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The cyclicality of on-the-job search[☆]

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ABSTRACT

On-the-job search is increasingly recognized as an important potential driver of labor market dynamics over the business cycle. Using the UK Labor Force Survey, we find robust empirical evidence that on-the-job search is countercyclical and that the cyclical fluctuations have important repercussions for labor market dynamics. We also find that the cyclical pattern is not explained by precautionary search motives but rather appears to be driven by job-ladder-motivated searches. This finding is surprising because, as we confirm, the expected returns to on-the-job search are procyclical. We find evidence that three features of search behavior may contribute to this finding: greater search effort in response to lower job-to-job transition probabilities, a prevalence of non-pecuniary motivated searches that are less affected by lower expected wage gains, and procyclicality in average match quality, which has a significant impact on the search behavior of new hires over the business cycle.

1. Introduction

The search behavior of workers has important consequences for labor market outcomes. In particular, a growing literature views the cyclicality of on-the-job search (OJS) as a potentially important driver of labor market dynamics over the business cycle (Pissarides, 1994, 2000; Krause and Lubik, 2010; Eeckhout and Lindenlaub, 2019; Gertler et al., 2020; Engbom, 2021; Bradley, 2022). The literature argues that since OJS can crowd-out job search by the unemployed, the cyclicality of OJS can have important repercussions for the efficiency with which a slack labor market clears under search frictions. However, despite broad recognition of the crucial role that OJS plays in labor market dynamics, there is a limited understanding of its cyclical properties. On one hand, there is a conventional view that OJS will move procyclically as it is generally assumed that workers are motivated to engage in costly search to find better jobs, which are harder to come by in a slack labor market (e.g., Pissarides, 1994, 2000). On the other hand, OJS may also provide insurance against unemployment, which would tend to increase the incentive for OJS when unemployment is high. Moreover, the lower likelihood of a job-to-job transition during a recession may also induce workers to compensate for lower transition probabilities by intensifying their search (Shimer, 2004). As a result, theoretical predictions on the cyclicality of OJS are divided, highlighting the need for empirical research to assess both how OJS evolves over the business cycle and what drives the cyclical patterns.

In this paper, we study the cyclicality of OJS using the UK labor force survey (UK-LFS), which contains information on the search activity and search motivations for a large sample of UK households, as well as a host of other relevant household and employment characteristics. The dataset enables us to provide a comprehensive picture of OJS activity over a period that overlaps with the great recession, providing significant variation in the unemployment rate to assess how OJS responds to changes in labor market conditions. In particular, our empirical analysis makes three main contributions to the literature.

First, counter to the conventional view, we find robust evidence that OJS is countercyclical: both the likelihood of a worker searching on the job and the intensity of the search increase when the labor market is slack and decrease when the labor market is tight. This empirical finding is robust to the inclusion of a battery of control variables, and we show – using a decomposition of aggregate OJS fluctuations in the spirit of Borowczyk-Martins and Lalé (2019) – that the cyclical pattern is not explained by fluctuations in the workforce composition but rather by the behavioral responses of individual workers to changes in labor market conditions. The magnitude of the cyclical fluctuations is also sufficiently large to have real macroeconomic implications. In

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particular, using our data to conduct a counterfactual exercise on the Beveridge curve, we show that taking into account the cyclicality of OJS may explain a substantial part of the shift in the Beveridge curve that was observed in the UK during the great recession. Moreover, on the basis of EU labor force surveys, we find similar cyclical patterns of OJS in a sample of 31 European countries, establishing the countercyclicality of OJS as a stylized fact of European labor markets.

Our main empirical findings are consistent with prior evidence in Elsby et al. (2015) and Ahn and Shao (2021), which highlight similar countercyclical patterns of OJS in the US. However, both of these studies have some limitations. Elsby et al. (2015) use job-to-job transitions to construct an indirect measure of OJS, which is likely confounded by features of the job matching process that are not directly related to actual search behavior. Ahn and Shao (2021) use a direct measure of OJS from the American Time Use Survey (ATUS), but OJS appears to be considerably underreported in the ATUS, resulting in a small and possibly selected OJS sample. More importantly, the richer information about search activity in the UK-LFS enables us to provide a more comprehensive picture of OJS activity than that found in these previous studies, providing further insights into the drivers of changes in OJS over the business cycle.

Our second major contribution compares the relative empirical importance of two main reasons for OJS that have been proposed in the literature: a precautionary motive (searching to insure against unemployment) and a job-ladder motive (searching for better jobs). An increase in OJS for precautionary motives seems a natural response to an increased risk of unemployment, and this is the rationalization for the countercyclicality of OJS proposed in Ahn and Shao (2021). However, the UK-LFS contains information on the "reason for search", allowing us to assess the absolute and relative importance of this motive empirically. While we do find that precautionary search increases with unemployment, we find that the relevance of these searches in explaining the countercyclicality of OJS is considerably smaller than increases in job-ladder-motivated searches. As a result, the precautionary motive for search does not rationalize the countercyclicality of OJS, which is driven more by the response of job-ladder-motivated search to changes in the unemployment rate.

Based on conventional views of OJS, the countercyclicality of job-ladder searches seems surprising because, as we also confirm, transition probabilities (the likelihood of search resulting in a successful job-to-job transition) and wage gains (the expected increase in wages resulting from a successful search) are both substantially lower when the labor market is slack. Since transition probabilities and wage gains are key determinants of the expected pecuniary benefit of a job-ladder-motivated search, the search incentives appear to be highly procyclical (i.e., lower when the labor market is slack). Our third contribution is to provide some insights as to why, nevertheless, OJS is countercyclical based on several factors that have been suggested in the prior literature but are not accounted for in the conventional view.

First, as argued in Shimer (2004), theoretical predictions about the anticipated response to a lower transition probability in a slack labor market are ambiguous. While lower transition probabilities reduce the expected returns of search, the lower chance of achieving a match may also encourage more search effort, resulting in higher search intensity. Using information on the number of search methods employed for OJS as a proxy for search intensity, we find evidence that an increase in search intensity to compensate for a lower transition probability could be a relevant factor in the cyclicality of OJS.[1]

Second, a growing literature argues that job seekers often care about non-pecuniary benefits of work (e.g., Hwang et al., 1998; Nosal and Rupert, 2007; Sullivan and To, 2014; Hall and Mueller, 2018; Sorkin, 2018). While the incentive effect of lower wage gains would seem unambiguous, the impact of this negative incentive effect may depend on how much job-ladder searchers care about pecuniary versus non-pecuniary benefits. We therefore disentangle job-ladder-motivated search further into search motivated by pecuniary benefits (higher wages) and non-pecuniary benefits (other job aspects such as better amenities). We find that, while both pecuniary and non-pecuniary motivated search increase when unemployment is high, non-pecuniary-motivated search contributes substantially more to the cyclicality of job-ladder-motivated searches than does pecuniary-motivated search.

Finally, a growing literature argues that match quality may be procyclical and, in particular, that new matches that occur during a downturn have a lower average quality (e.g., Bowlus, 1995; Barlevy, 2002). Since match quality impacts the incentive to search, new hires may be more likely to search if they were hired during a recession (when average match quality is low) than if they were hired when the labor market is tight (and average match quality is high). To assess whether this channel contributes to the cyclical pattern of OJS, we look at the search activity of new hires during the recession versus that of other workers. Consistent with the idea that match quality deteriorates during a recession, and that this impacts search behavior, we find that new hires search less than other workers when the labor market is tight but search more than other workers when the labor market is slack.

Overall, we therefore find empirical support for at least three mechanisms, suggested in the prior literature, that can all contribute to the cyclical pattern we observe for OJS, in addition to the precautionary motive. While our evidence is not conclusive, the findings may nevertheless provide guidance about potential considerations for future theoretical and empirical work on the role of OJS in labor market dynamics over the business cycle. Our findings highlight that it may be important to consider the behavioral responses to changes in transition probabilities, provide further evidence of the salience of non-pecuniary benefits for job-ladder-motivated searches, especially as a driver of OJS during recessions, and indicate that procyclicality in average match quality may have a significant impact on the search behavior of new hires over the business cycle.

The remainder of the paper proceeds as follows. Section 2 describes the data of the UK-LFS that we use in the empirical analyses. Section 3 presents the empirical strategy for our main analysis. Section 4 presents the empirical results, establishing the cyclical properties of OJS, its impact on labor market dynamics, and the main drivers of the cyclical pattern. Section 5 discusses the implications of the results, and Section 6 concludes. Details about the data, corresponding analysis for the EU-LFS, and additional robustness results for the cyclical properties of OJS are provided in Appendix.

2. Data

The UK-LFS samples approximately 60,000 households living in the UK (about 120,000 individuals) every quarter. The households are interviewed face-to-face when first included in the survey and by telephone thereafter (see Gomes, 2012, for a detailed description). In this study, we use the years 1992–2019 and restrict the sample to workers who are employed.

UK-LFS respondents report whether they search for a job and, if they do, what methods they use to search, as well as the reasons why they search. To analyze job search behavior at the extensive margin, we create a dichotomous variable taking a value of one if a respondent reports looking for a different or additional job, which we call OJS activity. To analyze job search behavior at the intensive margin, we use the number of methods used to search (Shimer, 2004), which we refer to as OJS intensity. Due to changes in the questionnaire, we analyze search intensity starting in 1997. We have no information on the time spent on job search, but Mukoyama et al. (2018) show that for unemployed workers, there is a strong positive correlation

[1] While the number of search methods is our best proxy for search intensity (see Section 2), our findings are also consistent with the findings in Ahn and Shao (2021) from the ATUS, which has more information about how much time workers spend on search activity.

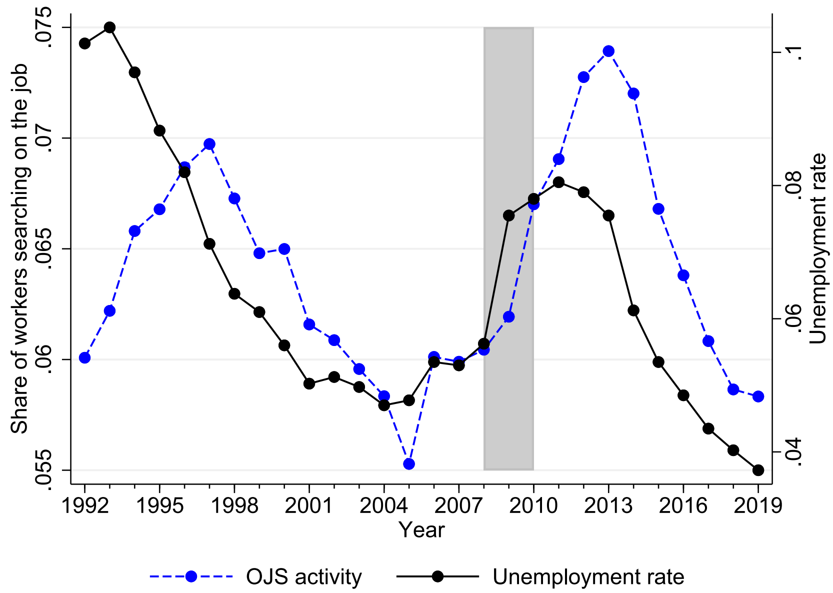


Fig. 1. OJS activity and the unemployment rate for the UK.
Notes: The yearly average share of employed workers searching on the job (left y-axis) and yearly average unemployment rate (right y-axis) are depicted for the years 1992–2019. The gray bar indicates the great recession. Data from the UK-LFS are depicted.

between the number of search methods used and the time spent on job search, implying that the number of search methods contains valuable information on the intensity of job search. However, we are cognizant that the number of search methods is only a proxy for search intensity and, as we discuss below, one that we cannot validate using the data. We, therefore, focus most of our analysis on the extensive activity measure.

In our sample, 6.4% of workers report that they are searching on the job. This share is larger compared to other studies for the US and the UK, which report 4.4% and 4.3% of employed workers search on the job, respectively (Fallick and Fleischman, 2004; Fujita, 2012).[2] Workers that search on the job use on average four different methods.

Fig. 1, depicts the variation in the yearly average of the unemployment rate and the share of workers reporting OJS activity over the sample period. The variation in the extent of OJS activity and the unemployment rate is sizeable, ranging from 5.5% to 7.3% and from 3.7% to 10.4%, respectively. The figure shows that the share of workers that search on the job is positively related to and lagging behind the unemployment rate. The share of workers that search on the job starts to increase significantly during the great recession, and keeps rising thereafter. The share of workers searching on the job reaches its peak 3 years after the end of the great recession and starts to decline sharply to pre-recession levels as the unemployment rate declines.[3]

Fig. 2 depicts the variation in the yearly average of the unemployment rate and the average number of search methods over the years 1997–2019. The average number of search methods ranges from 3.45 to 4.35. The figure shows that OJS intensity decreases over the sample period, likely reflecting technological advancements such as increased use of the internet. Yet, during the recession, search intensity increases sharply and falls again as the unemployment rate decreases. There appears to be a slight positive correlation between the unemployment rate and search intensity.

Concerning the reasons why workers search on the job, Table A.1 in the appendix shows all the reasons included in the data.[4] We categorize a search motivation as *precautionary search* if the reason listed for the search is that the "present job may come to an end". We categorize job-ladder-motivated search as searches for a *better* job if the listed reasons include "pay unsatisfactory in present job; wants to work longer hours than in present job; wants to work shorter hours than in present job; journey to work unsatisfactory in present job; wants to change sector; wants to change occupation; Other aspects of present job unsatisfactory; present job is to fill in time before finding another job". We further disaggregate the better category into better for *pecuniary* reasons, which is related to pay, hence the listed reason is "pay unsatisfactory in present job" and *non-pecuniary* reasons that include all listed reasons except for the financial one. We code each of these reasons as a binary variable taking a value of 1 if the respondent mentions the reason as one of their three main reasons; otherwise, the variable takes a value of 0.

