The Cyclicality of On-the-Job Search[*]

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January 29, 2023

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: income effects that induce 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 that has a significant impact on the search behavior of new hires over the business cycle.

Keywords: Beveridge curve, Labor market dynamics, On-the-job search.
JEL Classification: E24, E32, J22, J64.

[*] We would like to thank Maximilian Mihm for his encouraging and insightful comments. We benefited from constructive feedback and suggestions from Christian Haefke, Etienne Wasmer, the editor, an associate editor and two anonymous referees at the European Economic Review. All results and conclusions are ours and not those of Eurostat, the European Commission, or any of the national statistical authorities whose data have been used.

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1 Introduction

It is widely recognized that 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 in order 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 an income effect, whereby workers compensate for lower transition probabilities by intensifying search and/or workers who, in a tight labor market would move into better jobs and cease search, continue searching for longer (see, e.g., Shimer, 2004 or Barlevy, 2002). 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 allows 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 decreases 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 large enough to have real macroeconomic implications. In 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, using EU labor force surveys we also 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 seems considerably underreported in the ATUS resulting in a small and possibly selected OJS sample.[1] More importantly, the richer information about search activity in the UK-LFS allows us to provide a more comprehensive picture of OJS activity than these previous studies, providing further insights into the drivers of changes in OJS over the business cycle.

Our second main 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.

We also find that not only does a worker's position in the job ladder (measured in terms of their wage residual) matter for search behavior, but also the effect of unemployment on search behavior is larger for workers who are lower down the ladder. This contributes to the overall countercyclical pattern of OJS because, as observed in Moscarini and Postel-Vinay (2018), the fall in job-to-job transitions in recessions has a especially large impact at the bottom of the job ladder.

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

[1] Mukoyama et al. (2018) also use the ATUS to study the countercyclicality of search behavior but focus mainly on the unemployed.

in a successful job-to-job transition) and wage-gains (the expected increase in the wage 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, for example, in Shimer (2004); Barlevy (2002), theoretical predictions about the anticipated response to a lower transition-probability are ambiguous because they depend on income effects. 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 and/or longer search duration. We do not observe how long individual workers search but, consistent with a cumulative impact of longer search duration, we do observe that search activity lags the unemployment rate. In addition, using information on the number of search methods employed for OJS as a proxy for search intensity, we find evidence that such income effects could be a relevant factor in the cyclicality of OJS.[2]

Second, a growing literature argues that workers often care about non-pecuniary benefits of their job (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 then depend on how much job-ladder searchers care about pecuniary versus non-pecuniay 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 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). 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 other workers. Consistent with the idea that match quality deteriorates during

[2]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.

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 role of income effects on 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 remaining 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 implication 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 A.

2 Data

The UK-LFS samples about 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 that 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 value one if a respondent reports looking for a different or additional job. To analyze job search behavior at the intensive margin, we use the number of methods used to search (Shimer, 2004).[3] 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 between the number of search methods used and the time spent on job search, implying

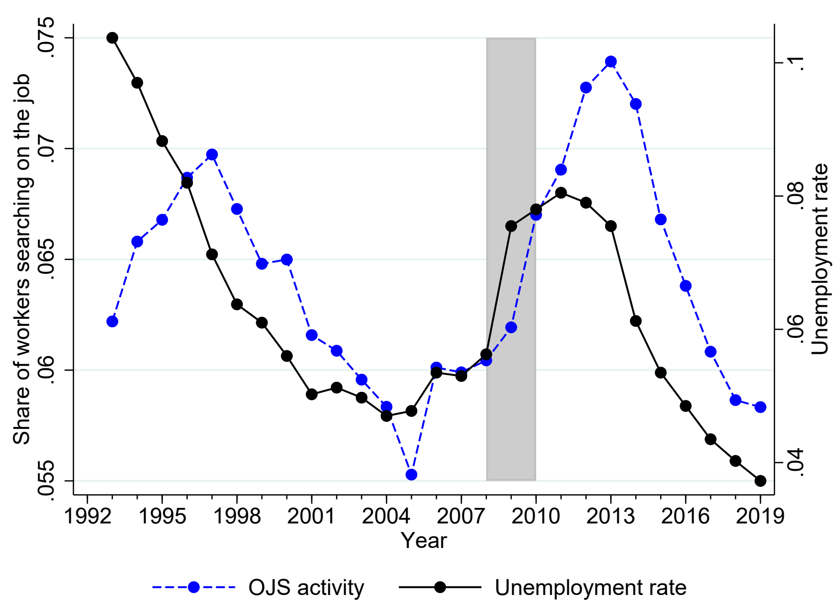
[3]Respondents can report up to 14 methods.

that the number of search methods contains valuable information on the intensity of job search.

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).[4] Workers that search on the job use on average four different methods.

Figure 1, depicts the variation in the yearly average of the unemployment rate and the share of workers reporting search activity over the sample period. The variation in the extent of job search 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.

Figure 1: Search activity and the unemployment rate for the UK



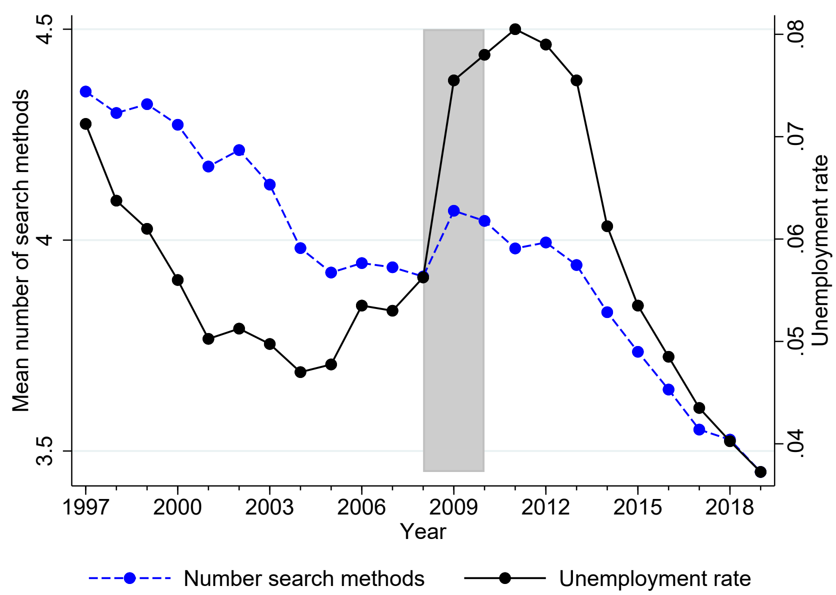
Notes: The yearly average share of employed workers searching on the job (left y-axis) and yearly average unemployment rate (right y-axis) are depicted for the years 1992-2019. The grey bar indicates the great recession. Data from the UK-LFS are depicted.

Figure 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 job search intensity decreases over the sample pe-

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

riod. Yet, during the recession search intensity increases sharply and falls again as the unemployment rate decreases. There seems to be a slight positive correlation between the unemployment rate and search intensity.

Figure 2: Search intensity and the unemployment rate for the UK



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

Concerning the reasons why workers search on the job, Table A-1 in the appendix shows all the reasons we have in the data.[5] We categorize a search motivation as *precautionary search* if the reason listed for search is that the "present job may come to an end". We categorize job-ladder motivated search as search 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 which 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 reasons 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 the tenure at the current employer which is measured

[5]Respondent can indicate up to three reasons why they search for a job.

as the number of months with the current employer; the current occupation which is a categorical variable with nine categories ranging from manager to elementary occupations; 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 hours to above 45 hours. 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, training on the job, mortgage payments, and wage residuals. 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 or not and whether there is firm-specific training in their job. The 1 quarter data only provide us with the reported wage for the respondent in quarter 1. We use this variable to construct wage residual which is a continuous variable. This residual is measured as the difference between a worker's actual wage reported for 1Q and their predicted wage based on their characteristics such as their education level, gender, age, age squared, tenure month, tenure month square, and firm size.

While the above data forms 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 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.[6] We, therefore, do not consider the number of search methods when using 2Q and 5Q. To validate that the data is comparable in terms of our OJS statistics, there are about 6.04% and 6.39% of workers in 2Q and 5Q, respectively (relative to 6.4% in 1Q data), reporting engaging in OJS in the first quarter. Despite this limitation, these longitudinal data allow us to analyze job-to-job transitions and wage dynamics where the 1Q data has its own limitations. In terms of transitions, the data allow 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.

[6] Since respondents only provide their main search method, it is not possible to construct a variable for the number of search methods they use. Consequently, is not possible to validate our measure of search intensity by checking if a higher number of search methods used leads to a higher probability of finding a new job.

