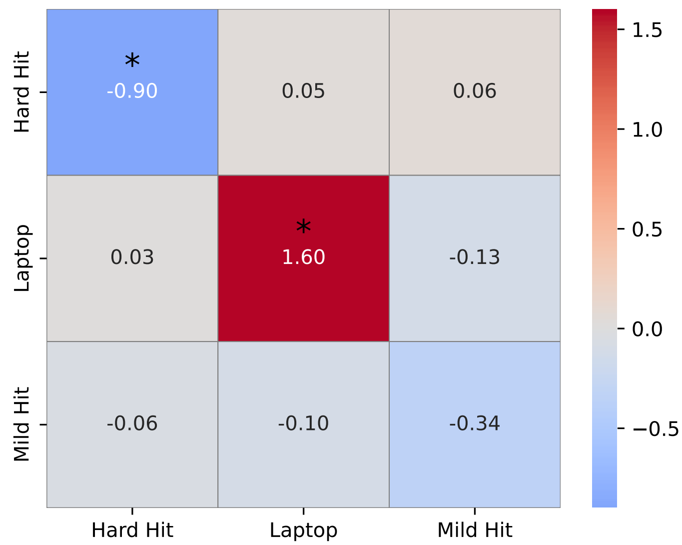

Figure 7: Each cell provides the AME of the GR on the likelihood of sector-to-sector transition, based on a logit regression as: $\ln\left(\frac{P(Y_i=1)}{1-P(Y_i=1)}\right) = \beta_0 + \beta_1 GR + \mathit{controls} + \varepsilon_i$. Hence, each represents the change in the probability of transitioning from a sector of origin (rows) to a sector of destination (columns) during the Great Resignation.

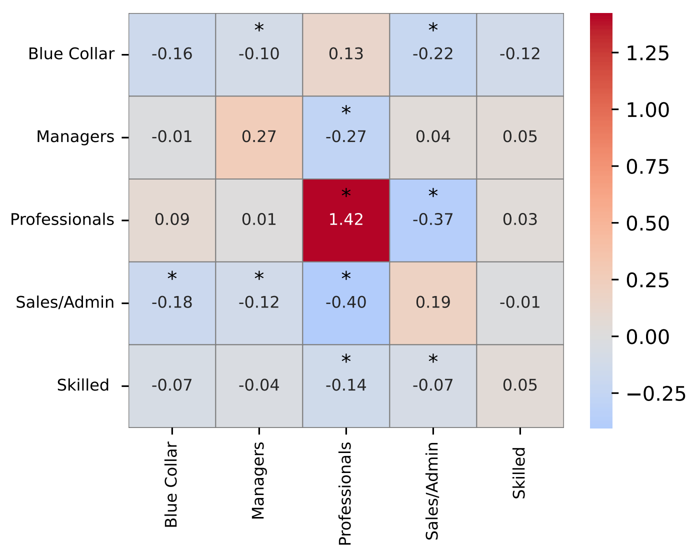

Figure 8: Each cell provides the AME of the GR on the likelihood of sector-to-sector transition, based on a logit regression as: $\ln\left(\frac{P(Y_i=1)}{1-P(Y_i=1)}\right) = \beta_0 + \beta_1 GR + \mathit{controls} + \varepsilon_i$. Hence, each cell represents the change in the probability of transitioning from an occupation of origin (rows) to an occupation of destination (columns) during the Great Resignation.

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