We use the information on a wide array of demographic and economic attributes of the respondents in our analyses. We consider tenure with the current employer, which is measured as the number of months with the current employer; current occupation, which is a categorical variable with nine categories ranging from manager to elementary occupations; and the sector of the current employer, which is also a categorical variable with fourteen categories ranging from agriculture to health. We also code dummy variables for whether the respondent is temporarily employed, part-time employed, or self-employed. Finally, we use a categorical variable for work hours with four categories ranging from 1–15 h to above 45 h. Additionally, we have information on sociodemographic variables such as age, gender, and region of residents, coded as 13 unique regions in the UK.

In further analysis, we use additional control variables for the education level, firm size as a measure of position on the job ladder (see, e.g., Moscarini and Postel-Vinay, 2018), training on the job, and mortgage payments. We code education dummies using seven categories of education ranging from no qualification to a university degree. For firm size, we use five categories ranging from 1–10 workers to over 50 workers. We also code dummies for whether the respondent has mortgage liability and whether there is firm-specific training in their job.

While the above data form our core cross-sectional data for analysis – henceforth 1Q data – in this paper, we use additional data as well. Complementary to 1Q data, there are two longitudinal datasets where

[2] The sample of Fallick and Fleischman (2004) includes the years 1997 and 1999 and the sample of Fujita (2012) spans the years 2002–2009.

[3] Independent work by Papac (2022) also uses UK-LFS data and documents the cyclicality of OJS. We became aware of this work in March 2023.

[4] Respondents can indicate up to three reasons they are searching for a job.

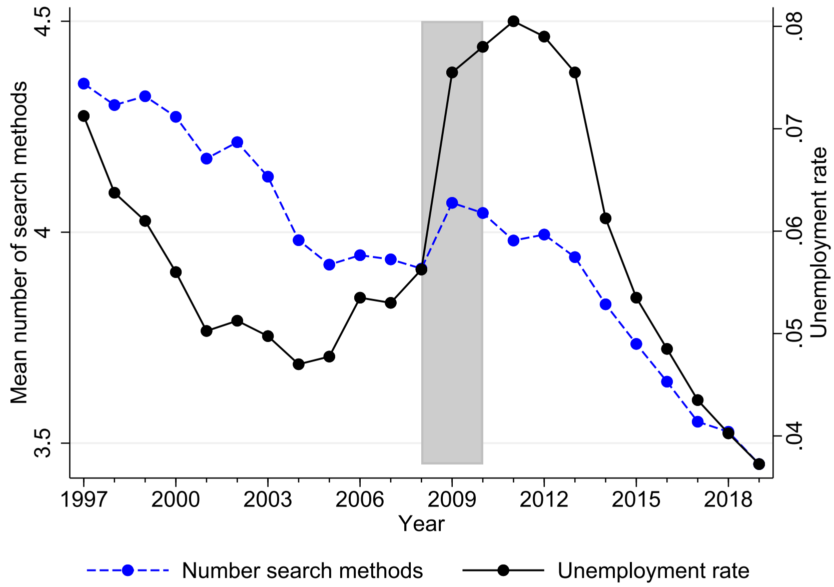


Fig. 2. OJS intensity and the unemployment rate for the UK.
Notes: The yearly average share of the number of search methods (left y-axis) and yearly average unemployment rate (right y-axis) are depicted for the years 1997–2019. The gray bar indicates the great recession. Data from the UK-LFS are depicted.

a smaller sample of respondents participate in a shorter questionnaire. Subsamples of 45,000 and 7,500 respondents, respectively, are followed in the second quarter (2Q dataset) and up to five consecutive quarters (5Q dataset). In our context, there are certain limitations to this data. For example, while the information on search motivations is collected in the 2Q and 5Q data, the search method information is limited to the main method of search. Since respondents provide only their main search method, it is not possible to construct a variable for the number of search methods they use in the 2Q data. One consequence of this data limitation is that it is not possible to validate our measure of search intensity by checking if a higher number of search methods used (input) leads to a higher probability of finding a new job (output), which would have indicated if the number of search methods used is a reliable proxy of how intensely workers search. We, therefore, focus our analysis only on the measure of OJS activity (extensive margin) rather than how hard workers search (intensive margin) apart from when the analysis is explicitly about intensity, as in Fig. 2. To validate that the data are comparable in terms of our OJS statistics, approximately 6.04% and 6.39% of workers in 2Q and 5Q, respectively (relative to 6.4% in 1Q data), report engaging in OJS in the first quarter. Despite this limitation, these longitudinal data enable us to analyze job-to-job transitions and wage dynamics, where the 1Q data has its own limitations. In terms of transitions, the data enable us to follow the labor market status in the first and second quarters from the 2Q data and wages in the first and fifth quarters in the 5Q data.

3. Empirical strategy

The previous section presents evidence that the extent of OJS activity and OJS intensity are positively related to the unemployment rate. To investigate the cyclical properties of OJS behavior more rigorously, we use regression analysis.

To study the extensive and intensive margin of OJS, we estimate various versions of the following model:

$$OJS\ activity/intensity_{iqt} = \alpha_0 + \alpha_1 Unemployment\ rate_{qt} + \mathbf{x}'_{\mathbf{iqt}}\boldsymbol{\phi} + \alpha_2 Year_t + \gamma_q + \varepsilon_{iqt} \quad (1)$$

where $OJS\ activity_{iqt}$ is a dichotomous variable taking a value of one if individual i in quarter q in year t reports looking for a job and $OJS\ intensity_{iqt}$ indicates the number of search methods used to search for a job. $\mathbf{x}_{\mathbf{iqt}}$ is a vector of controls, $Year_t$ is a linear time trend (we use year fixed effects instead of the linear time trend in some specifications), and γ_q is a set of binary variables indicating the quarter. The vector $\mathbf{x}_{\mathbf{iqt}}$ includes gender, age, and a set of indicator variables for the region of residence, as well as a variable indicating if the respondent is temporarily employed, part-time employed, self-employed, the number of years the respondent has been working for the current employer (tenure),[5] and a set of indicator variables for the occupation and sector of employment. ε_{iqt} is an error term.[6]

4. Results

In this section, we first present the regression results analyzing the cyclical properties of OJS behavior. We then assess the relevance of cyclical OJS on labor market dynamics based on the Beveridge curve. Then, we consider the importance of fluctuations in the composition of workers, before looking at search motivations and the role of match quality.

4.1. Cyclicality of OJS

Table 1 presents the regression results for the relationship between the unemployment rate and the respondents' OJS activity and OJS intensity. In this analysis, the key explanatory variable of interest, $Unemployment\ rate_{qt}$, is the unemployment rate in the UK in quarter q in year t. Column (1) depicts the results on OJS activity without any controls other than the linear time trend and indicator variables for the quarter. Column (2) depicts the results on OJS activity including a set of controls.[7] Columns (3) and (4) present the regression results from ordinary least squares regressions of the relationship between the unemployment rate and the number of search methods used by

[5] In our control variables, we also include tenure-squared but transform it by dividing the variable by 1000 to show the estimated parameter precisely.

[6] Clustering standard errors at the quarter-year level yield similar results, throughout.

[7] The reduction in sample size is attributed to missing values in the tenure month and sector variables. We do not impute these variables and instead assume that the missingness is random, as there is no discernible pattern in the missing values for either variable.

Table 1
OJS and Unemployment.

	(1) OJS Activity	(2) OJS Activity	(3) OJS Intensity	(4) OJS Intensity
Unemployment rate	0.204***	0.287***	6.724***	5.751***
	(0.007)	(0.008)	(0.295)	(0.293)
Male		2.117***		13.10***
		(0.030)		(0.834)
Age		0.225***		−0.558***
		(0.006)		(0.209)
Age sq.		−0.00407***		0.000975
		(0.000)		(0.003)
Self-employed		−0.663***		−35.46***
		(0.031)		(1.689)
Temporary Employment		9.331***		50.84***
		(0.079)		(1.168)
Part-time Employment		1.384***		8.962***
		(0.062)		(1.738)
Tenure		−0.0355***		−0.541***
		(0.000)		(0.015)
Tenure sq.		0.0584***		0.984***
		(0.001)		(0.049)
Work hours — 16–30 h		−0.0925*		−17.22***
		(0.056)		(1.435)
Work hours — 31–45 h		−0.656***		−22.12***
		(0.078)		(2.131)
Work hours — above 45 h		−0.870***		−28.34***
		(0.082)		(2.317)
Year	0.0251***	0.0471***	−3.277***	−2.902***
	(0.002)	(0.002)	(0.054)	(0.055)
Quarter FE	Yes	Yes	Yes	Yes
Sector FE	No	Yes	No	Yes
Region FE	No	Yes	No	Yes
Occupation FE	No	Yes	No	Yes
N	6 132 313	5 479 673	297 445	285 612

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Note: The coefficients and standard errors are multiplied by 100. The dependent variable in columns (1)-(2) is a binary variable indicating whether a respondent is looking for a job, and the dependent variable in columns (3)-(4) indicates the number of search methods used. Columns (1) and (3) depict the results including a linear time trend and a set of binary variables indicating the quarter. Columns (2) and (4) depict the results when additionally including the full set of control variables. Person weights are used in all regressions. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels. Robust standard errors are reported in parentheses.

employed searchers (OJS intensity). We restrict the sample to workers that report that they are searching for a job and exclude the years before 1997.

The coefficient of the unemployment rate is positive and statistically significant at the 1% level for both OJS activity and OJS intensity. This finding is in line with the observation in Fig. 1 that OJS activity and the unemployment rate and in Fig. 2 that OJS intensity and the unemployment rate are positively correlated. The results in columns (2) and (4) show that these positive relationships are not driven by observable compositional shifts in the pool of employed workers.

If we take the coefficient of column (2) to quantify the relationship between the unemployment rate and the likelihood that a worker is searching on the job, we see that an increase in the unemployment rate from 5.4% (2006) to 8.1% (2011) increases the likelihood that a worker searches on the job by 0.77 percentage points. Therefore, the share of workers who search on the job increases by 12.8%, from 6.0% in 2006 to 6.77% in 2011. To put this in perspective, the number of unemployed workers increased by approximately 0.92 Mill. from 1.67 Mill. in 2006 to 2.59 Mill. in 2011. Given our estimates, the number of employed searchers increased by 0.24 Mill. from 1.75 Mill. in 2006 to 1.99 Mill. in 2011.[8] Therefore, in times of high unemployment, there one-fourth more workers search for a job when cyclical changes in OJS activity are considered than when OJS is assumed to be constant.

The size of the relationship between the unemployment rate and the number of search methods is small. We find that the number of search methods increases by 0.16 if we look at the coefficient in column (4) and assume again that the unemployment rate increases from 5.4% (2006) to 8.1% (2011). We find a weak positive correlation between the unemployment rate and our measure of OJS intensity, indicating that employed workers search slightly more intensely when the labor market is slack and slightly less intensely when the labor market is tight.

In the Appendix Tables A.3 and A.4, we use data from 31 European countries to test whether our findings concerning the cyclical properties of OJS behavior can be generalized beyond the UK. Regarding OJS activity, the coefficient of the unemployment rate for the European sample is positive, statistically significant and of a similar size as that in Table 1. Moreover, in regards to OJS intensity, the coefficients of the unemployment rate are positive and statistically significant but smaller than those in Table 1. This suggests that the finding that, on average, the cyclical properties of OJS behavior observed in the UK, i.e., that workers are more likely to search on the job when the labor market is slack, can be generalized to a large set of countries.

In the Appendix, we conduct several robustness analyses of the results presented in Table 1. We show that these results are robust to using other unemployment rates (sector/occupation/region) (Table A.5), employing logit specification instead of OLS for the binary indicator of search activity (Table A.6), and accounting for the potential selection from the incidental truncation of the variable of search methods when the sample is restricted to searchers only (Table A.7). Additionally, we expand the set of control variables to assess whether certain omitted variables biased our results provided above (Tables A.8–A.9). Further discussion of these results is presented in Appendix.

4.2. OJS and the Beveridge curve

To show the quantitative importance of the observed fluctuations in OJS behavior, we focus on its impact on Beveridge curve dynamics. In particular, we focus on the observed outward shift of the UK Beveridge curve amid the great recession. Elsby et al. (2015) develop a convenient way to assess the impact of fluctuations of OJS by constructing a counterfactual Beveridge curve that would be observed if OJS were constant and comparing it to the realized (true) Beveridge curve. This exercise enables one to measure the importance of fluctuation in OJS on Beveridge curve dynamics by estimating the amount of the outward shift in the Beveridge curve observed around the great recession that was a result of an increase in OJS. To apply this approach to the UK, we use quarterly vacancy rate and unemployment rate data for the UK from 2003 until 2019 to derive the UK's realized Beveridge curve for this period. Using our direct measure of OJS activity, we then construct a counterfactual Beveridge curve that treats OJS as constant at an initial value.

Let u be the unemployment rate and v the vacancy rate. The usual matching function $m(u, v)$ then determines hiring in the economy.[9] If we include OJS activity s, the matching function becomes $m(u+s, v)$. Moreover, with constant returns to scale we can define $f(\sigma\theta) = m(1, v/(u+s))$, with $\sigma = u/(u+s)$ and labor market tightness $\theta = v/u$, as the job finding rate. The negative relationship between the job finding rate and OJS via σ reflects that employed job seekers compete with unemployed job seekers for the same vacancies, which reduces the probability for the unemployed of finding a job.

The law of motion determining the evolution of unemployment is:

$$\frac{du}{dt} = \lambda(1-u) - f(\sigma\theta)u, \tag{2}$$

[8] The numbers of unemployed and employed individuals were taken from the Office for National Statistics.

[9] This derivation follows Elsby et al. (2015).