3 Empirical Strategy

The previous section shows suggestive evidence that the extent of OJS activity as well as job search 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:

$$\begin{aligned} Search\ activity/intensity_{iqt} = \alpha_0 \quad &+ \quad \alpha_1 Unemployment\ rate_{qt} + \mathbf{x_{iqt}}'\phi \\ &+ \quad \alpha_2 Year_t + \gamma_q + \varepsilon_{iqt} \end{aligned} \tag{1}$$

where $Search\ activity_{iqt}$ is a dichotomous variable taking value one if individual i at quarter q in year t reports looking for a job and $Search\ intensity_{iqt}$ indicates the number of search methods used to search for a job. $\mathbf{x_{iqt}}$ 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 $\mathbf{x_{iqt}}$ includes the 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 had been working for the current employer (tenure), and a set of indicator variables for the occupation as well as sector of employment. ε_{iqt} is an error term.[7] We estimate five different versions of this model. First, we only include the unemployment rate, the linear time trend, and the set of binary variables indicating the quarter. Second, we additionally include the vector of controls $\mathbf{x_{iqt}}$. In the first two specifications the explanatory variable of key interest, $Unemployment\ rate_{qt}$, is the unemployment rate in the UK at quarter q in year t. In the third specification, the key independent variable is the quarterly unemployment rate of the sector the respondent works in.[8] In the fourth specification, the key independent variable is the quarterly unemployment rate in the region of residence of the respondent.[9] In the fifth specification, the key independent variable is the quarterly unemployment rate in the occupation of the respondent.[10] For the last three specifications, we include year fixed effects instead of a linear time trend.[11] We use person weights in our regressions.[12]

[7] Clustering standard errors at the quarter-year level yield similar results, throughout.
[8] Data on the sectoral quarterly unemployment is available starting in 1995.
[9] Data on the regional quarterly unemployment is available starting in 2001.
[10] Data on the occupational quarterly unemployment is available starting in 2001.
[11] Using year-quarter fixed effects yields similar results.
[12] Unweighted regressions yield similar results.

4 Results

In this section, we first show the regression results analyzing the cyclical properties of OJS behavior. We then assess the relevance of cyclical OJS on labor market dynamics by looking at the Beveridge curve. We then look at 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. The results of a linear probability model are depicted.[13] Column (1) depicts the results without any controls, besides the linear time trend and indicator variables for the quarter. Column (2) depicts the results including a set of controls. Columns (3), (4), and (5) use the sectoral, regional, and occupational unemployment rate instead of the countrywide unemployment rate, respectively. For the specifications (3)-(5) year fixed effects instead of a linear time trend are included.

The coefficient of the unemployment rate is positive and statistically significant, throughout. This finding is in line with the observation in Figure 1 that OJS activity and the unemployment rate are positively correlated. The results in column (2) show that this positive relationship is not driven by observable compositional shifts in the pool of employed workers. Columns (3) − (5) show that the likelihood of workers searching on the job is larger in sectors/regions/occupations in which the unemployment rate is higher. The size of the coefficient for the unemployment rate varies across the different specifications. 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 that 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 about 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.[14] This means that in times of high unemployment there are one-fourth more workers that search for a job when cyclical changes in OJS activity are considered than when OJS is assumed to be constant. In the next section, we will discuss the quantitative importance of these findings for unemployment fluctuations in more detail.

Table 2 presents the regression results on the relationship between the unemployment rate

[13] Estimating probit or logit models yields similar results.

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

Table 1: Search and Unemployment

	(1)	(2)	(3)	(4)	(5)
	1997-2019	**1997-2019**	**1997-2019**	**2001-2019**	**2001-2019**
Unemployment rate	0.204***	0.287***	0.340***	0.148***	0.473***
	(0.007)	(0.008)	(0.014)	(0.024)	(0.022)
Male		2.117***	2.088***	1.926***	2.002***
		(0.030)	(0.031)	(0.037)	(0.038)
Age		0.225***	0.227***	0.241***	0.242***
		(0.006)	(0.006)	(0.007)	(0.007)
Age sq.		-0.00407***	-0.00408***	-0.00418***	-0.00425***
		(0.000)	(0.000)	(0.000)	(0.000)
Self-employed		-0.663***	-0.660***	-0.574***	-0.560***
		(0.031)	(0.032)	(0.038)	(0.040)
Temporary Employment		9.331***	9.276***	9.250***	9.418***
		(0.079)	(0.081)	(0.100)	(0.104)
Part-time Employment		1.384***	1.413***	1.554***	1.544***
		(0.062)	(0.063)	(0.073)	(0.076)
Tenure		-0.0355***	-0.0351***	-0.0328***	-0.0337***
		(0.000)	(0.000)	(0.000)	(0.000)
Tenure sq.		0.0584***	0.0577***	0.0534***	0.0553***
		(0.001)	(0.001)	(0.001)	(0.001)
Work hours - 16-30 hrs.		-0.0925*	-0.0956*	-0.133*	-0.121*
		(0.056)	(0.057)	(0.070)	(0.072)
Work hours - 31-45 hrs.		-0.656***	-0.628***	-0.692***	-0.683***
		(0.078)	(0.080)	(0.095)	(0.099)
Work hours - above 45 hrs.		-0.870***	-0.851***	-0.818***	-0.871***
		(0.082)	(0.083)	(0.099)	(0.103)
Year	0.0251***	0.0471***			
	(0.002)	(0.002)			
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	6132313	5479673	5224743	3622706	3332496

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.

and the number of search methods used by employed searchers. We restrict the sample to workers that report that they are searching for a job and exclude the years before 1997. The results of ordinary least squares regressions for the same specifications as in Table 1 are depicted.[15] The coefficients of the unemployment rate are positive and statistically significant at the 1% level, but for the regression in column (4) where the coefficient is positive but statistically not significant. The results show that this positive relationship is not driven by observable compositional shifts in the pool of searchers and that the search intensity of workers is greater in sectors/occupations

[15]Estimating Poisson models produces similar results.

Table 2: Search Intensity and Unemployment

	(1)	(2)	(3)	(4)	(5)
	1997-2019	**1997-2019**	**1997-2019**	**2001-2019**	**2001-2019**
Unemployment rate	6.724***	5.751***	4.795***	0.283	2.263***
	(0.295)	(0.293)	(0.523)	(0.732)	(0.575)
Male		13.10***	13.05***	13.34***	13.97***
		(0.834)	(0.834)	(0.950)	(0.990)
Age		-0.558***	-0.568***	-0.372	-0.529**
		(0.209)	(0.209)	(0.239)	(0.248)
Age sq.		0.000975	0.00112	-0.000290	0.000707
		(0.003)	(0.003)	(0.003)	(0.003)
Self-employed		-35.46***	-35.42***	-32.88***	-31.99***
		(1.689)	(1.688)	(1.893)	(1.979)
Temporary Employment		50.84***	50.85***	50.31***	50.86***
		(1.168)	(1.168)	(1.360)	(1.401)
Part-time Employment		8.962***	8.870***	9.842***	9.243***
		(1.738)	(1.738)	(1.935)	(2.017)
Tenure		-0.541***	-0.543***	-0.512***	-0.531***
		(0.015)	(0.015)	(0.017)	(0.018)
Tenure sq.		0.984***	0.987***	0.900***	0.956***
		(0.049)	(0.049)	(0.054)	(0.058)
Work hours - 16-30 hrs.		-17.22***	-17.28***	-19.78***	-18.32***
		(1.435)	(1.434)	(1.639)	(1.682)
Work hours - 31-45 hrs.		-22.12***	-22.16***	-24.42***	-24.13***
		(2.131)	(2.131)	(2.405)	(2.488)
Work hours - above 45 hrs.		-28.34***	-28.40***	-30.53***	-30.29***
		(2.317)	(2.317)	(2.629)	(2.722)
Year	-3.277***	-2.902***			
	(0.054)	(0.055)			
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	297445	285612	285612	215999	200159

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 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. ***, **, * denote statistical significance at the 1%, 5%, and 10% level. Robust standard errors are reported in parentheses.

in which the unemployment rate is higher. The size of this relationship is small. We find that the number of search methods increases by 0.16, if we look at the coefficient in column (2) 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 for search 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 search activity, the coefficient of the unemployment rate for the European sample is positive, statistically significant and of similar size as in Table 1. Moreover, in regards to search intensity, the coefficients of the unemployment rate is positive and statistically significant but smaller than in Table 2. These findings suggest that on average the cyclical properties of OJS behavior observed in the UK, 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 an additional robustness analysis in Tables A-5 and A-6, we expand the set of control variables to assess whether certain omitted variables biased our results provided above. The coefficients estimated for these control variables show that relative to no education the search of educated respondents is higher, and respondents who have training offered by their workplace search less (although 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 relative to smaller firms (1-10 workers), and respondents who have higher wage residuals search less. The main takeaway from these robustness exercises is that the baseline results reported in Table 1 and Table 2 are robust to the inclusion of these additional variables and search activity and intensity remain countercyclical.

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 obtain if OJS were constant and comparing it to the realized (true) Beveridge curve. This exercise allows 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, 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.[16] If we include OJS activity s, the matching function becomes $m(u+s, v)$. Moreover, with constant returns to scale we can define $f(\sigma\theta) = m(1, v/(u+$

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

$s)$), 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:

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

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.