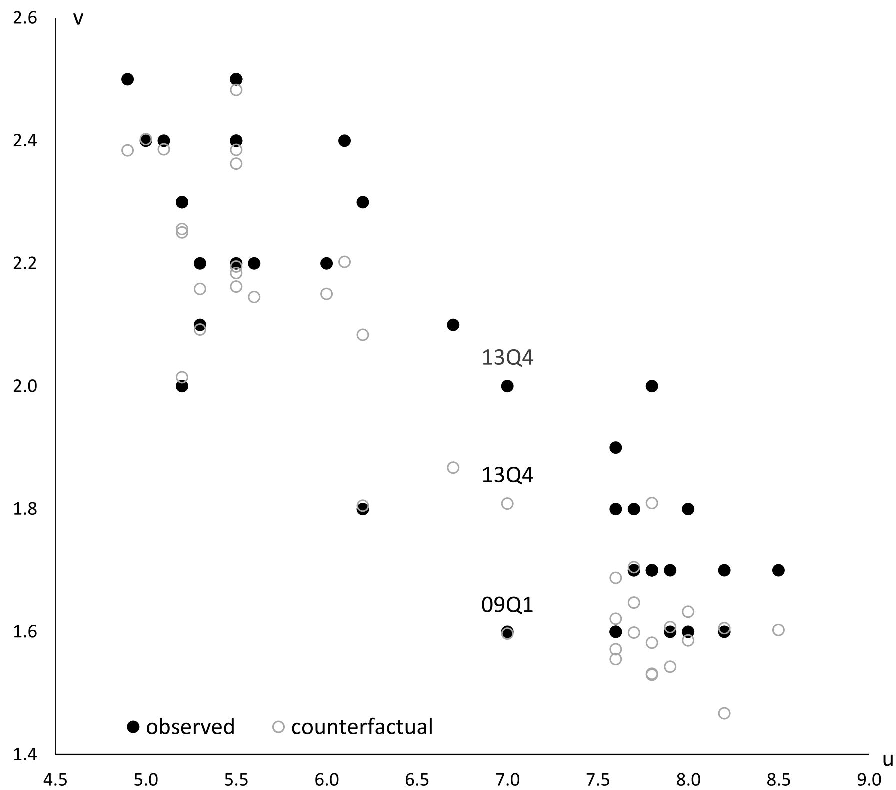


Fig. 3. OJS and the Beveridge curve for the UK.
Notes: The realized and counterfactual Beveridge curves are depicted with measures for the vacancy rate, unemployment rate, and OJS activity for the years 2003Q1–2015Q4.

where λ is the rate at which employed workers flow out of employment. Therefore, the first term on the right-hand side is the inflow to unemployment, and the second term is the outflow. OJS reduces the outflow without a corresponding change in the inflow, and unemployment increases with OJS activity.

The Beveridge curve is given by the unemployment and vacancy rates consistent with steady-state unemployment $\delta u/\delta t = 0$ such that:

$$\lambda(1-u) = f(\sigma\theta)u, \tag{3}$$

This Beveridge curve is negatively sloped in the v-u-space and shifts outwards if s increases.

Fig. 3 shows the realized (filled) and counterfactual (unfilled) Beveridge curves for the UK between 2003 and 2015.[10] The marked shift outward in the realized Beveridge curve that started amid the great recession is considerably more pronounced than the shift in the counterfactual Beveridge curve, indicating that OJS does indeed account for some of the shift. To quantify how much of the shift can be attributed to OJS, we take the first quarter of 2009 and the third quarter of 2013, both times at which the unemployment rate was at 7%. The vertical shift in the realized Beveridge curve is 0.4 percentage points, while the shift in the counterfactual curve is 0.22 percentage points. Therefore, the calculation shows that almost half of the shift can be accounted for by increased search activity of employed workers, highlighting a potentially important role for fluctuations in OJS for Beveridge curve dynamics in the UK.

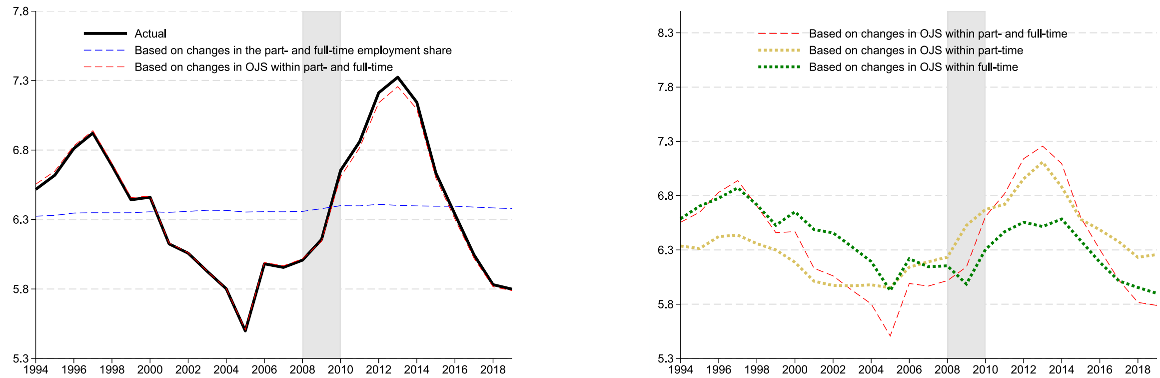
Several explanations have been proposed for the decline in aggregate matching efficiency that gives rise to shifts in the Beveridge curve (Ahn and Crane, 2020), such as occupational mismatch (Sahin et al., 2014), labor market heterogeneity (Barnichon and Figura, 2015), financial frictions (Christiano et al., 2015), a shift in the pool of job seekers towards long-term unemployed (Hall and Schulhofer-Wohl, 2018), and a change in the recruiting intensity of firms (Gavazza et al., 2018).

However, a growing number of papers consider OJS. Elsby et al. (2015) use job-to-job and unemployment-to-employment transitions to construct an indirect measure of OJS and use this measure to construct their counterfactual Beveridge curve. They find that less of the shift in the US Beveridge curve during the great recession can be explained by OJS, suggesting that it accounts for roughly one quarter.[11] In a recent quantitative model using the US data that matches some important features of OJS, Bradley (2022) estimates that his model can account for one-third of the observed shift in the US Beveridge curve, and in a similar framework, Engbom (2021) finds a model with OJS can effectively replicate the Beveridge curves dynamics in the US. Our findings add to this small but growing literature suggesting that OJS is a potentially important factor in outward shifts of the Beveridge curve.

Finally, the counterfactual exercise does not indicate the equilibrium path of u and v that would be realized in the absence of fluctuations in OJS activity. This counterfactual Beveridge curve is just one input into that equilibrium and does not consider the determination of vacancies. However, it highlights and quantifies the potential impact of the observed cyclical properties of OJS.

[10] 2003 is our first year because although we have data from 2001, there was a brief recession in the early 2000s and we want to capture only the time around the great recession.

[11] In the Appendix Fig. A.1, we provide an alternative counterfactual Beveridge curve for the UK using the same transitions as those used by Elsby et al. (2015) in their work for the US. The indirect measure is also countercyclical; thus, this exercise entails qualitatively similar results in terms of the outward shift in the Beveridge curve. Quantitatively, the results show that less of the shift can be explained by countercyclical OJS, with OJS accounting for slightly more than a third of the shift when we use transitions rather than our direct measure.



(a) Counterfactual OJS (b) Counterfactual OJS by Part- and Full-time

Fig. 4. Decomposition: Part- and Full-time Worker's OJS.
Notes: Fig. 4(a) presents two counterfactual OJSs. The first [blue] (second [red]) counterfactual is constructed by fixing the OJS behavior within the mentioned groups (weights of the groups) at the mean value in the sample. For comparison purposes, we also plot a black line that shows the actual OJS behavior over time. Fig. 4(b) decomposes the second counterfactual into two additional counterfactuals for each mentioned group [yellow for group 1 and green for group 2] by allowing only one group's OJS to vary at a time while keeping the weights and the OJS behavior of the other group constant at the mean values in the sample. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.3. Composition effects

We find in Table 1 that part-time and temporary workers are more likely to search on the job. While the regression analysis controls for these factors as potential confounders, we now study in more detail the importance for OJS activity of fluctuations in the employment composition of part-time and temporary workers. Borowczyk-Martins and Lalé (2019, 2020) study the importance of such compositional fluctuations in part-time and involuntary part-time workers over the business cycle and show that fluctuations in the shares of part-time workers play an important role in hour-per-worker cyclicality. Similar to Borowczyk-Martins and Lalé (2019), we separate the fluctuations in aggregate OJS activity into fluctuations in the share of part-time and temporary workers and the search within these groups. We start with the identity:

$$s_t = \omega_t^i s_t^i + \omega_t^j s_t^j, \tag{4}$$

where ω_t^i (ω_t^j) is the share of workers in part-time or temporary (full-time or permanent) employment and s_t^i (s_t^j) is the search of part-time or temporary (full-time or permanent) workers. Since $\omega_t^i + \omega_t^j = 1$, we can concentrate on the share of one of the groups, which in our case will be part-time and temporary workers. Eq. (4) then implies that fluctuations in search can be separated into changes in the search activity of these types of workers and changes in their employment share. We consider counterfactual series of search holding the search (share) fixed to their respective sample means while letting the shares (search) move to see how closely they track the overall search behavior.

Starting with part-time versus full-time workers, Fig. 4(a) shows the two counterfactual series of OJS based on changes in the employment share of part-time workers (blue line) and changes in the OJS of part- and full-time workers (red line). Changes in the share of part-time workers hardly move at all with overall search (black line), while search within the groups tracks overall search almost perfectly. Fig. 4(b) shows the search behavior within the employment groups and highlights that the search behavior of both part-time (yellow line) and full-time (green line) workers fluctuates to contribute to the counterfactual search behavior (red line) with part-time workers playing a more significant role during the great recession.

Similar results are obtained when we look at temporary versus permanent in Fig. 5(a). The shares do not contribute substantially to the cyclicality, indicating that the overall search is driven by the fluctuations in search behavior within the groups, with permanent workers playing the more prominent role (Fig. 5(b)). Overall, both these decompositions suggest that fluctuations in worker shares do not play a significant role in the fluctuation of OJS activity.

We can also conduct the same decomposition for workers with a short tenure on the job (≤4 years) versus workers with a long tenure (>4 years). Again, we find that fluctuations in the tenure composition of the workforce do not explain the cyclical fluctuations of OJS (Fig. 6(a)). Fig. 6(b) shows that while OJS is countercyclical for both short and long job tenures, the cyclical reaction is both more pronounced and occurs earlier for short-tenure workers. Thus, the search behavior of longer-tenure workers lags behind the search behavior of workers with a shorter job tenure.

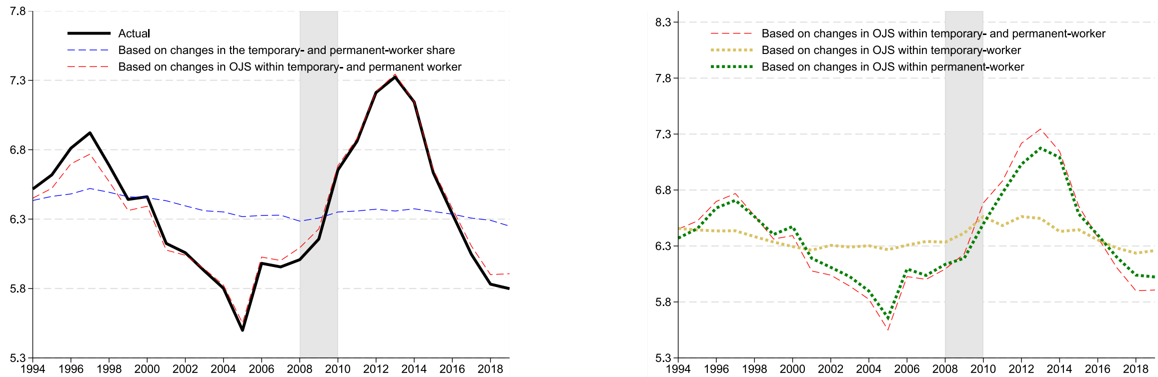
4.4. Search motivations

To start to develop an understanding of the reasons that OJS activity is countercyclical, we consider the motivations for search given by respondents in the UK-LFS. In Table 2, we present results from regression specification 1, where we disaggregate OJS into different search motivations (job-ladder vs. precautionary search). Column (5) shows that, consistent with the findings of Ahn and Shao (2021) for the US, precautionary search in the UK is countercyclical. However, Columns (2)–(4) also show that job-ladder search – better jobs for both pecuniary and non-pecuniary reasons – is also countercyclical. Moreover, the coefficients indicate that the effect of unemployment is larger for those looking for better jobs than it is for those engaging in precautionary search, suggesting that the former and not the latter may be the more important driver of countercyclical OJS.[12]

To illustrate the relative importance of the different search motivations in driving fluctuations in OJS, Fig. 7(a) decomposes the overall change in search (black line) into those looking for better jobs (blue line) and those conducting precautionary searches (red line). The figure shows that fluctuations in search are almost always driven mainly by those looking for a better job, except for during the first half of the great recession. These results show that it is primarily search by workers looking for better jobs that drives countercyclical OJS in our data.