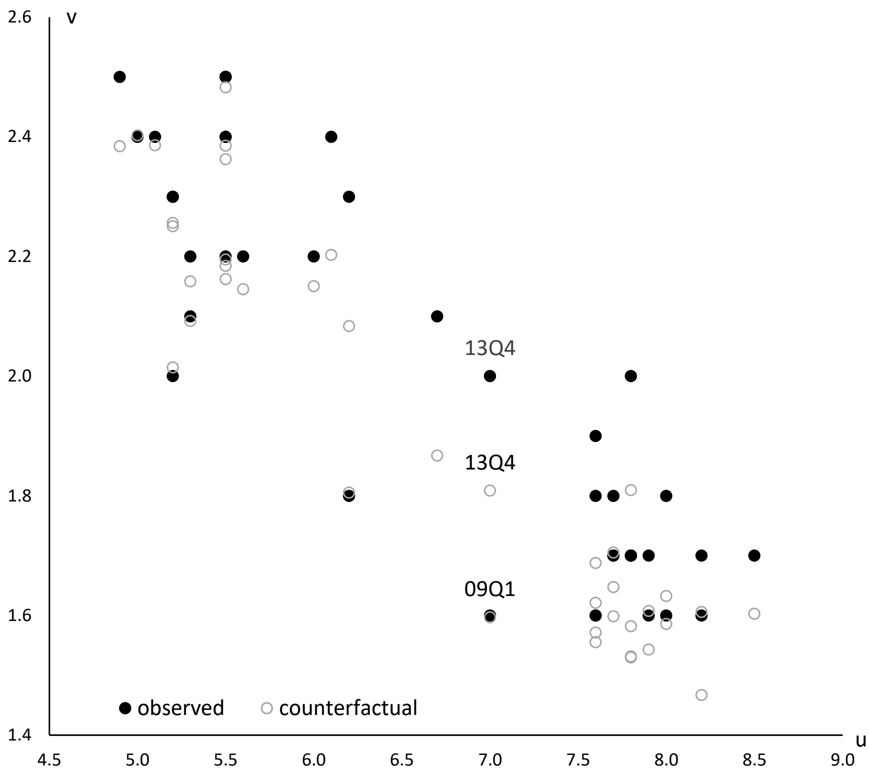
Figure 3 shows the realized (filled) and counterfactual (unfilled) Beveridge curves for the UK between 2003 and 2015.[17] As can be seen, the marked shift outward in the realized Beveridge curve that started amid the great recession is considerably more pronounced than the shift in the counterfactual 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 put forward 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 the change in 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

[17] 2003 is our first year since while 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.

Figure 3: OJS and the Beveridge curve for the UK



Notes: The realized and counterfactual Beveridge are depicted with measures for the vacancy rate, unemployment rate, and OJS activity for the years 2003Q1-2015Q4.

unemployment-to-employment transitions to construct an indirect measure of OJS, and use this to construct their counterfactual Beveridge curve. They find less of the shift in the US Beveridge curve during the great recession can be explained by OJS, suggesting it accounts for roughly one quarter.[18] 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) also finds a model with OJS can replicate well Beveridge curves dynamics in the US. Our findings adds to this small but growing literature suggesting that OJS is a potentially important factor in outward shifts of the Beveridge curve.

Finally, it is important to note that 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

[18]In the Appendix Figure A-1, we provide an alternative counterfactual Beveridge curve for the UK using transitions as used by Elsby et al. (2015) in their work for the US. The indirect measure is also countercyclical and as such this exercise entails qualitatively similar results in terms of the outward shift in the Beveridge curve. Quantitatively the results show 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.

determination of vacancies. However, it highlights and quantifies the potential impact of the observed cyclical properties of OJS.

4.3 Compositional fluctuations

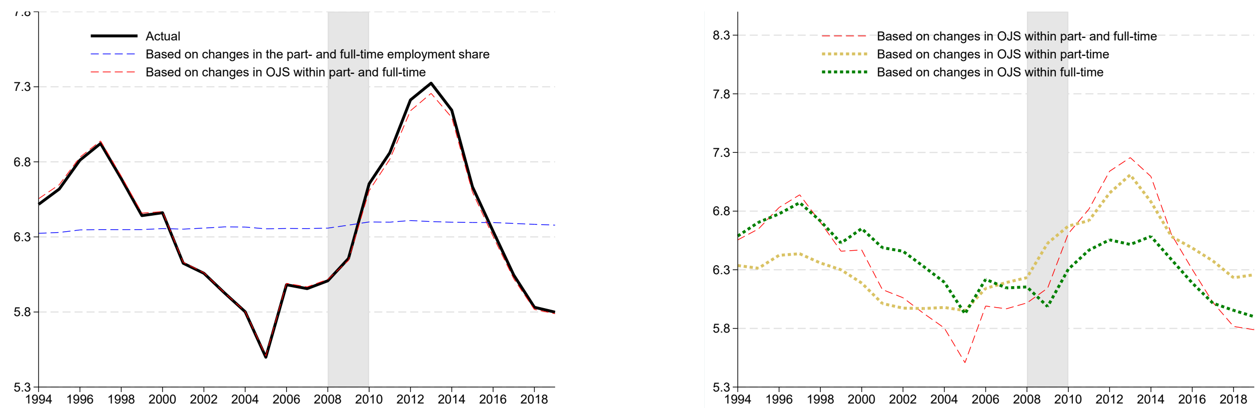
We find in Table 1 that part-time and temporary workers are more likely to search on the job. While the regression analysis controls for these factors as potential confounders, we now study in more detail the importance of fluctuations in the employment composition of part-time and temporary workers. 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 into the 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. Equation 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, Figure 4.1 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 worker (red line). We see 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. Figure 4.2 shows the search behavior within the employment groups and highlights that search of both part-time (yellow line) and full-time (green line) workers fluctuate to contribute to the counterfactual search behavior (red line) with part-time playing a more significant role during the great recession.

Figure 4: Decomposition: Part- and Full-time Worker's OJS

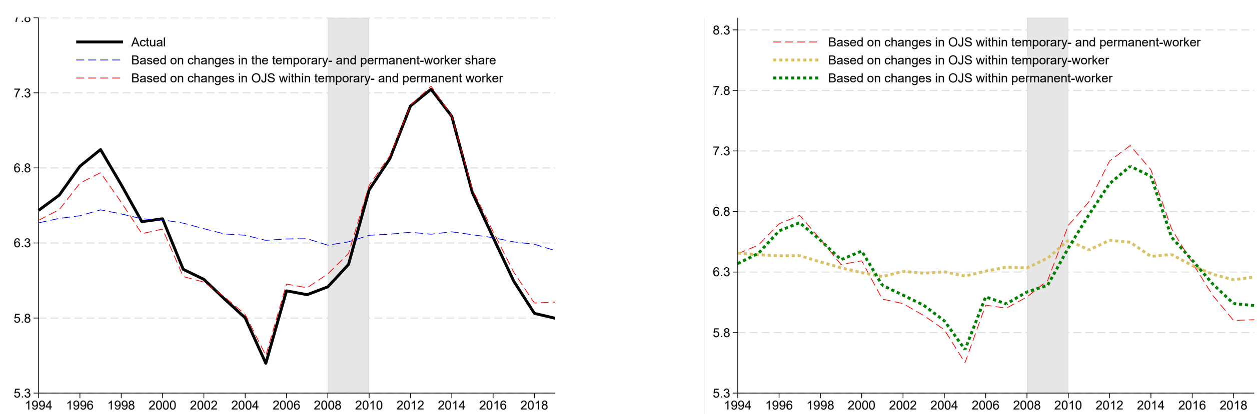


4.1: Counterfactual OJS

4.2: Counterfactual OJS by Part- and Full-time

Notes: Figure 4.1 presents two counterfactual OJS. 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 the black line that shows the actual OJS behavior over time. Figure 4.2 decomposes the second counterfactual into two additional counterfactuals for each mentioned group [yellow for group 1 and green for group 2] by only allowing one group's OJS at a time to vary while keeping the weights and the OJS behavior of the other group constant at the mean values in the sample.

Figure 5: Decomposition: Temporary- and Permanent-worker's OJS



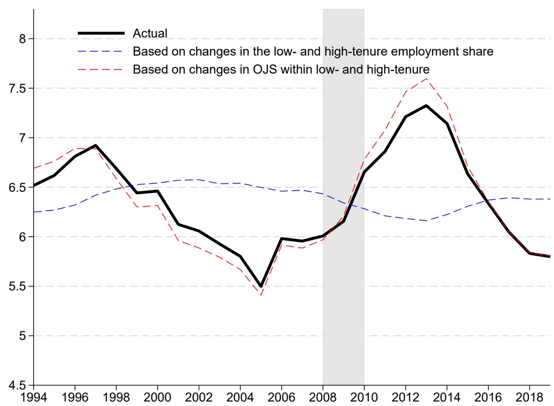
5.1: Counterfactual OJS

5.2: Counterfactual OJS by Temporary- and Permanent-worker

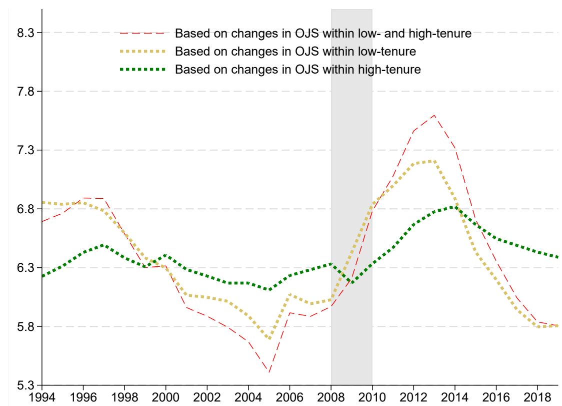
Notes: Figure 5.1 presents two counterfactual OJS. The first [blue] (second [red]) counterfactual is constructed by fixing the OJS behavior within the mentioned groups (weights of the groups) at the mean value in the sample. For comparison purposes, we also plot the black line that shows the actual OJS behavior over time. Figure 5.2 decomposes the second counterfactual into two additional counterfactuals for each mentioned group [yellow for group 1 and green for group 2] by only allowing one group's OJS at a time to vary while keeping the weights and the OJS behavior of the other group constant at the mean values in the sample.