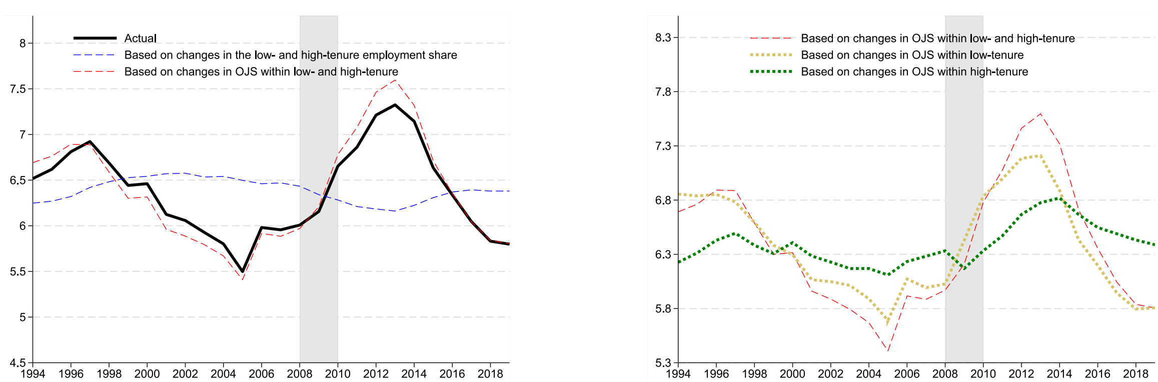
Fig. 7(b) also decomposes the change in search of those looking for better jobs (blue line) into those looking for better jobs for pecuniary (yellow line) and non-pecuniary (green line) reasons. Both contribute to fluctuations in job-ladder search before the great recession, but during the great recession and its aftermath, those looking for better jobs for non-pecuniary reasons drive the fluctuations.

[12] Table A.10 in the Appendix includes additional controls and shows the results are robust.



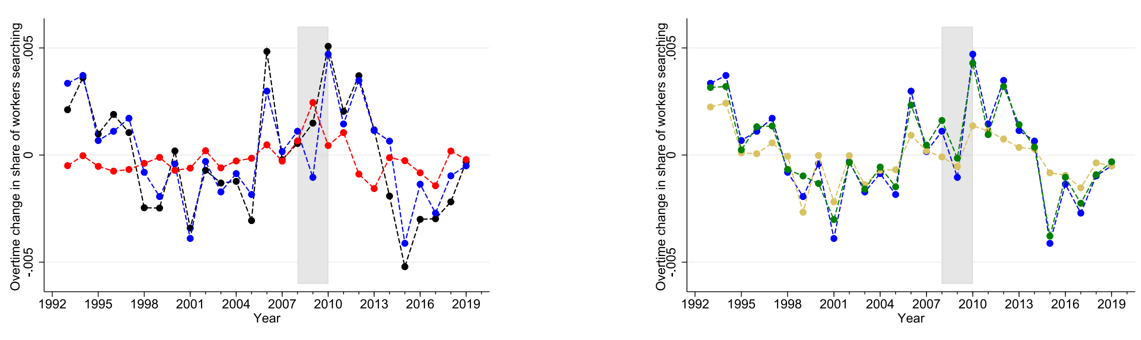
(a) Counterfactual OJS　(b) Counterfactual OJS by Temporary- and Permanent-worker

Fig. 5. Decomposition: Temporary- and Permanent-worker's OJS.
Notes: Fig. 5(a) presents two counterfactual OJSs. The first [blue] (second [red]) counterfactual is constructed by fixing the OJS behavior within the mentioned groups (weights of the groups) at the mean value in the sample. For comparison purposes, we also plot a black line that shows the actual OJS behavior over time. Fig. 5(b) decomposes the second counterfactual into two additional counterfactuals for each mentioned group [yellow for group 1 and green for group 2] by allowing only one group's OJS to vary at a time while keeping the weights and the OJS behavior of the other group constant at the mean values in the sample. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



(a) Counterfactual OJS　(b) Counterfactual OJS by Short and Long Tenure

Fig. 6. Decomposition: Short and Long Tenure Worker's OJS.
Notes: Fig. 6(a) presents two counterfactual OJSs. The first [blue] (second [red]) counterfactual is constructed by fixing the OJS behavior within the mentioned groups (weights of the groups) at the mean value in the sample. For comparison purposes, we also plot a black line that shows the actual OJS behavior over time. Fig. 6(b) decomposes the second counterfactual into two additional counterfactuals for each mentioned group [yellow for group 1 and green for group 2] by allowing only one group's OJS to vary at a time while keeping the weights and the OJS behavior of the other group constant at the mean values in the sample. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



(a) Decomposition of OJS by Better and Precautionary Search　(b) Decomposition of Better by Pecuniary and Non-pecuniary search

Fig. 7. Decomposition: OJS Motivations.
Notes: Fig. 7(a) presents the changes in the proportion of workers engaging in OJS [black] and the changes disaggregated by motivations relating to better [blue] and precautionary search [red]. In Fig. 7(b), for comparison purposes, we also plot a blue line that shows the changes in the better split, disaggregated by motivation relating to pecuniary [yellow] and non-pecuniary [green] reasons. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Motivations for OJS.

	(1) OJS Activity	(2) Better	(3) Better (Pecuniary)	(4) Better (Non-pecuniary)	(5) Precautionary Search
Unemployment rate	0.287***	0.148***	0.0796***	0.185***	0.0600***
	(0.008)	(0.006)	(0.004)	(0.006)	(0.003)
Male	2.117***	1.370***	0.817***	1.086***	0.0384***
	(0.030)	(0.024)	(0.015)	(0.023)	(0.009)
Age	0.225***	0.0605***	0.0343***	0.0744***	0.0563***
	(0.006)	(0.004)	(0.003)	(0.004)	(0.002)
Age sq.	−0.00407***	−0.00164***	−0.000701***	−0.00168***	−0.000669***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Self-employed	−0.663***	−1.483***	−0.543***	−1.241***	0.0643***
	(0.031)	(0.022)	(0.014)	(0.020)	(0.009)
Temporary Employment	9.331***	1.672***	0.554***	3.553***	4.864***
	(0.079)	(0.053)	(0.033)	(0.056)	(0.045)
Part-time Employment	1.384***	1.004***	−0.0302	1.181***	−0.280***
	(0.062)	(0.050)	(0.030)	(0.048)	(0.018)
Tenure	−0.0355***	−0.0225***	−0.0103***	−0.0192***	−0.00312***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure sq.	0.0584***	0.0368***	0.0163***	0.0319***	0.00545***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Work hours — 16–30 h	−0.0925*	0.925***	0.403***	1.045***	0.381***
	(0.056)	(0.042)	(0.023)	(0.040)	(0.013)
Work hours — 31–45 h	−0.656***	0.854***	0.479***	0.933***	0.427***
	(0.078)	(0.061)	(0.036)	(0.058)	(0.021)
Work hours — above 45 h	−0.870***	0.987***	0.412***	1.153***	0.283***
	(0.082)	(0.064)	(0.038)	(0.061)	(0.022)
Year	0.0471***	0.0360***	−0.00495***	0.0467***	0.00444***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
N	5 479 673	5 479 673	5 502 134	5 502 134	5502134

Note: The coefficients and standard errors are multiplied by 100. The dependent variable in column (1) is a binary variable indicating if a respondent is looking for a job; the dependent variable in columns (2) and (5) is a binary variable indicating if a respondent is a better job searcher or precautionary searcher. Columns (3) and (4) further disaggregate better job searchers with pecuniary and non-pecuniary motivations, respectively. The results are based on a specification that includes a linear time trend and a set of binary variables indicating the quarter and the full set of control variables. Person weights are used in all regressions. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels. Robust standard errors are reported in parentheses.

4.5. Match quality

There is significant evidence that match quality deteriorates during recessions, especially for new hires (e.g., Bowlus, 1995). To assess if a deterioration in match quality is an important factor in the cyclicality of OJS , we look at the OJS activity of new hires (tenure less than 1 year) versus other workers. We estimate Specification Eq. (5).

$$\begin{aligned} OJS\ activity_{iqt} = {} & \alpha_0 + \alpha_1 Unemployment\ rate_{qt} \\ & + \alpha_2 Year_t + \alpha_3 Short\ tenure_{iqt} \\ & + \alpha_4 Unemployment\ rate_{qt} \times Short\ tenure_{iqt} \\ & + \mathbf{x}'_{\mathbf{iqt}} \boldsymbol{\phi} + \gamma_q + \varepsilon_{iqt} \end{aligned} \tag{5}$$

where, as in Eq. (2), $OJS\ activity_{iqt}$ is a dichotomous variable taking a value of one if individual i in quarter q in year t reports looking for a job. $\mathbf{x}_{\mathbf{iqt}}$ is a vector of controls, $Year_t$ is a linear time trend (we use year fixed effects instead of the linear time trend in some specifications), and γ_q is a set of binary variables indicating the quarter. The vector $\mathbf{x}_{\mathbf{iqt}}$ includes gender, age, and a set of indicator variables for the region of residence, as well as a variable indicating if the respondent is temporarily employed, part-time employed, self-employed, the number of years the respondent has been working for the current employer (tenure), and a set of indicator variables for the occupation and sector of employment. We include a dummy variable for $Short\ Tenure_{iqt}$ that takes a value of 1 if tenure months are less than equal to 12 and is otherwise 0. ε_{iqt} is an error term.

Table 3 presents the results. The coefficient on short tenure shows that, in general, new hires search less than do other workers. However, the coefficient on the interaction with unemployment shows that the search behavior of new hires reacts more to changes in the unemployment rate than does that for other workers. Therefore, new hires search less than other workers when the labor market is tight but search more than other workers when the labor market is slack.[13]

5. Reasons for countercyclical OJS

From a conventional view, job-ladder searchers should react to the returns from search, reflected by the transition probability (i.e., probability of finding a new match) and the wage gain (i.e., the expected change in their wage if they find a new match). We begin this section by considering how these two types of returns relate to OJS.

To assess the impact on OJS activity of the probability of finding a new match, we use the 2Q data to estimate the transition probabilities conditional on a worker engaging in OJS.[14] Fig. 8 shows that the transition probabilities for those who search are higher, in

[13] Table A.11 in the Appendix includes additional controls and shows the results are robust.

[14] To estimate transition probabilities every year, we define the dependent variable as the possible market status in quarter 2 as being employed at the same job, employed at a different job, unemployed or not in the labor force. We estimate a multinomial logit with these four possible outcomes for a worker who is employed in quarter 1. We include in the regression worker's search behavior as a dummy that takes a value of 1 if the worker is involved in OJS, as well as additional controls for worker's education dummies, age, and age squared. Since the data cover respondents for two quarters, we have their OJS for each quarter. We define a worker engaging in OJS based on their OJS reported for quarter 1.

Table 3
OJS, Short Tenure and Unemployment.

	(1) OJS Activity	(2) OJS Activity	(3) OJS Activity	(4) OJS Activity
Unemployment rate	0.182***	0.261***	0.0701***	0.370***
	(0.00817)	(0.0141)	(0.0243)	(0.0221)
Short Tenure	−3.474***	−1.739***	−2.464***	−2.421***
	(0.145)	(0.0864)	(0.154)	(0.0930)
Unemployment rate*Short Tenure	0.619***	0.436***	0.454***	0.554***
	(0.0228)	(0.0174)	(0.0265)	(0.0186)
Male	2.113***	2.076***	1.917***	1.969***
	(0.0304)	(0.0311)	(0.0368)	(0.0384)
Age	0.233***	0.239***	0.246***	0.262***
	(0.00560)	(0.00576)	(0.00693)	(0.00725)
Age sq.	−0.00413***	−0.00419***	−0.00422***	−0.00442***
	(0.0000616)	(0.0000633)	(0.0000756)	(0.0000792)
Self-employed	−0.655***	−0.623***	−0.566***	−0.544***
	(0.0316)	(0.0322)	(0.0384)	(0.0400)
Temporary Employment	9.206***	9.238***	9.159***	9.300***
	(0.0791)	(0.0810)	(0.100)	(0.104)
Part-time Employment	1.366***	1.374***	1.534***	1.484***
	(0.0627)	(0.0637)	(0.0732)	(0.0767)
Tenure	−0.0350***	−0.0353***	−0.0333***	−0.0349***
	(0.000283)	(0.000290)	(0.000341)	(0.000358)
Tenure sq.	0.0573***	0.0579***	0.0541***	0.0571***
	(0.000558)	(0.000572)	(0.000664)	(0.000706)
Work hours — 16–30 h	−0.0621	−0.0610	−0.121*	−0.0413
	(0.0560)	(0.0574)	(0.0699)	(0.0724)
Work hours — 31–45 h	−0.621***	−0.593***	−0.675***	−0.590***
	(0.0787)	(0.0804)	(0.0952)	(0.0992)
Work hours — above 45 h	−0.843***	−0.826***	−0.811***	−0.804***
	(0.0820)	(0.0837)	(0.0994)	(0.104)
Year	0.0491***			
	(0.00175)			
Year FE	No	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
N	5 436 546	5 183 370	3 591 072	3303844

Notes: The coefficients and standard errors are multiplied by 100. The dependent variable is a binary variable indicating if a respondent is looking for a job. Column (1) depicts the results including a linear time trend and a set of binary variables indicating the quarter. Column (2) and column (3) use the sectoral and regional unemployment rate as the main independent variable, respectively. Column (4) uses the occupational unemployment rate as the main independent variable. For specifications (2)-(4), year fixed effects instead of a linear time trend are included. All columns include an interaction between the unemployment rate and short tenure, where short tenure is measured as a binary variable taking a value of 1 if the tenure months are less than or equal to 12. Person weights are used in all regressions. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels. Robust standard errors are reported in parentheses.

general, and also highly procyclical, indicating that the returns to OJS in terms of transition probabilities are procyclical. Notably, however, countercyclical OJS may still have an impact on job-to-job transitions, making them less procyclical than they would be if OJS was also procyclical. One way to see this impact is by noting (see Elsby et al., 2015 and Appendix A.3) that the job finding probabilities as measured by unemployment-to-employment transitions are even more procyclical than job-to-job transitions, which suggests that the countercyclical OJS does play a role in mitigating the drop in the probability that workers find another job during a recession. However, this mitigating impact does not explain why OJS is countercyclical since the transition probabilities are nevertheless highly procyclical.

The role that wages play in the decision to search is more nuanced. In Burdett and Mortensen (1998), workers make job-to-job transitions only if the offered wage is higher than the wage earned at their present employer, and the returns to job-to-job transition are directly tied to wage gains. However, in Postel-Vinay and Robin (2002), movers may accept lower wages when an outside offer comes from a more productive firm as they count on future wage increases as a result of outside offers received at the new employer. To take into account both of these settings, Fig. 9 uses 5Q data and shows both the difference in the log wage of movers[15] doing OJS versus not doing OJS[16] (Fig. 9(a)) and the proportion of job movers who do OJS that take a wage cut when moving versus those that take a wage cut that do not do OJS (Fig. 9(b)).The wage gains in Fig. 9(a) show a sharp drop during the great recession for workers doing OJS, inconsistent with the sharp increase in OJS in that period. There is also little systematic difference in the wage gains for workers doing OJS versus those that do not search, suggesting that OJS does not play a significant role in the magnitude of wage gains of workers that switch jobs. Fig. 9(b) shows that the proportion of movers taking pay cuts over time fluctuates slightly more for workers doing OJS relative to those that do not search, but neither appear to show a cyclical pattern. As a result, there is little in this pattern that explains countercyclical OJS.

[15] We define mover as a binary variable that takes a value of 1 if for any respondent, their reported month with the current employer is reset between quarter 1 and quarter 5; otherwise, the variable takes a value of 0 for stayers when each successive quarter has an additional 3 months added to the preceding quarter's reported months with the current employer.

[16] Since the 5Q data gives us OJS for each quarter, for a mover, we consider the OJS to be 1 if the respondent engaged in search in any quarter prior to them moving; otherwise, the OJS for the mover is 0.

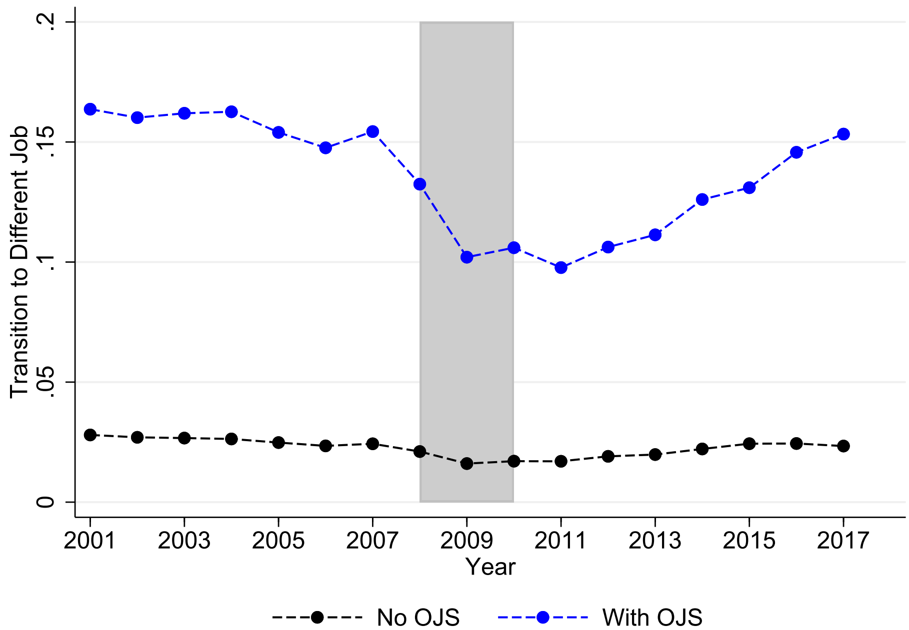
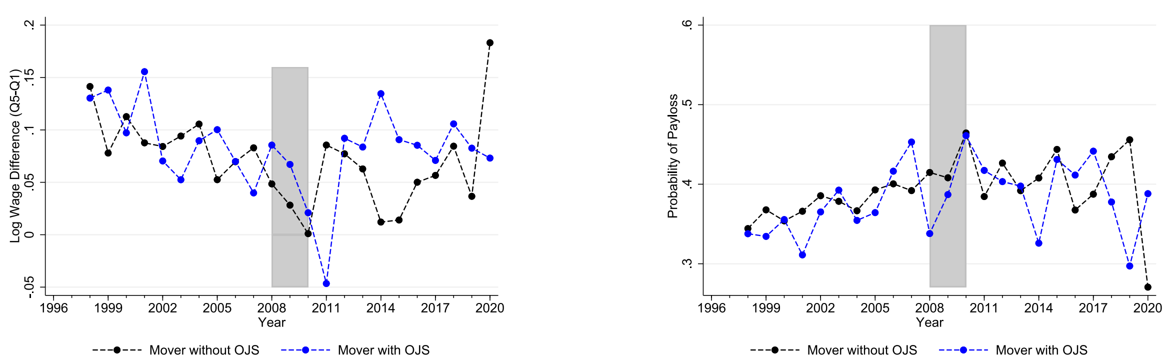


Fig. 8. Job-to-Job Transitions (2Q).
Notes: Fig. 8 presents job-to-job transitions using the 2Q data for workers who do OJS [blue] and who do not do OJS [black]. The transition probabilities, for each year, are estimated using a multinomial logit with four possible outcomes in quarter 2 (employed at the same job, employed at a different job, unemployed or not in the labor force) for a worker who is employed in quarter 1. We include in the regression the worker's search behavior as a dummy that takes a value of 1 if the worker does OJS, as well as additional controls for the worker's education dummies, age, and age squared. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



(a) Log Wage Difference (b) Probability of Payloss

Fig. 9. Transition and Wage Gains (5Q) of Movers by date and year 5.
Notes: Fig. 9(a) presents wage gains for a mover using the 5Q data, where wage gain is the difference in wages reported in Q5 and in Q1. Fig. 9(b) depicts the associated probability of wage loss using the 5Q data, where the wage loss is measured as the negative wage gain between Q5 and Q1's reported wages. All wages are real and hourly and are depicted for movers participating in OJS [blue] and not participating in OJS [black]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The conventional view of OJS, for instance, that in Pissarides (1994, 2000), implies that the reduction in the probability of finding a new match discourages workers from engaging in costly search. However, Shimer (2004) suggests that the reduction in the likelihood of finding a match may encourage workers to search more intensely as it becomes harder to find a match in a recession, which implies countercyclical OJS. Consistent with this idea that lower transition probabilities encourage a more intensive search, Table 1 shows that the number of search methods employed is countercyclical.

While the response to lower transition probabilities depends on the behavioral response of workers discussed above, the incentive effect of lower wage gains appears unambiguous. However, the importance of lower wage gains also depends on how much workers care about the pecuniary benefits of jobs. Table 2 shows workers search more during downturns for both pecuniary and non-pecuniary reasons. However, the decomposition in Fig. 7(b) also shows that non-pecuniary-motivated search contributes substantially more to the cyclicality of job-ladder-motivated search than does pecuniary-motivated search. This result provides a rationale as to why the drop in wage growth shown in Fig. 9(a) may not reduce search activity as one might anticipate. If searchers are looking for a new job for reasons other than pay and are therefore less concerned with wage gains (e.g., Hwang et al., 1998; Nosal and Rupert, 2007; Sullivan and To, 2014; Hall and Mueller, 2018; Sorkin, 2018), then a fall in wages when moving to a new job may be less of a search deterrent.

Finally, the prior literature has shown that match quality deteriorates in a downturn, especially for new matches. Looking at the OJS activity of new hires (Table 3), we find that new hires search less than other workers when the labor market is tight but search substantially more than other workers when the labor market is slack. This result suggests that workers that are newly matched are less likely to search when labor market conditions are favorable for them as they have recently found new employment. However, as matches deteriorate in a downturn, they search more than other workers because the matches they have recently made are of particularly low quality.

The patterns in Fig. 6(b) are consistent with responses by hires matched during the recession to deteriorating match quality during the recession (yellow line). However, we also see a lagged and less pronounced response from workers who were likely matched before the recession (green line). This finding may be due to workers being forced to search longer as the job ladder becomes harder to climb during a recession, which would be consistent with an increase in search duration leading to an accumulation of search activity that clears well into the recovery. Therefore, on one hand, the increase in search behavior at the start of the great recession is driven by short-tenure workers who are more likely to have been matched during the recession, consistent with a deterioration in the quality of new matches, which has an immediate impact on search behavior by new hires. On the other hand, there is a lagged response for longer-tenure workers, who are matched before the recession, which is consistent with a cumulative effect of increased search duration as the job ladder becomes harder to climb in a downturn.

In summary, we find evidence for three reasons why, despite the lower returns to search in downturns, OJS is countercyclical. First, the increase in the difficulty of finding a new match in a downturn may increase the intensity of search. Second, as workers search primarily for better jobs for non-pecuniary reasons, the reduction in the opportunity for wage growth during a recession does not reduce the incentive to search as much as would be anticipated. Third, there is evidence that the reduction in match quality during a recession increases search activity, especially for new hires.

6. Conclusion

On-the-job search is increasingly recognized as an important potential driver of labor market dynamics over the business cycle, yet there is limited empirical research on its cyclical properties. Using the UK Labor Force Survey, we find robust empirical evidence that OJS is countercyclical. We also find that the magnitude of the cyclical fluctuations is a potentially important driver of labor market dynamics, explaining a substantial part of the shift in the UK Beveridge curve related to the great recession. Moreover, using the EU Labor Force survey, we find a similar pattern across 31 European countries, establishing the countercyclicality of OJS as a stylized fact of European labor markets.

The finding that OJS is countercyclical is surprising when viewed through the lens of conventional OJS models because, as we confirm, the expected benefits of OJS are procyclical. Moreover, while a precautionary motive for OJS may be countercyclical, we find that this is not sufficient to explain the cyclical properties of OJS, which are driven by countercyclical searches for better jobs rather than the fear of losing the current job.

However, the conventional view of OJS misses some important potential features of search behavior, which have been identified in the prior literature. First, the response to lower job-to-job transition probabilities during a downturn can depend on behavioral responses, such as an increase in search effort. Second, lower wage gains from a successful search during a recession may not deter searchers who are primarily concerned with the non-pecuniary benefits of their jobs. Third, a deterioration in average match quality in a slack labor market may induce increased search activity, especially by new hires who are matched during the recession. We find evidence that all three of these factors may contribute to the observed countercyclical pattern of OJS and thereby provide an impetus for future theoretical and empirical work on OJS to take each of these mechanisms into consideration.

Table A.1
Reasons why workers search on the job.

Reasons	Share of on-the-job searchers stating a reason
Precautionary Search	
Present job may come to an end	0.13
Better Search	
Better (Pecuniary)	
Pay unsatisfactory in present job	0.24
Better (Non-pecuniary)	
Present job is to fill in time before finding another job	0.10
Respondent wants to work longer hours than in present job	0.09
Additional Job	0.08
Journey to work unsatisfactory in present job	0.06
Respondent wants to work shorter hours than in present job	0.05
Respondent wants to change sector of occupation	0.07
Other aspects of present job unsatisfactory	0.28
Other Search	
Other reasons	0.20

Notes: The sample is restricted to respondents who search for a job. Data from the UK-LFS are depicted.

Data availability

The authors do not have permission to share data.

Appendix

A.1. Reasons for search

A.2. Results for EU

We use data from 31 countries[17] to test whether our findings concerning the cyclical properties of OJS behavior can be generalized beyond the UK. The EU-LFS data are from a quarterly and annual representative survey among households covering members above the age of 15.[18] Job search behavior in the EU-LFS is measured in the same way as in the UK-LFS.

We estimate a similar set of regressions as presented in Section 4.1. As the dependent variable, we use either a binary variable indicating whether an employed worker is searching on the job or a variable indicating the number of methods used to search on the job. We include gender, age, and a set of indicator variables for the country of residence, as well as a variable indicating if the respondent is temporarily employed, part-time employed, self-employed, the number of years the respondent has been working for the current employer (tenure), and a set of indicator variables for the occupation. We estimate four different versions of this model. First, we include only the countrywide quarterly unemployment rate, year fixed effects, and the set of binary variables indicating the quarter and country of residence. Second, we additionally include the control variables. In the third specification, we restrict the sample to the years 1999–2019. In the first three specifications, the key explanatory variable of interest is the quarterly unemployment rate in the country of residence of the respondent. In the fourth specification, the key independent variable is the yearly

[17] Table A.2 shows the countries and years included in the sample.
[18] For a detailed description of the data, we refer the reader to https://ec.europa.eu/eurostat/statistics-explained/index.php?title=EU_labour_force_survey.

Table A.2
Countries and time periods in the EU-LFS sample.

Country	Countrywide quarterly unemployment rate	Regional yearly unemployment rate
Austria	1995–2019	1999–2019
Belgium	1992–2019	1999–2019
Bulgaria	2001–2019	2003–2019
Switzerland	2010–2019	2001–2019
Cyprus	1999–2019	2000–2019
Czech Republic	1997–2019	1999–2019
Germany	1992–2019	2002–2019
Denmark	1992–2019	2007–2019
Estonia	1997–2019	No observations
Spain	1992–2019	1999–2019
Finland	1995–2019	1999–2019
France	2003–2019	1999–2019
Greece	1992–2019	1999–2019
Croatia	2002–2019	2007–2019
Hungary	1996–2019	1999–2019
Ireland	1992–2019	1999–2019
Iceland	2003–2019	1999–2019
Italy	1992–2019	1999–2019
Lithuania	1999–2019	1999–2019
Luxembourg	1992–2019	1999–2019
Latvia	1998–2019	1999–2019
Malta	2009–2019	2009–2019
Netherlands	1992–2019	No observations
Norway	1996–2019	1999–2019
Poland	1997–2019	1999–2019
Portugal	1993–2019	1999–2019
Romania	1997–2019	1999–2019
Sweden	1995–2019	1999–2019
Slovenia	1996–2019	2001–2019
Slovakia	1997–2019	1998–2019
United Kingdom	1992–2019	1999–2019

Notes: The table shows the countries and years included in sample for the regressions depicted in Table A.3 and A.4.

unemployment rate in the region of residence of the respondent. In the last specification, we also include country-year fixed effects and a set of binary variables indicating the region of residence.