Similar results are obtained when we look at temporary versus permanent in Figure 5.1. The shares do not contribute much 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 (Figure 5.2). Overall, both these decompositions suggest fluctuations in the worker shares do not play a significant role in the fluctuation of OJS activity.

Figure 6: Decomposition: Low- and High-tenure Worker's OJS



6.1: Counterfactual OJS



6.2: Counterfactual OJS by Low- and High-tenure

Notes: Figure 6.1 presents two counterfactual OJS. 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 the black line that shows the actual OJS behavior over time. Figure 6.2 decomposes the second counterfactual into two additional counterfactuals for each mentioned group [yellow for group 1 and green for group 2] by only allowing one group's OJS at a time to vary while keeping the weights and the OJS behavior of the other group constant at the mean values in the sample.

We can also conduct the same decomposition for workers with a low tenure on the job (≤ 4 years) versus workers with a high tenure (> 4 years). Again, we find that fluctuations in the tenure composition of the workforce do not explain the cyclical fluctuations of OJS (Figure 6.1). Figure 6.2 shows that, while OJS is countercyclical for both low and high job tenures, the cyclical reaction is both more pronounced and occurs earlier for low tenure workers. This shows that the search behavior of higher tenure workers lags behind the search behavior of workers with a low job tenure.

4.4 Search motivations

To start to develop an understanding for the reasons that OJS is countercylical, we now consider the motivations for search given by respondents in the UK-LFS. In Table 3, we present results from a regression specification 1 where we disaggregate OJS into different search motivations (job-ladder vs. precautionary search). Column (5) shows that, consistent with the finding by 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 show that the effect of unemployment is larger for those looking for better jobs than those engaging in precautionary search, suggesting the former and not the latter may be the more important driver of countercyclical OJS.[19]

Table 3: Motivations for Search

	(1) OJS	(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 hrs.	-0.0925*	0.925***	0.403***	1.045***	0.381***
	(0.056)	(0.042)	(0.023)	(0.040)	(0.013)
Work hours - 31-45 hrs.	-0.656***	0.854***	0.479***	0.933***	0.427***
	(0.078)	(0.061)	(0.036)	(0.058)	(0.021)
Work hours - above 45 hrs.	-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	5479673	5479673	5502134	5502134	5502134

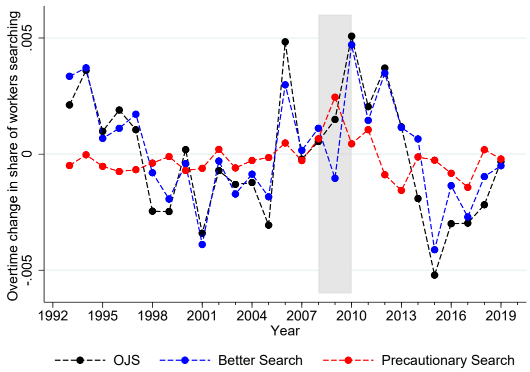
Note: The coefficients and standard errors are multiplied by 100. The dependent variable in column (1) is a binary variable indicating if a respondent is looking for a job; the dependent variable in columns (2) and (5) is a binary variable if a respondent is a better job searcher or precautionary searcher. Columns (3) and (4) further disaggregate the 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% level. Robust standard errors are reported in parentheses.

To illustrate the relative importance of the different search motivations in driving fluctuations

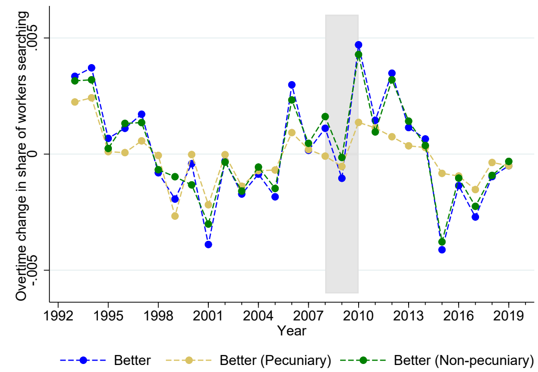
[19]Table A-7 in the Appendix includes additional controls and shows the results are robust.

in OJS, Figure 7.1 decomposes the overall change in search (black line) into those looking for better jobs (blue line) and those doing precautionary search (red line). The figure shows that fluctuations in search are almost always driven mainly by those looking for a better job apart from in 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.

Figure 7: Decomposition: OJS Motivations



7.1: Decomposition of OJS by Better and Precautionary Search



7.2: Decomposition of Better by Pecuniary and Non-pecuniary search

Notes: Figure 7.1 presents 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 Figure 7.2 for comparison purposes, we also plot the black line that shows the changes in better split disaggregated by motivation relating to pecuniary [blue] and nonpecuniary [green] reasons.

Figure 7.2 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, it is those looking for better jobs for non-pecuniary reasons that drive the fluctuations.

Finally, we use wage residuals as a proxy for a worker's position on the job ladder.[20] To assess how the position influences search behavior over the business cycle, we then use the following interaction specification 5 to interact the wage residual with the unemployment rate:

$$\begin{aligned} Search\ activity_{iqt} &= \alpha_0 + \alpha_1 Unemployment\ rate_{qt} + \alpha_2 Year_t + \alpha_3 Wage\ residual_{iqt} \\ &+ \alpha_4 Unemployment\ rate_{qt} \times Wage\ residual_{iqt} + \mathbf{x_{iqt}}'\phi + \gamma_q + \varepsilon_{iqt} \end{aligned} \tag{5}$$

[20] As mentioned above, the residuals are the difference between a worker's actual wage and their predicted wage based on their characteristics such as their education level, gender, age, age squared, tenure month, tenure month square, firm size.

Table 4: Search, Job-Ladder Position, and Unemployment

	(1)	(2)	(3)	(4)
		Interaction		
Unemployment rate	0.233***	0.336***	0.165***	0.352***
	(0.019)	(0.036)	(0.055)	(0.050)
Wage Residual	-1.778***	-1.153***	-1.173***	-1.098***
	(0.246)	(0.138)	(0.230)	(0.142)
Unemployment rate*Residual	-0.152***	-0.368***	-0.236***	-0.379***
	(0.039)	(0.031)	(0.039)	(0.035)
Male	1.929***	1.923***	1.721***	1.762***
	(0.067)	(0.068)	(0.081)	(0.084)
Age	0.241***	0.241***	0.248***	0.241***
	(0.013)	(0.013)	(0.016)	(0.017)
Age sq.	-0.00443***	-0.00443***	-0.00446***	-0.00445***
	(0.000)	(0.000)	(0.000)	(0.000)
Self-employed	-2.936***	-3.536***	-2.694***	-3.137***
	(0.222)	(0.259)	(0.292)	(0.295)
Temporary Employment	9.329***	9.281***	9.171***	9.386***
	(0.166)	(0.168)	(0.211)	(0.219)
Part-time Employment	1.125***	1.144***	1.342***	1.175***
	(0.141)	(0.142)	(0.163)	(0.170)
Tenure	-0.0385***	-0.0384***	-0.0372***	-0.0379***
	(0.001)	(0.001)	(0.001)	(0.001)
Tenure sq.	0.0590***	0.0588***	0.0567***	0.0582***
	(0.001)	(0.001)	(0.002)	(0.002)
Work hours - 16-30 hrs.	-0.0550	-0.0895	-0.0186	-0.116
	(0.123)	(0.125)	(0.154)	(0.160)
Work hours - 31-45 hrs.	0.257	0.250	0.364*	0.171
	(0.177)	(0.178)	(0.213)	(0.221)
Work hours - above 45 hrs.	0.288	0.250	0.492**	0.176
	(0.187)	(0.189)	(0.226)	(0.235)
Year	0.0794***			
	(0.004)			
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	1201451	1175353	815665	751035

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. All columns include an interaction between the unemployment rate and wage residual where wage residual is a continuous variable measured as the difference between the actual wage and the predicted wage (from a mincer equation). Person weights are used in all regressions. ***, **, * denote statistical significance at the 1%, 5%, and 10% level. Robust standard errors are reported in parentheses.