Table A.3 presents the regression results for the relationship between the unemployment rate and the respondents' OJS activity. The coefficient of the unemployment rate is positive, statistically significant and of similar size as that in Table 1. Table A.4 presents the regression results for the relationship between the unemployment rate and the number of search methods used by the respondents. The coefficient of the unemployment rate is positive and statistically significant but smaller than that in Table 1. These findings suggest that, on average, the cyclical properties of OJS behavior observed in the UK, i.e., that workers are more likely to search on the job when the labor market is slack, can be generalized to a large set of countries.

A.3. Transitions and the UK beveridge curve

Elsby et al. (2015) use job-to-job ($\pi_{JJ'}$) and unemployment-to-employment (π_{UE}) transitions to construct an OJS series. In particular, assuming employed and unemployed individuals search in the same market, we obtain $\pi_{UE} = f(\sigma\theta)$ and $\pi_{JJ'} = \frac{sf(\sigma\theta)}{1-u}$, which can be used to derive search s. Using our UK-LSF data to estimate the job-to-job and unemployment-to-employment transitions for the UK, we construct such a series of search for the UK and present the resulting counterfactual Beveridge curve (gray dots) along with the counterfactual using our data (white dots) and the realized Beveridge curve (black dots) in Fig. A.1. As with the direct measure of OJS activity, the indirect measure using the transitions is countercyclical so the counterfactual Beveridge curve is to the left of the actual Beveridge curve during and after the recession. This reflects that the unemployment-to-employment transitions are even more procyclical than the job-to-job transitions, indicating that countercyclical OJS does go some way to offsetting the fall in the job finding rates of workers in the recession.

Table A.3
OJS activity EU-LFS.

Sample Period	1992–2019		1999–2019	
	(1)	(2)	(3)	(4)
Unemployment rate	0.261*** (0.001)	0.263*** (0.001)	0.288*** (0.001)	0.116*** (0.003)
Male		1.051*** (0.008)	1.058*** (0.009)	1.068*** (0.009)
Age		0.373*** (0.002)	0.384*** (0.002)	0.362*** (0.002)
Age sq.		−0.005*** (0.000)	−0.005*** (0.000)	−0.005*** (0.000)
Self-employed		−0.566*** (0.010)	−0.524*** (0.011)	−0.485*** (0.011)
Temporary employment		5.950*** (0.018)	5.814*** (0.019)	6.038*** (0.020)
Part-time employment		4.125*** (0.020)	4.060*** (0.021)	4.362*** (0.021)
Tenure		−0.031*** (0.000)	−0.031*** (0.000)	−0.031*** (0.000)
Tenure sq.		0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Work hours 20–34 h		−2.499*** (0.021)	−2.536*** (0.022)	−2.606*** (0.023)
Work hours 35–45 h		−2.766*** (0.022)	−2.836*** (0.023)	−2.838*** (0.024)
Work hours above 45 h		−2.203*** (0.023)	−2.296*** (0.024)	−2.362*** (0.025)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Country-Year FE	No	No	No	Yes
Quarter FE	Yes	Yes	Yes	Yes
Region FE	No	No	No	Yes
Occupation FE	No	Yes	Yes	Yes
Observations	61,331,814	59,248,290	54,072,422	48,523,449

Notes: The coefficients and standard errors are multiplied by 100. The dependent variable is a binary variable indicating if a respondent is looking for a job. Column (1) depicts the results including a linear time trend and a set of binary variables indicating the quarter. Column (2) depicts the results additionally including the full set of control variables. Column (3) restricts the sample to the years 1999–2019. Column (4) uses the regional yearly unemployment rate as the main independent variable. Person weights are used in all regressions. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels. Robust standard errors are reported in parentheses.

Table A.4
OJS intensity EU-LFS.

Sample Period	1992–2019		1999–2019	
	(1)	(2)	(3)	(4)
Unemployment rate	0.799*** (0.054)	0.991*** (0.053)	0.678*** (0.055)	
Male		6.713*** (0.315)	6.918*** (0.325)	6.856*** (0.325)
Age		1.318*** (0.084)	1.332*** (0.087)	0.720*** (0.088)
Age sq.		−0.023*** (0.001)	−0.023*** (0.001)	−0.016*** (0.001)
Self-employed		6.254*** (0.548)	6.384*** (0.569)	9.088*** (0.565)
Temporary employment		30.65*** (0.373)	31.35*** (0.386)	30.43*** (0.389)
Part-time employment		22.02*** (0.593)	22.96*** (0.619)	16.52*** (0.591)
Tenure		−0.469*** (0.005)	−0.481*** (0.005)	−0.461*** (0.005)
Tenure sq.		0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Work hours 20–34 h.		−15.72*** (0.471)	−16.10*** (0.482)	−15.84*** (0.491)
Work hours 35–45 h.		−8.973*** (0.672)	−8.811*** (0.697)	−14.52*** (0.675)
Work hours above 45 h.		−7.508*** (0.729)	−6.467*** (0.757)	−12.78*** (0.749)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Country-Year FE	No	No	No	Yes
Quarter FE	Yes	Yes	Yes	Yes
Region FE	No	No	No	Yes
Occupation FE	No	Yes	Yes	Yes
Observations	2,419,437	2,331,398	2,218,451	1,955,079

Notes: The coefficients and standard errors are multiplied by 100. The dependent variable indicates the number of search methods used. The sample is restricted to workers who search on the job. Column (1) depicts the results including a linear time trend and a set of binary variables indicating the quarter. Column (2) depicts the results additionally including the full set of control variables. Column (3) restricts the sample to the years 1999–2019. Column (4) uses the regional yearly unemployment rate as the main independent variable. Person weights are used in all regressions. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels. Robust standard errors are reported in parentheses.

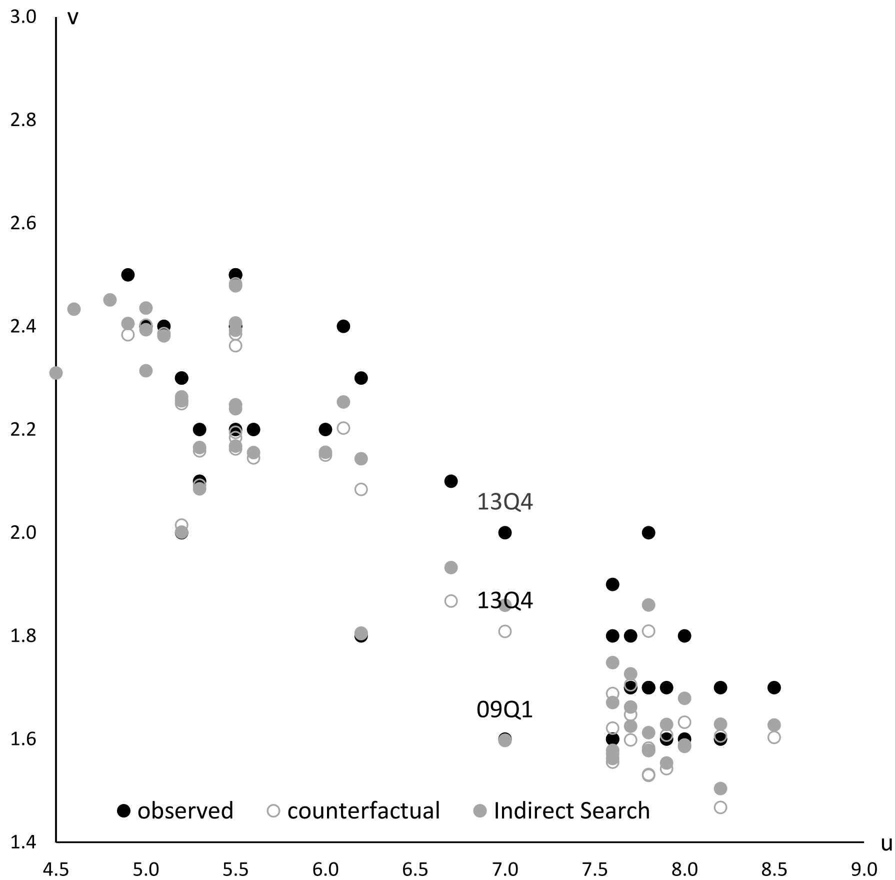


Fig. A.1. OJS and the Beveridge curve for the UK.
Notes: The realized and counterfactual Beveridge curves from Section 4.2 are depicted along with the counterfactual curve using an indirect measure of OJS derived from the transition probabilities.

Again for the first quarter of 2009 and the third quarter of 2013, the vertical shift in the realized Beveridge curve is 0.4 percentage points, while the shift in the counterfactual curve when we use our measure of OJS is 0.22 percentage points. When using the indirect measure, the shift is slightly more pronounced when OJS is held constant (0.26 percentage points). The indirect measure therefore suggests that slightly over a third of the shift in the UK Beveridge curve is due to countercyclical OJS.

A.4. Robustness

In this section, we provide robustness analyses for Table 1, where we presented our results using the countrywide unemployment rate. In Table A.5, we instead use the sectoral, regional, and occupational unemployment rates. For each of the specifications, year fixed effects instead of a linear time trend are included.[19]

The dependent variable for columns (1)–(3) is OJS activity, whereas the dependent variable in columns (4)–(6) is search intensity. In columns (1) and (4), the key independent variable is the quarterly unemployment rate of the sector the respondent works in. For the second specification, we present our results in columns (2) and (5), where the key independent variable is the quarterly unemployment rate in the region of residence of the respondent. For the last specification, in columns (3) and (6), the key independent variable is the quarterly unemployment rate in the occupation of the respondent.[20] We use person weights in our regressions.[21]

The coefficients of the unemployment rate are generally positive and statistically significant at the 1% level, but the estimated effect of the regional unemployment rate on search intensity in column (5) yields positive but statistically non-significant coefficients. The results show that except for regional unemployment, the positive relationships we estimate here, relative to what we presented in Table 1, are greater in sectors/occupations in which the unemployment rate is higher.

In the next exercise in Table A.6, we use the logit specification instead of the ordinary linear specification that we employed in Table 1 to model the binary variable of search activity. We estimate the relationship for all the employment rates we use for the last robustness exercise. We show that regardless of the employment rate used, the estimate of this variable remains positive and significant at the 1% level. Our results are robust to this alternative specification.

In the next exercise, we employ the Heckman selection model to account for the fact that the search intensity analysis in Table 1 is restricted to the sample of on-the-job searchers, resulting in incidental truncation. To account for this issue, we add an explicit selection equation to our population model of interest (that is, all employed workers). The selection estimation uses a probit model and generates

[19] Using year-quarter fixed effects yields similar results.

[20] Data on the sectoral quarterly unemployment are available starting in 1995, data on regional quarterly unemployment are available starting in 2001, and data on occupational quarterly unemployment are available starting in 2001.

[21] Unweighted regressions yield similar results.

Table A.5
OJS and alternative Unemployment rates: Robustness Table 1.

	(1) OJS Activity	(2)	(3)	(4) OJS Intensity	(5)	(6)
	1997–2019	2001–2019	2001–2019	1997–2019	2001–2019	2001–2019
Unemployment rate	0.340***	0.148***	0.473***	4.795***	0.283	2.263***
	(0.014)	(0.024)	(0.022)	(0.523)	(0.732)	(0.575)
Male	2.088***	1.926***	2.002***	13.05***	13.34***	13.97***
	(0.031)	(0.037)	(0.038)	(0.834)	(0.950)	(0.990)
Age	0.227***	0.241***	0.242***	−0.568***	−0.372	−0.529**
	(0.006)	(0.007)	(0.007)	(0.209)	(0.239)	(0.248)
Age sq.	−0.00408***	−0.00418***	−0.00425***	0.00112	−0.000290	0.000707
	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)
Self-employed	−0.660***	−0.574***	−0.560***	−35.42***	−32.88***	−31.99***
	(0.032)	(0.038)	(0.040)	(1.688)	(1.893)	(1.979)
Temporary Employment	9.276***	9.250***	9.418***	50.85***	50.31***	50.86***
	(0.081)	(0.100)	(0.104)	(1.168)	(1.360)	(1.401)
Part-time Employment	1.413***	1.554***	1.544***	8.870***	9.842***	9.243***
	(0.063)	(0.073)	(0.076)	(1.738)	(1.935)	(2.017)
Tenure	−0.0351***	−0.0328***	−0.0337***	−0.543***	−0.512***	−0.531***
	(0.000)	(0.000)	(0.000)	(0.015)	(0.017)	(0.018)
Tenure sq.	0.0577***	0.0534***	0.0553***	0.987***	0.900***	0.956***
	(0.001)	(0.001)	(0.001)	(0.049)	(0.054)	(0.058)
Work hours — 16–30 h.	−0.0956*	−0.133*	−0.121*	−17.28***	−19.78***	−18.32***
	(0.057)	(0.070)	(0.072)	(1.434)	(1.639)	(1.682)
Work hours — 31–45 h.	−0.628***	−0.692***	−0.683***	−22.16***	−24.42***	−24.13***
	(0.080)	(0.095)	(0.099)	(2.131)	(2.405)	(2.488)
Work hours — above 45 h.	−0.851***	−0.818***	−0.871***	−28.40***	−30.53***	−30.29***
	(0.083)	(0.099)	(0.103)	(2.317)	(2.629)	(2.722)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5 224 743	3 622 706	3 332 496	285 612	215 999	200 159

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Notes: The coefficients and standard errors are multiplied by 100. The dependent variable is the search activity in columns (1)–(3) and the number of search methods used in columns (4)–(6). The sample is restricted to workers who search on the job. All specifications include the full set of control variables along with the time, sector, region, and occupation fixed effects. Columns (1) and (4) use the sectoral and columns (2) and (5) use the regional unemployment rate as the main independent variable, respectively. Columns (3) and (6) use the occupational unemployment rate as the main independent variable. Person weights are used in all regressions. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels. Robust standard errors are reported in parentheses.