The results are shown in Table 4. We can see from the estimated effects that lower residuals (relative to higher residuals) are associated with a higher likelihood of search in general. The estimated effect of the unemployment rate along with that of the interaction between wage residuals and unemployment confirms that lower residuals are associated with higher search activity when the market is slack. From this result, we can infer workers with a lower position on the job ladder are more likely to search, and that they react more than workers higher on the job ladder to an increase in the unemployment rate. This finding indicates that changes in job ladder over the business cycle play an important role in the cyclicality of OJS.[21]

4.5 Match quality

There is significant evidence that match quality deteriorates in 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 search activity of new hires (tenure less than 1 year) versus other workers. We take a version of Specification 5 but with a dummy variable for Short Tenure rather than the wage residual. Table 5 shows the results. The coefficient on Short Tenure shows that, in general, new hires search less than 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 for other workers. Therefore, 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.[22]

5 Discussion

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 start this section by considering how these two types of returns relate to OJS.

To assess the impact on OJS of the probability of finding a new match, we use the 2Q data to estimate the transition-probabilities conditional on, respectively, a worker engaging in OJS or not.[23] Figure 8 shows that the transition-probabilities for those who search are higher in general

[21] Table A-8 in the Appendix includes the additional controls and shows theses results are robust.

[22] Table A-9 in the Appendix includes additional controls and shows the results are robust.

[23] For estimating 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 the dummy of 1 if the worker is involved in OJS and 0 otherwise, as well as additional controls for worker's education dummies, age, age squared. Since the data covers 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 5: Search, Short Tenure and Unemployment

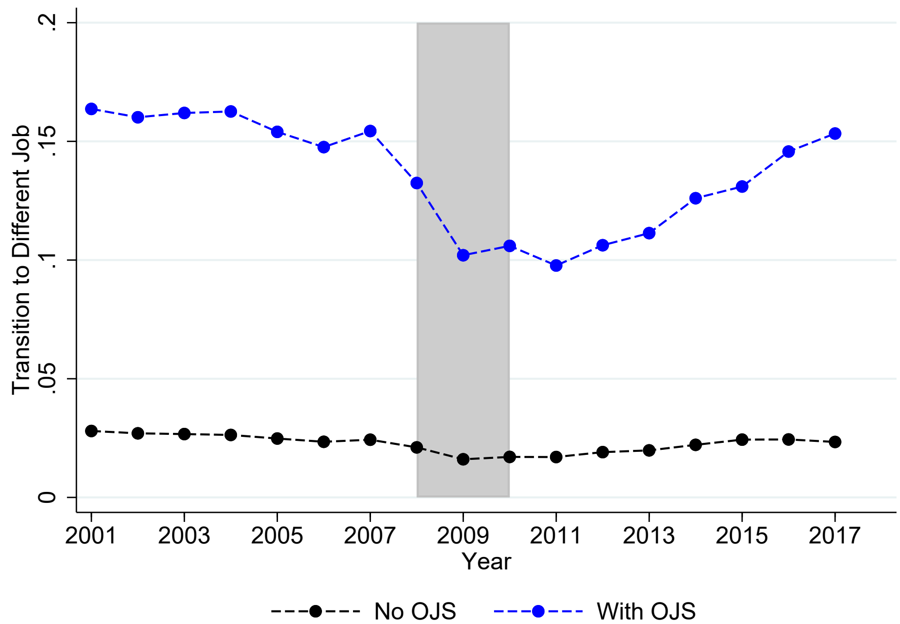
	(1)	(2)	(3)	(4)
	Interaction			
Unemployment rate	0.182***	0.261***	0.0701***	0.370***
	(0.00817)	(0.0141)	(0.0243)	(0.0221)
Short Tenure	-3.474***	-1.739***	-2.464***	-2.421***
	(0.145)	(0.0864)	(0.154)	(0.0930)
Unemployment rate*Short Tenure	0.619***	0.436***	0.454***	0.554***
	(0.0228)	(0.0174)	(0.0265)	(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 hrs.	-0.0621	-0.0610	-0.121*	-0.0413
	(0.0560)	(0.0574)	(0.0699)	(0.0724)
Work hours - 31-45 hrs.	-0.621***	-0.593***	-0.675***	-0.590***
	(0.0787)	(0.0804)	(0.0952)	(0.0992)
Work hours - above 45 hrs.	-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	5436546	5183370	3591072	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. Columns (1) depict the results including a linear time trend and a set of binary variables indicating the quarter. Columns (2) and columns (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 the 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 equal to 12. Person weights are used in all regressions. ***, **, * denote statistical significance at the 1%, 5%, and 10% level. Robust standard errors are reported in parentheses.

and also highly procyclical. As a result, we would expect OJS to be procyclical if workers only reacted to substitution effects from their probability of finding a job.

The role that wages play in the decision to search is more nuanced. In Burdett and Mortensen

Figure 8: Job to Job Transitions (2Q)



Notes: Figure 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 worker's search behavior as the dummy of 1 if the worker does OJS and 0 otherwise, as well as additional controls for worker's education dummies, age, age squared.

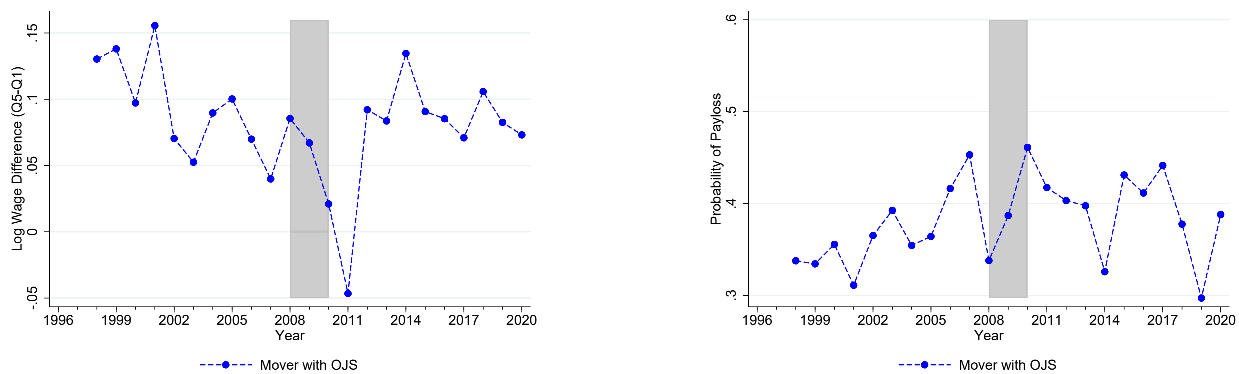
(1998) workers make job-to-job transitions only if the offered wage is higher than the wage earned at their present employer, and the returns to job-to-job transition are directly tied to wage gains. However, in Postel-Vinay and Robin (2002) movers may accept lower wages when an outside offer comes from more productive firms as they count on future wage increases as a result of outside offers received at the new employer. To take into account both these settings, Figure 9 uses 5Q data and shows both the difference in the log wage of movers[24] doing OJS[25] (Figure 9.1) and the proportion of job movers who do OJS that take a wage cut when moving (Figure 9.2).

The wage gains in Figure 9.1 show a sharp drop during the great recession, inconsistent with the sharp increase in OJS in that period. Figure 9.2 shows the proportion of movers taking pay cuts over time fluctuates but does not appear to show a cyclical pattern. As a result, there is little in this pattern that explains countercyclical OJS.

[24]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 in between quarter 1 and quarter 5, otherwise the variable takes a value of 0 for stayers when each successive quarter has additional 3 months added to the preceding quarter's reported months with the current employer.

[25]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.

Figure 9: Transition and Wage Gains (5Q) Mover by date and year 5



9.1: Log Wage Difference

9.2: Probability of Payloss

Notes: Figure 9.1 presents wage gains for a mover using the 5Q data where wage gain is the difference in wages reported in Q5 and in Q1. Figure 9.2 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 depicted for movers doing the OJS.

The conventional view of OJS, for instance 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. Moreover, workers may be forced to search longer as the job ladder becomes harder to climb (Barlevy, 2002). Both these factors would imply countercyclical OJS. Consistent with the idea that lower transition-probabilities encourage a more intensive search, Table 2 shows that the number of search methods employed is countercyclical. This finding supports the argument that income effects could induce countercyclical OJS responses. We do not observe how long individual workers search. However, we do observe a lag in the response of OJS to changes in labor market conditions (Figure 1), especially for work workers with a higher job-tenure who are not matched during the recession (Figure 6.2), which is consistent with an increase in search duration leading to an accumulation of search activity over the business cycle.

While the response to lower transition-probabilities depends on the income effects discussed above, the incentive effect of lower wage-gains would seem unambiguous. However, the importance of lower wage-gains also depends on how much workers care about the pecuniary benefits of jobs. Table 3 shows workers search more on the job in downturns for both pecuniary and non-pecuniary reasons. However, the decomposition in Figure 7.2 also shows that non-pecuniary motivated search contributes substantially more to the cyclicality of job-ladder motivated search than pecuniary motivated search. This result provides a rationale as to why the drop in wage growth shown in Figure 9.1 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 search activity of new hires (Table 5), 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 Figure 6.2 are consistent both with responses by hires matched during the recession to deteriorating match quality, and a cumulative effect on search activity coming from longer search duration. On one hand, the increase in search behavior at the start of the great recession is driven by low tenure workers, who are more likely to have been matched during the recession, consistent with a deterioration in the quality of new matches that has an immediate impact on search behavior by new hires. On the other hand, there is a lagged response for higher tenure workers, who are matched before the recession, which is more consistent with a cumulative effect of increased search duration induced by responses to lower transition-probabilities.