Table A.6
Logit Specification: Robustness Table 1.

	(1) OJS Activity	(2) OJS Activity	(3) OJS Activity	(4) OJS Activity	(5) OJS Activity
Unemployment rate	3.380***	4.940***	5.959***	2.593***	5.421***
	(0.117)	(0.135)	(0.254)	(0.420)	(0.331)
Male		34.02***	33.49***	30.85***	31.76***
		(0.491)	(0.502)	(0.601)	(0.621)
Age		8.093***	8.104***	8.318***	8.380***
		(0.101)	(0.104)	(0.126)	(0.130)
Age sq.		−0.125***	−0.125***	−0.126***	−0.128***
		(0.001)	(0.001)	(0.002)	(0.002)
Self-employed		−19.98***	−19.99***	−18.18***	−18.02***
		(0.746)	(0.762)	(0.910)	(0.942)
Temporary Employment		85.46***	85.17***	85.88***	86.67***
		(0.618)	(0.636)	(0.790)	(0.813)
Part-time Employment		21.59***	22.01***	24.42***	23.90***
		(1.030)	(1.049)	(1.215)	(1.262)
Tenure		−0.635***	−0.623***	−0.587***	−0.601***
		(0.007)	(0.007)	(0.008)	(0.009)
Tenure sq.		0.546***	0.524***	0.474***	0.500***
		(0.022)	(0.023)	(0.026)	(0.027)
Work hours — 16–30 h.		−1.167	−1.278*	−1.851**	−1.805*
		(0.741)	(0.760)	(0.920)	(0.946)

(*continued on next page*)

the inverse Mills ratio, which is then included as an additional variable in the population model. As it is critical for this specification that the vector of independent variables in the population model is a strict subset of the vector of independent variables in the selection equation, we choose the simplest subset by including the year and unemployment rate for this specification. In column (1), we use the country-wide unemployment rate, whereas for columns (2), (3) and (4), we use sectoral, regional, and occupational unemployment rates, respectively.

The results show that there is indeed a selection bias, and even after accounting for the inverse Mills ratio ($lambda$), the estimated

Table A.6 (*continued*).

	(1) OJS Activity	(2) OJS Activity	(3) OJS Activity	(4) OJS Activity	(5) OJS Activity
Work hours — 31–45 h.		−9.881***	−9.521***	−10.52***	−10.52***
		(1.199)	(1.224)	(1.447)	(1.498)
Work hours — above 45 h.		−14.28***	−14.13***	−13.55***	−14.78***
		(1.293)	(1.322)	(1.576)	(1.631)
Year	0.417***	0.730***			
	(0.028)	(0.029)			
Year FE	No	No	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Sector FE	No	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	Yes	Yes	Yes
N	6 132 313	5 479 673	5 224 743	3 622 706	3332496

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Notes: The coefficients and standard errors are multiplied by 100 and obtained using a logit specification. The dependent variable is a binary variable indicating if a respondent is looking for a job. Column (1) depicts the results including a linear time trend and a set of binary variables indicating the quarter. Column (2) depicts the results additionally including the full set of control variables. Columns (3) and (4) use the sectoral and regional unemployment rate as the main independent variable, respectively. Column (5) uses the occupational unemployment rate as the main independent variable. For specifications (3)-(5), year fixed effects instead of a linear time trend are included. Person weights are used in all regressions. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels. Robust standard errors are reported in parentheses.

Table A.7
Heckman Selection Specification: Robustness Table 1.

	(1) OJS Intensity	(2) OJS Intensity	(3) OJS Intensity	(4) OJS Intensity
Unemployment rate	2.193***	2.729***	2.777***	2.634***
	(0.289)	(0.320)	(0.284)	(0.345)
Year	−3.071***	−3.196***	−3.521***	−3.558***
	(0.054)	(0.055)	(0.078)	(0.092)
	OJS	OJS	OJS	OJS
Unemployment rate	2.630***	3.122***	2.138***	2.543***
	(0.077)	(0.085)	(0.076)	(0.094)
Male	15.27***	15.53***	14.35***	14.82***
	(0.228)	(0.231)	(0.263)	(0.275)
Age	3.748***	3.767***	3.875***	3.901***
	(0.051)	(0.052)	(0.059)	(0.062)
Age sq.	−0.0584***	−0.0587***	−0.0593***	−0.0601***
	(0.001)	(0.001)	(0.001)	(0.001)
Self-employed	−9.672***	−10.04***	−9.382***	−9.290***
	(0.346)	(0.350)	(0.398)	(0.416)
Temporary Employment	46.03***	46.04***	46.59***	46.96***
	(0.337)	(0.340)	(0.397)	(0.412)
Part-time Employment	9.262***	9.233***	9.766***	9.687***
	(0.467)	(0.473)	(0.527)	(0.552)
Tenure	−0.303***	−0.304***	−0.295***	−0.302***
	(0.003)	(0.003)	(0.004)	(0.004)
Tenure sq.	0.332***	0.332***	0.323***	0.337***
	(0.009)	(0.009)	(0.010)	(0.011)
Work hours — 16–30 h	−1.422***	−1.518***	−1.708***	−1.647***
	(0.373)	(0.376)	(0.432)	(0.449)
Work hours — 31–45 h	−4.169***	−4.223***	−4.743***	−4.669***
	(0.563)	(0.569)	(0.644)	(0.672)
Work hours — above 45 h	−5.654***	−5.857***	−5.805***	−6.226***
	(0.608)	(0.615)	(0.699)	(0.729)
Year	0.283***	0.318***	0.582***	0.705***
	(0.014)	(0.015)	(0.021)	(0.024)
Mills lambda	−139.0***	−139.9***	−135.8***	−137.3***
	(1.463)	(1.474)	(1.710)	(1.767)
Quarter FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes

(*continued on next page*)

effect of the unemployment rate and search methods remain positive and significant, albeit the effects are smaller than those estimated in Table 1. The main difference is that regional unemployment, which initially showed a non-significant positive effect, now has a significant positive effect.

In an additional robustness analysis in Tables A.8 and A.9, we expand the set of control variables to assess whether certain omitted variables biased our results. The coefficients estimated for these control variables show that relative to no education, the search behavior of educated respondents is higher, and respondents who have training

Table A.7 (*continued*).

	(1) OJS Intensity	(2) OJS Intensity	(3) OJS Intensity	(4) OJS Intensity
Region FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
N	4 798 406	4 694 880	3 625 228	3334466

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Notes: The coefficients and standard errors are multiplied by 100 and obtained using a Heckman-selection specification. The selection equation for whether a person engages in OJS is modeled with all the control variables used in Table 1. For the number of search methods used, we include linear time trends. The dependent variable indicates the number of search methods used. The sample is restricted to workers who search on the job. Column (1) uses economy-wide unemployment rate, where as Columns (2)–(4) use the sectoral, regional, and occupational unemployment rate, respectively as the main independent variable. Person weights are used in all regressions. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels. Robust standard errors are reported in parentheses.

Table A.8
OJS and Unemployment: Robustness Table 1.

	(1) OJS Activity (1997–2019)	(2) OJS Activity	(3) OJS Activity	(4) OJS Activity (2001–2019)	(5) OJS Activity
Unemployment rate	0.204***	0.252***	0.311***	0.218***	0.422***
	(0.007)	(0.012)	(0.023)	(0.033)	(0.029)
Male		2.153***	2.130***	2.093***	2.168***
		(0.046)	(0.047)	(0.051)	(0.053)
Age		0.115***	0.118***	0.131***	0.135***
		(0.009)	(0.010)	(0.011)	(0.011)
Age sq.		−0.00293***	−0.00297***	−0.00311***	−0.00321***
		(0.000)	(0.000)	(0.000)	(0.000)
Self-employed		−0.0429	−0.214	−0.0299	−0.359*
		(0.152)	(0.174)	(0.184)	(0.191)
Temporary Employment		9.917***	9.878***	9.863***	10.02***
		(0.122)	(0.125)	(0.139)	(0.145)
Part-time Employment		1.467***	1.460***	1.494***	1.495***
		(0.096)	(0.097)	(0.104)	(0.109)
Tenure		−0.0326***	−0.0323***	−0.0314***	−0.0320***
		(0.000)	(0.000)	(0.000)	(0.000)
Tenure sq.		0.0542***	0.0536***	0.0520***	0.0535***
		(0.001)	(0.001)	(0.001)	(0.001)
Work hours — 16–30 h		−0.0870	−0.0970	−0.136	−0.106
		(0.086)	(0.088)	(0.098)	(0.101)
Work hours — 31–45 h		−0.392***	−0.415***	−0.559***	−0.507***
		(0.122)	(0.125)	(0.136)	(0.141)
Work hours — above 45 h		−0.544***	−0.567***	−0.646***	−0.664***
		(0.129)	(0.131)	(0.144)	(0.149)
Other qualifications		1.585***	1.557***	1.535***	1.540***
		(0.064)	(0.067)	(0.076)	(0.078)
Edu — gcse a-c or equiv		1.931***	1.881***	1.848***	1.845***
		(0.059)	(0.061)	(0.069)	(0.071)
Edu gce — a level or equiv		2.213***	2.164***	2.111***	2.092***
		(0.060)	(0.062)	(0.070)	(0.072)
Edu — higher education		3.471***	3.429***	3.347***	3.313***
		(0.078)	(0.080)	(0.088)	(0.091)
Edu — degree or equivalent		4.745***	4.672***	4.548***	4.667***
		(0.077)	(0.079)	(0.086)	(0.090)
Mortgage		−0.620***	−0.594***	−0.542***	−0.570***
		(0.037)	(0.038)	(0.041)	(0.043)
Firm specific training		−0.912***	−0.862***	−0.858***	−0.906***
		(0.037)	(0.040)	(0.044)	(0.045)
Firm size — 11–19 wrks.		0.123*	0.114	0.119	0.151*
		(0.070)	(0.072)	(0.078)	(0.081)
Firm size — 20–24 wrks.		−0.102	−0.113	−0.145	−0.163
		(0.091)	(0.092)	(0.100)	(0.104)
Firm size — Under 25 wrks.		0.0194	−0.00281	−0.0238	−0.0235
		(0.061)	(0.063)	(0.068)	(0.070)
Firm size — 25–49 wrks.		−0.0764	−0.0859	−0.0848	−0.0816
		(0.057)	(0.057)	(0.060)	(0.062)
Firm size — Over 24 wrks.		−0.182***	−0.172***	−0.229***	−0.261***
		(0.060)	(0.064)	(0.079)	(0.082)
Firm size — Over 50 wrks.		−0.563***	−0.584***	−0.585***	−0.645***
		(0.062)	(0.062)	(0.065)	(0.067)

(*continued on next page*)

Table A.8 (*continued*).

	(1) OJS Activity (1997–2019)	(2) OJS Activity	(3) OJS Activity	(4) OJS Activity (2001–2019)	(5) OJS Activity
Year	0.0251***	−0.000310			
	(0.002)	(0.003)			
Year FE	No	No	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Sector FE	No	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	Yes	Yes	Yes
N	6 132 313	2 419 752	2 313 924	1 928 109	1766685

Note: The coefficients and standard errors are multiplied by 100. The dependent variable is a binary variable indicating if a respondent is looking for a job. Column (1) depicts the results including a linear time trend and a set of binary variables indicating the quarter. Column (2) depicts the results additionally including the full set of control variables. Column (3) and (4) uses the sectoral and regional unemployment rate as the main independent variable, respectively. Column (5) uses the occupational unemployment rate as the main independent variable. For the specifications (3)-(5) year fixed effects instead of a linear time trend are included. Person weights are used in all regressions. ***, **, * denote statistical significance at the 1%, 5%, and 10% level. Robust standard errors are reported in parentheses.

Table A.9
OJS Intensity and Unemployment: Robustness Table 1.