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 in finding a new match in downturns may increase the intensity (and potentially also the duration) of search. Second, as workers search primarily for better jobs for non-pecuniary reasons, the reduction in the opportunity in wage growth in recessions does not reduce the incentive to search as much as would be anticipated. And, third, there is evidence that the reduction in match quality in recessions 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, and 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 income effects, which may also induce an increase in search effort (intensity and/or duration). 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. And, 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 countercyclical pattern of OJS that we observe, and thereby provide an impetus for future theoretical and empirical work on OJS to take each of these mechanisms into consideration.

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A Appendix

A.1 Reasons for search

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 occupation	0.07
Other aspects of present job unsatisfactory	0.28
Other Search	
Other reasons	0.20

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

A.2 Results for EU

We use data from 31 countries[26] to test whether our findings concerning the cyclical properties of OJS behavior can be generalized beyond the UK. The EU-LFS data is a quarterly and annual representative survey among households covering members above the age 15.[27] 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 the 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 is 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 only include 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 explanatory variable of key 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 unemployment rate in the region of residence of the respondents. 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 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 coefficients of the unemployment rate is positive and statistically significant but smaller than in Table 2. These findings suggest that on average the cyclical properties of OJS behavior observed in the UK, 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.

[26] Table A-2 shows the countries and years included in the sample.

[27] 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 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 for each country the countries and years included in sample for the regressions depicted in table A-3 and A-4.

Table A-3: Search 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 hrs.		-2.499^{***} (0.021)	-2.536^{***} (0.022)	-2.606^{***} (0.023)
Work hours 35-45 hrs.		-2.766^{***} (0.022)	-2.836^{***} (0.023)	-2.838^{***} (0.024)
Work hours above 45 hrs.		-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. Columns (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% level. Robust standard errors are reported in parentheses.

Table A-4: Search 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)	0.427^{***} (0.117)
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 hrs.		-15.72^{***} (0.471)	-16.10^{***} (0.482)	-15.84^{***} (0.491)
Work hours 35-45 hrs.		-8.973^{***} (0.672)	-8.811^{***} (0.697)	-14.52^{***} (0.675)
Work hours above 45 hrs.		-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

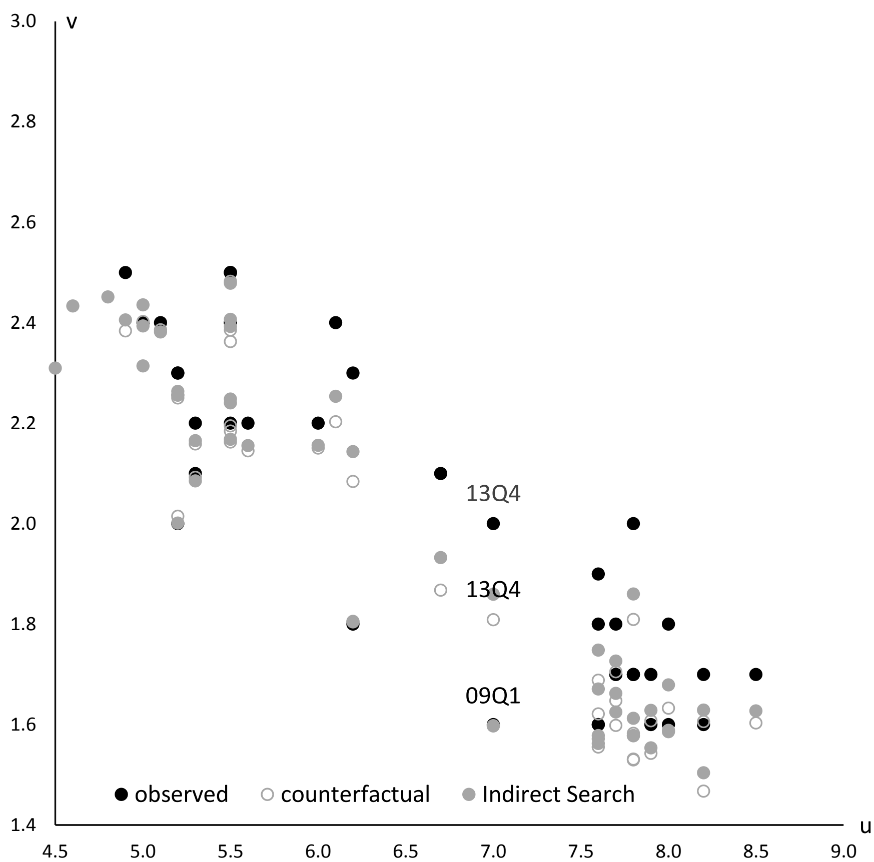
Notes: The coefficients and standard errors are multiplied by 100. The dependent variable indicates the number of search methods used. The sample is restricted to workers that search on the job. Column (1) depicts the results including a linear time trend and a set of binary variables indicating the quarter. Column (2) depicts the results additionally including the full set of control variables. Column (3) 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% level. Robust standard errors are reported in parentheses.

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 searchers and the unemployed search in the same market, we get $\pi_{UE} = f(\sigma\theta)$ 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 (see Section 5) we construct such a series of search for the UK and present the resulting counterfactual Beveridge curve (grey dots) along with the counterfactual using our data (white dots) and the realized Beveridge curve (black dots) in Figure A-1.

Again using 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. Using the indirect measure the shift is slightly more pronounces when OJS is held constant (0.26 percentage points). Using the indirect measure therefore suggests slightly over a third of the shift in the UK Beveridge curve is due to countercyclical OJS.

Figure A-1: OJS and the Beveridge curve for the UK



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

A.4 Robustness

Table A-5: Search and Unemployment – Table 1 Robustness:

	(1)	(2)	(3)	(4)	(5)
		(1997-2019)		(2001-2019)	
Unemployment rate	0.204***	0.213***	0.304***	0.209***	0.412***
	(0.007)	(0.024)	(0.047)	(0.065)	(0.057)
Male		2.091***	2.074***	2.035***	2.100***
		(0.092)	(0.093)	(0.100)	(0.104)
Age		0.0906***	0.0907***	0.105***	0.115***
		(0.019)	(0.020)	(0.021)	(0.022)
Age sq.		-0.00285***	-0.00286***	-0.00303***	-0.00320***
		(0.000)	(0.000)	(0.000)	(0.000)
Self-employed		-1.163***	-1.398***	-1.148***	-1.547***
		(0.309)	(0.347)	(0.365)	(0.379)
Temporary Employment		10.18***	10.16***	10.22***	10.41***
		(0.243)	(0.247)	(0.273)	(0.283)
Part-time Employment		1.340***	1.333***	1.371***	1.338***
		(0.184)	(0.185)	(0.197)	(0.205)
Tenure		-0.0373***	-0.0372***	-0.0370***	-0.0373***
		(0.001)	(0.001)	(0.001)	(0.001)
Tenure sq.		0.0600***	0.0596***	0.0595***	0.0603***
		(0.002)	(0.002)	(0.002)	(0.002)
Work hours - 16-30 hrs.		-0.154	-0.180	-0.194	-0.272
		(0.163)	(0.166)	(0.182)	(0.188)
Work hours - 31-45 hrs.		0.120	0.0934	0.0145	-0.0325
		(0.234)	(0.236)	(0.256)	(0.265)
Work hours - above 45 hrs.		0.0795	0.0560	0.0113	-0.112
		(0.248)	(0.251)	(0.272)	(0.282)
Wage Residual		-2.204***	-2.192***	-2.164***	-2.219***
		(0.080)	(0.081)	(0.088)	(0.092)
Other qualifications		1.482***	1.473***	1.448***	1.397***
		(0.131)	(0.134)	(0.151)	(0.154)
Edu - gcse a-c or equiv		1.413***	1.384***	1.387***	1.345***
		(0.119)	(0.121)	(0.135)	(0.139)
Edu gce - a level or equiv		1.673***	1.651***	1.633***	1.551***
		(0.124)	(0.126)	(0.141)	(0.144)
Edu - higher education		2.913***	2.894***	2.812***	2.707***
		(0.157)	(0.160)	(0.175)	(0.180)
Edu - degree or equivalent		3.743***	3.710***	3.606***	3.667***
		(0.153)	(0.155)	(0.168)	(0.175)
Mortgage		-0.691***	-0.666***	-0.663***	-0.692***
		(0.075)	(0.075)	(0.081)	(0.084)
Firm specific training		-0.900***	-0.887***	-0.953***	-1.007***
		(0.073)	(0.078)	(0.086)	(0.088)