	(1) OJS Intensity (1997–2019)	(2) OJS Intensity	(3) OJS Intensity	(4) OJS Intensity (2001–2019)	(5) OJS Intensity
Unemployment rate	6.724***	5.059***	4.038***	1.768*	2.098***
	(0.295)	(0.392)	(0.743)	(0.965)	(0.738)
Male		11.16***	11.13***	11.99***	12.53***
		(1.195)	(1.195)	(1.254)	(1.310)
Age		−1.291***	−1.287***	−1.141***	−1.302***
		(0.304)	(0.304)	(0.320)	(0.334)
Age sq.		0.0120***	0.0120***	0.0107***	0.0119***
		(0.004)	(0.004)	(0.004)	(0.004)
Self-employed					
Temporary Employment		50.36***	50.48***	50.67***	50.73***
		(1.725)	(1.724)	(1.825)	(1.882)
Part-time Employment		8.897***	8.855***	9.785***	8.818***
		(2.471)	(2.472)	(2.568)	(2.705)
Tenure		−0.483***	−0.484***	−0.468***	−0.483***
		(0.020)	(0.020)	(0.021)	(0.022)
Tenure sq.		0.949***	0.949***	0.899***	0.944***
		(0.063)	(0.063)	(0.066)	(0.070)
Work hours — 16–30 h		−18.86***	−18.93***	−19.74***	−16.97***
		(2.072)	(2.070)	(2.176)	(2.212)
Work hours — 31–45 h		−22.29***	−22.34***	−23.09***	−21.69***
		(3.077)	(3.076)	(3.215)	(3.329)
Work hours — above 45 h		−27.68***	−27.64***	−27.20***	−25.36***
		(3.376)	(3.376)	(3.538)	(3.675)
Other qualifications		27.33***	27.33***	28.04***	28.60***
		(2.425)	(2.424)	(2.616)	(2.689)
Edu — gcse a-c or equiv		39.61***	39.77***	41.74***	42.29***
		(2.225)	(2.225)	(2.397)	(2.471)
Edu gce — a level or equiv		49.24***	49.32***	51.46***	51.36***
		(2.264)	(2.265)	(2.438)	(2.517)
Edu — higher education		55.79***	55.84***	57.56***	58.70***
		(2.734)	(2.733)	(2.918)	(3.024)
Edu — degree or equivalent		63.97***	63.90***	65.15***	65.80***
		(2.459)	(2.458)	(2.622)	(2.700)
Mortgage		0.810	0.798	0.974	0.885
		(1.087)	(1.087)	(1.143)	(1.196)
Firm specific training		−8.984***	−9.037***	−8.790***	−9.858***
		(1.202)	(1.230)	(1.309)	(1.339)
Firm size — 11–19 wrks.		3.681*	3.609*	3.498*	3.664*
		(2.009)	(2.007)	(2.113)	(2.141)
Firm size — 20–24 wrks.		2.176	2.258	1.182	0.993
		(2.563)	(2.561)	(2.679)	(2.786)
Firm size — Under 25 wrks.		4.533**	4.440**	3.740**	4.747**
		(1.764)	(1.763)	(1.843)	(1.922)
Firm size — 25–49 wrks.		4.206***	4.221***	3.785**	4.971***
		(1.626)	(1.630)	(1.671)	(1.744)
Firm size — Over 24 wrks.		5.816***	5.659***	4.922**	5.043**

(*continued on next page*)

offered by their workplace search less (although the difference is not significant for search intensity). We also find that respondents who are associated with larger firms (more than 24 workers for search activity and mid-size firms of 20–24 workers for search intensity) search less

Table A.9 (*continued*).

	(1) OJS Intensity (1997–2019)	(2) OJS Intensity	(3) OJS Intensity	(4) OJS Intensity (2001–2019)	(5) OJS Intensity
		(1.969)	(2.047)	(2.367)	(2.475)
Firm size — Over 50 wrks.		0.122	0.131	−0.342	1.332
		(1.945)	(1.949)	(1.988)	(2.081)
Year	−3.277***	−3.851***			
	(0.054)	(0.100)			
Year FE	No	No	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Sector FE	No	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	Yes	Yes	Yes
N	297 445	129 458	129 458	116 196	107 186

Note: The coefficients and standard errors are multiplied by 100. The dependent variable indicates the number of search methods used. The sample is restricted to workers that search on the job. Column (1) depicts the results including a linear time trend and a set of binary variables indicating the quarter. Column (2) depicts the results additionally including the full set of control variables. Column (3) and (4) uses the sectoral and regional unemployment rate as the main independent variable, respectively. Column (5) uses the occupational unemployment rate as the main independent variable. For the specifications (3)-(5) year fixed effects instead of a linear time trend are included. Person weights are used in all regressions. Note in all specification, self-employed is dropped due to collinearity. ***, **, * denote statistical significance at the 1%, 5%, and 10% level. Robust standard errors are reported in parentheses.

Table A.10
Motivation for Search: Robustness Table 2.

	(1) OJS Activity	(2) Better	(3) Better (Pecuniary)	(4) Better (Non-pecuniary)	(5) Precautionary Search
Unemployment rate	0.252***	0.137***	0.0663***	0.174***	0.0603***
	(0.012)	(0.009)	(0.006)	(0.009)	(0.004)
Male	2.153***	1.528***	0.870***	1.229***	0.0120
	(0.046)	(0.038)	(0.023)	(0.036)	(0.014)
Age	0.115***	−0.0177**	0.0350***	−0.0103	0.0612***
	(0.009)	(0.008)	(0.005)	(0.007)	(0.003)
Age sq.	−0.00293***	−0.000897***	−0.000777***	−0.000838***	−0.000743***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Self-employed	−0.0429	0.448***	−0.00533	0.487***	−0.429***
	(0.152)	(0.126)	(0.079)	(0.118)	(0.048)
Temporary Employment	9.917***	1.681***	0.657***	3.609***	5.295***
	(0.122)	(0.083)	(0.052)	(0.087)	(0.072)
Part-time Employment	1.467***	1.096***	−0.0608	1.284***	−0.282***
	(0.096)	(0.080)	(0.049)	(0.077)	(0.028)
Tenure	−0.0326***	−0.0219***	−0.00956***	−0.0185***	−0.00276***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure sq.	0.0542***	0.0357***	0.0149***	0.0308***	0.00487***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Work hours — 16–30 h	−0.0870	0.946***	0.501***	1.066***	0.393***
	(0.086)	(0.068)	(0.035)	(0.065)	(0.020)
Work hours — 31–45 h	−0.392***	0.893***	0.598***	0.924***	0.466***
	(0.122)	(0.099)	(0.057)	(0.095)	(0.032)
Work hours — above 45 h	−0.544***	0.968***	0.518***	1.103***	0.350***
	(0.129)	(0.105)	(0.061)	(0.100)	(0.034)
Other qualifications	1.585***	1.082***	0.389***	0.958***	0.00459
	(0.064)	(0.053)	(0.035)	(0.049)	(0.019)
Edu — gcse a-c or equiv	1.931***	1.312***	0.425***	1.227***	0.0645***
	(0.059)	(0.049)	(0.032)	(0.045)	(0.018)
Edu — gce a level or equiv	2.213***	1.512***	0.480***	1.399***	0.0394**
	(0.060)	(0.050)	(0.032)	(0.046)	(0.018)
Edu — higher education	3.471***	2.478***	0.817***	2.301***	0.0921***
	(0.078)	(0.064)	(0.040)	(0.059)	(0.024)
Edu — degree or equivalent	4.745***	3.345***	0.946***	3.247***	0.193***
	(0.077)	(0.064)	(0.040)	(0.060)	(0.023)
Mortgage	−0.620***	−0.381***	−0.257***	−0.278***	−0.0115
	(0.037)	(0.030)	(0.019)	(0.029)	(0.012)
Firm specific training	−0.912***	−0.754***	−0.303***	−0.645***	−0.104***
	(0.037)	(0.030)	(0.019)	(0.028)	(0.012)
Firm size — 11–19 wrks.	0.123*	0.357***	0.106***	0.343***	−0.0314*
	(0.070)	(0.058)	(0.036)	(0.055)	(0.019)
Firm size — 20–24 wrks.	−0.102	0.203***	0.115**	0.159**	−0.104***
	(0.091)	(0.075)	(0.049)	(0.070)	(0.025)

(*continued on next page*)

Table A.10 (*continued*).

	(1) OJS Activity	(2) Better	(3) Better (Pecuniary)	(4) Better (Non-pecuniary)	(5) Precautionary Search
Firm size — Under 25 wrks.	0.0194	0.351***	0.0769**	0.326***	−0.0266
	(0.061)	(0.051)	(0.032)	(0.048)	(0.018)
Firm size — 25–49 wrks.	−0.0764	0.169***	−0.0806***	0.213***	0.0370**
	(0.057)	(0.046)	(0.029)	(0.043)	(0.018)
Firm size — Over 24 wrks.	−0.182***	0.125***	−0.131***	0.286***	−0.0178
	(0.060)	(0.048)	(0.030)	(0.045)	(0.019)
Firm size — Over 50 wrks.	−0.563***	−0.229***	−0.299***	−0.118**	−0.0379*
	(0.062)	(0.049)	(0.030)	(0.047)	(0.020)
Year	−0.000310	0.00453*	−0.0185***	0.0235***	−0.0000605
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
N	2 419 752	2 419 752	2 432 027	2 432 027	2432027

Note: The coefficients and standard errors are multiplied by 100. The dependent variable in column (1) is a binary variable indicating if a respondent is looking for a job; the dependent variable in columns (2) and (5) is a binary variable indicating if a respondent is a better job searcher or precautionary searcher. Columns (3) and (4) further disaggregate better job searchers with pecuniary and non-pecuniary motivations, respectively. The results are based on the specification that includes a linear time trend and a set of binary variables indicating the quarter and the full set of control variables. Person weights are used in all regressions. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels. Robust standard errors are reported in parentheses.

Table A.11
OJS, Short-Tenure and Unemployment: Robustness Table 3.

	(1) OJS Activity	(2) OJS Activity	(3) OJS Activity	(4) OJS Activity
Unemployment rate	0.164***	0.218***	0.148***	0.312***
	(0.0118)	(0.0227)	(0.0333)	(0.0293)
Short Tenure	−3.121***	−2.118***	−2.409***	−2.984***
	(0.220)	(0.136)	(0.224)	(0.134)
Unemployment rate*Short Tenure	0.561***	0.507***	0.451***	0.647***
	(0.0352)	(0.0277)	(0.0383)	(0.0258)
Male	2.151***	2.118***	2.082***	2.130***
	(0.0464)	(0.0473)	(0.0512)	(0.0535)
Age	0.119***	0.129***	0.134***	0.155***
	(0.00951)	(0.00975)	(0.0107)	(0.0111)
Age sq.	−0.00296***	−0.00307***	−0.00314***	−0.00340***
	(0.000106)	(0.000108)	(0.000119)	(0.000123)
Self-employed	0.158	−0.0109	0.170	−0.259
	(0.153)	(0.174)	(0.185)	(0.192)
Temporary Employment	9.816***	9.872***	9.776***	9.919***
	(0.122)	(0.125)	(0.140)	(0.145)
Part-time Employment	1.458***	1.430***	1.490***	1.447***
	(0.0960)	(0.0974)	(0.104)	(0.109)
Tenure	−0.0321***	−0.0324***	−0.0312***	−0.0327***
	(0.000471)	(0.000481)	(0.000522)	(0.000550)
Tenure sq.	0.0531***	0.0536***	0.0517***	0.0543***
	(0.000985)	(0.00100)	(0.00108)	(0.00115)
Work hours — 16–30 h	−0.0905	−0.0991	−0.148	−0.0570
	(0.0867)	(0.0887)	(0.0986)	(0.101)
Work hours — 31–45 h	−0.395***	−0.416***	−0.564***	−0.434***
	(0.123)	(0.125)	(0.136)	(0.142)
Work hours — above 45 h	−0.556***	−0.578***	−0.660***	−0.611***
	(0.129)	(0.132)	(0.144)	(0.150)
Other qualifications	1.568***	1.531***	1.519***	1.481***
	(0.0647)	(0.0669)	(0.0769)	(0.0786)
Edu — gcse a-c or equiv	1.902***	1.825***	1.823***	1.736***
	(0.0594)	(0.0612)	(0.0692)	(0.0711)
Edu — gce a level or equiv	2.189***	2.114***	2.085***	1.989***
	(0.0604)	(0.0623)	(0.0706)	(0.0724)
Edu — higher education	3.447***	3.369***	3.319***	3.180***
	(0.0779)	(0.0799)	(0.0884)	(0.0911)
Edu — degree or equivalent	4.725***	4.631***	4.525***	4.587***
	(0.0773)	(0.0790)	(0.0866)	(0.0899)

(*continued on next page*)

Table A.11 (*continued*).

	(1) OJS Activity	(2) OJS Activity	(3) OJS Activity	(4) OJS Activity
Mortgage	−0.614***	−0.598***	−0.532***	−0.589***
	(0.0373)	(0.0379)	(0.0409)	(0.0427)
Firm specific training	−0.885***	−0.854***	−0.857***	−0.927***
	(0.0369)	(0.0398)	(0.0440)	(0.0450)
Firm size — 11–19 wrks.	0.128*	0.122*	0.128	0.163**
	(0.0704)	(0.0719)	(0.0785)	(0.0813)
Firm size — 20–24 wrks.	−0.103	−0.119	−0.143	−0.159
	(0.0910)	(0.0927)	(0.101)	(0.104)
Firm size — Under 25 wrks.	0.0204	0.00119	−0.0206	−0.00787
	(0.0616)	(0.0628)	(0.0679)	(0.0707)
Firm size — 25–49 wrks.	−0.0825	−0.0856	−0.0867	−0.0546
	(0.0567)	(0.0574)	(0.0598)	(0.0624)
Firm size — Over 24 wrks.	−0.172***	−0.153**	−0.225***	−0.219***
	(0.0597)	(0.0644)	(0.0792)	(0.0822)
Firm size — Over 50 wrks.	−0.566***	−0.591***	−0.573***	−0.621***
	(0.0618)	(0.0625)	(0.0649)	(0.0677)
Year	0.00273			
	(0.00313)			
Year FE	No	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
N	2 402 780	2 297 666	1 914 055	1753888

Notes: The coefficients and standard errors are multiplied by 100. The dependent variable is a binary variable indicating if a respondent is looking for a job. Column (1) depicts the results including a linear time trend and a set of binary variables indicating the quarter. Column (2) and column (3) use the sectoral and regional unemployment rate as the main independent variable, respectively. Column (4) uses the occupational unemployment rate as the main independent variable. For specifications (2)-(4), year fixed effects instead of a linear time trend are included. All columns include an interaction between the unemployment rate and short tenure, where short tenure is measured as a binary variable taking a value of 1 if the tenure months are less than or equal to 12. Person weights are used in all regressions. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels. Robust standard errors are reported in parentheses.

relative to those associated with smaller firms (1–10 workers). The main takeaway from these robustness exercises is that the baseline results reported in Table 1 are robust to the inclusion of these additional variables, and search activity and intensity remain countercyclical.

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