Continued on next page

Table A-5 – continued from previous page

	(1)	(2)	(3)	(4)	(5)
		(1997-2019)		(2001-2019)	
Firm size - 11-19 wrks.		0.153	0.166	0.130	0.108
		(0.140)	(0.141)	(0.153)	(0.159)
Firm size - 20-24 wrks.		-0.156	-0.171	-0.194	-0.197
		(0.179)	(0.181)	(0.196)	(0.202)
Firm size - Under 25 wrks.		-0.00514	-0.00793	-0.0555	-0.107
		(0.122)	(0.124)	(0.133)	(0.138)
Firm size - 25-49 wrks.		-0.131	-0.140	-0.160	-0.174
		(0.112)	(0.113)	(0.117)	(0.122)
Firm size - Over 24 wrks.		-0.391^{***}	-0.286^{**}	-0.409^{***}	-0.469^{***}
		(0.120)	(0.127)	(0.153)	(0.158)
Firm size - Over 50 wrks.		-0.638^{***}	-0.647^{***}	-0.656^{***}	-0.685^{***}
		(0.122)	(0.123)	(0.127)	(0.133)
Year	0.0251^{***}	0.0358^{***}			
	(0.002)	(0.006)			
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	6132313	668717	651528	556515	511160

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-6: Search Intensity and Unemployment – Table 2 Robustness

	(1)	(2)	(3)	(4)	(5)
		(1997-2019)			(2001-2019)
Unemployment rate	6.724***	5.314***	5.544***	1.234	3.118**
	(0.295)	(0.656)	(1.243)	(1.630)	(1.263)
Male		9.826***	9.862***	9.726***	10.00***
		(2.053)	(2.052)	(2.160)	(2.280)
Age		-1.278**	-1.269**	-1.161**	-1.230**
		(0.519)	(0.519)	(0.547)	(0.578)
Age sq.		0.0115*	0.0114*	0.0103	0.0109
		(0.007)	(0.007)	(0.007)	(0.007)
Temporary Employment		45.83***	45.94***	46.34***	46.45***
		(3.001)	(2.999)	(3.199)	(3.327)
Part-time Employment		7.377*	7.190*	8.849*	6.602
		(4.370)	(4.365)	(4.540)	(4.899)
Tenure		-0.481***	-0.486***	-0.468***	-0.499***
		(0.032)	(0.032)	(0.034)	(0.036)
Tenure sq.		0.967***	0.972***	0.926***	1.022***
		(0.101)	(0.101)	(0.104)	(0.114)
Work hours - 16-30 hrs.		-21.97***	-22.13***	-23.41***	-23.33***
		(3.545)	(3.543)	(3.746)	(3.917)
Work hours - 31-45 hrs.		-20.32***	-20.57***	-21.70***	-24.17***
		(5.396)	(5.392)	(5.650)	(6.015)
Work hours - above 45 hrs.		-26.34***	-26.66***	-25.26***	-27.32***
		(5.862)	(5.858)	(6.154)	(6.546)
Wage Residual		-13.19***	-12.93***	-12.64***	-13.30***
		(2.374)	(2.380)	(2.523)	(2.642)
Other qualifications		23.28***	23.10***	25.00***	25.34***
		(4.029)	(4.026)	(4.337)	(4.480)
Edu - gcse a-c or equiv		33.75***	33.62***	35.81***	36.72***
		(3.740)	(3.736)	(4.009)	(4.147)
Edu gce - a level or equiv		39.93***	39.84***	42.21***	42.86***
		(3.854)	(3.852)	(4.130)	(4.280)
Edu - higher education		42.05***	41.89***	43.83***	45.98***
		(4.646)	(4.642)	(4.953)	(5.170)
Edu - degree or equivalent		49.44***	49.21***	50.13***	51.57***
		(4.240)	(4.238)	(4.505)	(4.690)
Mortgage		-0.475	-0.439	0.119	0.409
		(1.852)	(1.852)	(1.949)	(2.057)
Firm specific training		-7.363***	-6.183***	-5.067**	-6.349***
		(2.005)	(2.054)	(2.188)	(2.255)
Firm size - 11-19 wrks.		0.982	0.707	0.638	2.697
		(3.330)	(3.328)	(3.514)	(3.702)
Firm size - 20-24 wrks.		8.569*	8.403*	8.069*	6.697
		(4.509)	(4.511)	(4.727)	(4.932)

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Table A-6 – continued from previous page

	(1)	(2)	(3)	(4)	(5)
		(1997-2019)			(2001-2019)
Firm size - Under 25 wrks.		3.381	3.385	2.577	2.770
		(3.008)	(3.007)	(3.158)	(3.313)
Firm size - 25-49 wrks.		3.785	3.848	3.438	4.431
		(2.764)	(2.770)	(2.843)	(2.997)
Firm size - Over 24 wrks.		5.030	4.223	1.801	1.021
		(3.267)	(3.378)	(3.885)	(4.049)
Firm size - Over 50 wrks.		-1.441	-1.336	-1.950	-0.623
		(3.253)	(3.258)	(3.329)	(3.524)
Year	-3.277***	-4.201***			
	(0.054)	(0.167)			
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	297445	42219	42219	37706	34754

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-7: Motivation for Search: Robustness Table 3

	(1) OJS	(2) Better	(3) Better (Pecuniary)	(4) Better (Non-pecuniary)	(5) Precautionary Search
Unemployment rate	0.213***	0.0881***	0.0459***	0.121***	0.0683***
	(0.024)	(0.019)	(0.012)	(0.018)	(0.008)
Male	2.091***	1.496***	0.867***	1.217***	0.0327
	(0.092)	(0.076)	(0.048)	(0.073)	(0.029)
Age	0.0906***	-0.0588***	-0.00589	-0.0251*	0.0654***
	(0.019)	(0.016)	(0.010)	(0.015)	(0.006)
Age sq.	-0.00285***	-0.000579***	-0.000402***	-0.000782***	-0.000804***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Self-employed	-1.163***	-0.433*	-0.778***	0.0643	-0.340***
	(0.309)	(0.257)	(0.163)	(0.242)	(0.096)
Temporary Employment	10.18***	1.343***	0.432***	3.511***	5.876***
	(0.243)	(0.165)	(0.103)	(0.175)	(0.149)
Part-time Employment	1.340***	0.989***	-0.0706	1.138***	-0.233***
	(0.184)	(0.156)	(0.096)	(0.150)	(0.054)
Tenure	-0.0373***	-0.0260***	-0.0111***	-0.0219***	-0.00313***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Tenure sq.	0.0600***	0.0408***	0.0166***	0.0351***	0.00547***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Work hours - 16-30 hrs.	-0.154	0.807***	0.363***	0.860***	0.450***
	(0.163)	(0.128)	(0.072)	(0.125)	(0.041)
Work hours - 31-45 hrs.	0.120	1.248***	0.666***	1.096***	0.588***
	(0.234)	(0.192)	(0.114)	(0.185)	(0.064)
Work hours - above 45 hrs.	0.0795	1.346***	0.583***	1.311***	0.474***
	(0.248)	(0.204)	(0.122)	(0.196)	(0.069)
Wage Residual	-2.204***	-1.832***	-1.239***	-1.317***	0.0356
	(0.080)	(0.063)	(0.039)	(0.060)	(0.025)
Other qualifications	1.482***	1.053***	0.330***	0.989***	-0.00227
	(0.131)	(0.109)	(0.073)	(0.100)	(0.040)
Edu - gcse a-c or equiv	1.413***	0.975***	0.178***	1.066***	0.0136
	(0.119)	(0.099)	(0.066)	(0.092)	(0.037)
Edu - gce a level or equiv	1.673***	1.071***	0.135**	1.209***	0.00237
	(0.124)	(0.102)	(0.069)	(0.095)	(0.038)
Edu - higher education	2.913***	2.006***	0.410***	2.091***	0.0723
	(0.157)	(0.130)	(0.083)	(0.121)	(0.050)
Edu - degree or equivalent	3.743***	2.559***	0.470***	2.766***	0.176***
	(0.153)	(0.127)	(0.082)	(0.119)	(0.048)
Mortgage	-0.691***	-0.405***	-0.278***	-0.323***	-0.0140
	(0.075)	(0.062)	(0.039)	(0.058)	(0.024)
Firm specific training	-0.900***	-0.758***	-0.332***	-0.646***	-0.106***

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Table A-7 – continued from previous page

	(1) OJS	(2) Better	(3) Better (Pecuniary)	(4) Better (Non-pecuniary)	(5) Precautionary Search
	(0.073)	(0.059)	(0.038)	(0.056)	(0.024)
Firm size - 11-19 wrks.	0.153	0.404***	0.0379	0.351***	-0.0199
	(0.140)	(0.116)	(0.074)	(0.110)	(0.040)
Firm size - 20-24 wrks.	-0.156	0.142	0.0984	0.0237	-0.187***
	(0.179)	(0.150)	(0.102)	(0.141)	(0.046)
Firm size - Under 25 wrks.	-0.00514	0.364***	0.0267	0.275***	-0.0602*
	(0.122)	(0.102)	(0.065)	(0.096)	(0.036)
Firm size - 25-49 wrks.	-0.131	0.137	-0.145**	0.155*	0.0375
	(0.112)	(0.092)	(0.059)	(0.087)	(0.035)
Firm size - Over 24 wrks.	-0.391***	-0.0256	-0.218***	0.108	-0.0369
	(0.120)	(0.098)	(0.063)	(0.092)	(0.040)
Firm size - Over 50 wrks.	-0.638***	-0.321***	-0.397***	-0.206**	-0.00279
	(0.122)	(0.099)	(0.062)	(0.094)	(0.041)
Year	0.0358***	0.0323***	-0.00953***	0.0483***	-0.000253
	(0.006)	(0.005)	(0.003)	(0.005)	(0.002)
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	668717	668717	668783	668783	668783

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 if a respondent is a better job searcher or precautionary searcher. Columns (3) and (4) further disaggregate the 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% level. Robust standard errors are reported in parentheses.

Table A-8: Search, Job-Ladder Position and Unemployment: Robustness Table 4

	(1)	(2)	(3)	(4)
	Interaction Model			
Unemployment rate	0.212***	0.297***	0.198***	0.348***
	(0.024)	(0.047)	(0.065)	(0.057)
Wage Residual	-1.420***	-0.790***	-0.819***	-1.041***
	(0.298)	(0.178)	(0.270)	(0.165)
Unemployment rate*Residual	-0.133***	-0.341***	-0.235***	-0.300***
	(0.049)	(0.040)	(0.046)	(0.040)
Male	2.092***	2.081***	2.029***	2.087***
	(0.092)	(0.093)	(0.100)	(0.104)
Age	0.0904***	0.0879***	0.104***	0.0984***
	(0.019)	(0.020)	(0.021)	(0.022)
Age sq.	-0.00284***	-0.00283***	-0.00302***	-0.00303***
	(0.000)	(0.000)	(0.000)	(0.000)
Self-employed	-1.346***	-2.040***	-1.557***	-2.019***
	(0.318)	(0.358)	(0.377)	(0.386)
Temporary Employment	10.18***	10.14***	10.22***	10.39***
	(0.243)	(0.247)	(0.273)	(0.283)
Part-time Employment	1.340***	1.321***	1.374***	1.307***
	(0.184)	(0.185)	(0.197)	(0.205)
Tenure	-0.0373***	-0.0372***	-0.0369***	-0.0371***
	(0.001)	(0.001)	(0.001)	(0.001)
Tenure sq.	0.0599***	0.0596***	0.0595***	0.0601***
	(0.002)	(0.002)	(0.002)	(0.002)
Work hours - 16-30 hrs.	-0.154	-0.202	-0.196	-0.305
	(0.163)	(0.166)	(0.182)	(0.188)
Work hours - 31-45 hrs.	0.119	0.0645	0.0134	-0.0686
	(0.234)	(0.236)	(0.256)	(0.265)
Work hours - above 45 hrs.	0.0794	0.0168	0.0163	-0.165
	(0.248)	(0.251)	(0.272)	(0.282)
Year	0.0357***			
	(0.006)			
Other qualifications	1.482***	1.440***	1.449***	1.281***
	(0.131)	(0.134)	(0.151)	(0.155)
Edu - gcse a-c or equiv	1.415***	1.335***	1.384***	1.169***
	(0.119)	(0.121)	(0.135)	(0.141)
Edu - gce a level or equiv	1.674***	1.590***	1.631***	1.348***
	(0.124)	(0.126)	(0.141)	(0.146)
Edu - higher education	2.917***	2.842***	2.811***	2.513***
	(0.157)	(0.160)	(0.175)	(0.181)
Edu - degree or equivalent	3.749***	3.647***	3.608***	3.461***
	(0.153)	(0.155)	(0.168)	(0.176)
Mortgage	-0.692***	-0.662***	-0.664***	-0.686***
	(0.075)	(0.075)	(0.081)	(0.084)

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Table A-8 – continued from previous page

	(1)	(2)	(3)	(4)
	Interaction Model			
Firm specific training	-0.899***	-0.883***	-0.952***	-0.999***
	(0.073)	(0.078)	(0.086)	(0.088)
Firm size - 11-19 wrks.	0.154	0.162	0.130	0.0804
	(0.140)	(0.141)	(0.153)	(0.159)
Firm size - 20-24 wrks.	-0.155	-0.176	-0.190	-0.235
	(0.179)	(0.181)	(0.196)	(0.202)
Firm size - Under 25 wrks.	-0.00454	-0.0130	-0.0536	-0.155
	(0.122)	(0.124)	(0.133)	(0.138)
Firm size - 25-49 wrks.	-0.131	-0.147	-0.159	-0.228*
	(0.112)	(0.113)	(0.117)	(0.122)
Firm size - Over 24 wrks.	-0.390***	-0.293**	-0.407***	-0.522***
	(0.120)	(0.127)	(0.153)	(0.158)
Firm size - Over 50 wrks.	-0.637***	-0.638***	-0.655***	-0.731***
	(0.122)	(0.123)	(0.127)	(0.133)
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	668717	651528	556515	511160

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. All columns include an interaction between the unemployment rate and wage residual where wage residual is a continuous variable measured as the difference between the actual wage and the predicted wage (from a mincer equation). 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: Search, Short-Tenure and Unemployment: Robustness Table 5

	(1)	(2)	(3)	(4)
	Interaction Model			
Unemployment rate	0.141***	0.208***	0.157**	0.277***
	(0.0240)	(0.0470)	(0.0655)	(0.0564)
Short Tenure	-2.647***	-2.364***	-1.915***	-3.682***
	(0.468)	(0.272)	(0.438)	(0.262)
Unemployment rate*Short Tenure	0.465***	0.542***	0.344***	0.757***
	(0.0766)	(0.0563)	(0.0743)	(0.0498)
Male	2.093***	2.065***	2.028***	2.058***
	(0.0922)	(0.0932)	(0.100)	(0.104)
Age	0.0934***	0.0997***	0.107***	0.134***
	(0.0194)	(0.0197)	(0.0215)	(0.0223)
Age sq.	-0.00287***	-0.00295***	-0.00305***	-0.00337***
	(0.000214)	(0.000217)	(0.000237)	(0.000245)
Self-employed	-0.956***	-1.143***	-0.970***	-1.381***
	(0.310)	(0.348)	(0.366)	(0.379)
Temporary Employment	10.13***	10.19***	10.17***	10.35***
	(0.245)	(0.249)	(0.274)	(0.284)
Part-time Employment	1.348***	1.314***	1.375***	1.288***
	(0.185)	(0.186)	(0.198)	(0.206)
Tenure	-0.0374***	-0.0379***	-0.0372***	-0.0388***
	(0.000922)	(0.000933)	(0.00101)	(0.00105)
Tenure sq.	0.0600***	0.0607***	0.0599***	0.0625***
	(0.00189)	(0.00191)	(0.00205)	(0.00214)
Work hours - 16-30 hrs.	-0.156	-0.187	-0.210	-0.229
	(0.164)	(0.166)	(0.183)	(0.189)
Work hours - 31-45 hrs.	0.132	0.101	0.0136	0.0466
	(0.234)	(0.237)	(0.256)	(0.266)
Work hours - above 45 hrs.	0.0781	0.0482	-0.00169	-0.0513
	(0.249)	(0.252)	(0.273)	(0.283)
Wage Residual	-2.207***	-2.213***	-2.173***	-2.256***
	(0.0803)	(0.0812)	(0.0882)	(0.0921)
Other qualifications	1.468***	1.443***	1.428***	1.322***
	(0.132)	(0.134)	(0.152)	(0.155)
Edu - gcse a-c or equiv	1.392***	1.330***	1.367***	1.234***
	(0.120)	(0.122)	(0.136)	(0.140)
Edu - gce a level or equiv	1.648***	1.592***	1.603***	1.433***
	(0.124)	(0.126)	(0.141)	(0.145)
Edu - higher education	2.898***	2.832***	2.791***	2.559***
	(0.158)	(0.161)	(0.176)	(0.181)
Edu - degree or equivalent	3.715***	3.649***	3.571***	3.559***
	(0.153)	(0.155)	(0.169)	(0.176)
Mortgage	-0.701***	-0.682***	-0.670***	-0.720***
	(0.0750)	(0.0757)	(0.0810)	(0.0845)

Continued on next page

Table A-9 – continued from previous page

	(1)	(2)	(3)	(4)
	Interaction Model			
Firm specific training	-0.878***	-0.876***	-0.946***	-1.020***
	(0.0734)	(0.0787)	(0.0860)	(0.0880)
Firm size - 11-19 wrks.	0.151	0.168	0.129	0.105
	(0.140)	(0.142)	(0.154)	(0.159)
Firm size - 20-24 wrks.	-0.165	-0.180	-0.200	-0.194
	(0.180)	(0.182)	(0.196)	(0.202)
Firm size - Under 25 wrks.	-0.00349	-0.0000337	-0.0486	-0.0873
	(0.123)	(0.124)	(0.133)	(0.138)
Firm size - 25-49 wrks.	-0.139	-0.136	-0.166	-0.139
	(0.112)	(0.113)	(0.117)	(0.123)
Firm size - Over 24 wrks.	-0.393***	-0.277**	-0.420***	-0.436***
	(0.120)	(0.128)	(0.154)	(0.158)
Firm size - Over 50 wrks.	-0.630***	-0.644***	-0.639***	-0.655***
	(0.122)	(0.123)	(0.127)	(0.133)
Year	0.0377***			
	(0.00628)			
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	664453	647358	552859	507805

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. Columns (1) depict the results including a linear time trend and a set of binary variables indicating the quarter. Columns (2) and columns (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 the 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 equal to 12. Person weights are used in all regressions. ***, **, * denote statistical significance at the 1%, 5%, and 10% level. Robust standard errors are reported in parentheses.