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Essays on Job Search and Job Choice

A dissertation submitted in partial satisfaction of the
requirements for the degree Doctor of Philosophy
in Economics

by

Anthony Joseph Papac

2023

ABSTRACT OF THE DISSERTATION

Essays on Job Search and Job Choice

by

Anthony Joseph Papac
Doctor of Philosophy in Economics
University of California, Los Angeles, 2023
Professor Till von Wachter, Chair

This dissertation consists of two essays on job search and job choice. In Chapter 1, I examine how on-the-job search (OJS) effort of employed workers varies over the business cycle. First, I document new evidence that aggregate OJS effort rises during a recession, as more workers start searching on-the-job and average search intensity increases when unemployment rises. Next, I account for compositional changes in the pool of employed workers and job seekers over the business cycle and find that workers change their search behavior in response to changing economic conditions. In particular, workers are more likely to search due to fear of job loss and search for an additional job when unemployment is higher. In addition, I find that job seekers increase their search intensity when unemployment rises during a recession. In Chapter 2, I estimate the value that workers place on non-wage job characteristics and assess their impact on compensation inequality in Germany. First, I evaluate the incidence of four key job attributes and find large disparities in the prevalence of job attributes by gender, education, and age. Next, I analyze an experiment given as part of a national survey in Germany to estimate the value that workers place on eight non-wage job attributes.

In particular, I find that workers are willing to pay 31% of their wage to have a permanent employment contract, 13% of their wage for good promotion opportunities, 10% of their wage for schedule flexibility, and 8% of their wage to avoid overtime work requirements. Finally, I find that accounting for the incidence and valuation of non-wage job characteristics widens compensation inequality in Germany.

The dissertation of Anthony Joseph Papac is approved.

Daniel Haanwinckel Junqueira

Maurizio Mazzocco

Yotam Shem-Tov

Till von Wachter, Committee Chair

University of California, Los Angeles

2023

Contents

List of Figures

List of Tables

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VITA

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Chapter 1

On-the-Job Search Over the Business Cycle: Evidence from the United Kingdom

1.1 Introduction

On-the-job search (OJS) plays an important role in labor market dynamics over the business cycle. For example, OJS affects the reallocation of workers to new, more productive sectors and it affects the speed with which an economy exits from a recession, as employed workers compete with unemployed workers for a limited number of job openings. Despite the importance of OJS in understanding labor market dynamics, little is known about OJS behavior of workers over the business cycle. This is largely due to the scarcity of surveys asking *employed* workers about their job search activity. While many surveys ask unemployed workers about job search activity, few surveys ask employed workers about job search, and those that do tend to be cross-sectional in nature, span a limited number of years, and do not ask workers about their motives for searching for another job.

This paper studies the cyclical properties of OJS with data that overcomes these shortcomings. More specifically, I analyze the cyclicality of OJS using data from the UK Labour Force Survey (LFS), which follows workers for up to five quarters, spans three recessions over three decades, and asks workers *why* they are searching for another job, allowing for an analysis of how reasons for OJS change over the business cycle. As such, I document new evidence on the top reasons for OJS and their prominence during recessions and booms. In particular, I find that the top three reasons for OJS are: (i) search for better non-wage job amenities, (ii) search for better pay, and (iii) search due to fear of job loss. While the precautionary motive represents the third most popular reason for OJS, it plays a much more prominent role during recessions, as the share of workers searching due to fear of job loss nearly matches the share of workers searching for better pay.[1]

This paper analyzes the overall cyclicality of OJS along two margins: the extensive and intensive margins. While the extensive margin represents the share of employed workers who decide to engage in OJS, the intensive margin reflects how intensely employed job seekers search for another job. In this paper, I show that the search effort of employed workers is largely countercyclical along both margins. With respect to the extensive margin, I find that the share of workers searching for another job increases when unemployment is higher, driven by an increase in the share of workers who engage in OJS due to fear of job loss. With respect to the intensive margin, I show that average search intensity of job seekers rises during a recession. Finally, I construct a measure of aggregate search effort that combines both margins and find that aggregate search effort of employed workers is highly countercyclical.

Next, this paper disentangles the forces driving the countercyclicality of the aggregate time series. More specifically, it is possible that the aggregate results simply reflect changes in the composition of employed workers and job seekers over the business cycle rather than behavioral changes workers are making in response to changing economic conditions. For

1 Fujita (2010) first showed evidence of the precautionary motive of OJS in the UK using data from the LFS from 2002 to 2009. The present paper documents new evidence concerning the path and prominence of the precautionary motive over the business cycle.

example, the share of workers engaging in OJS may rise during a recession simply because the pool of employed workers remaining during a recession has a higher propensity for job search. Similarly, the observed increase in average search intensity during a recession may simply reflect that the types of workers who search for another job during a recession have higher search intensities on average.

This paper leverages the panel structure of the UK LFS to determine whether the countercyclicality of aggregate OJS is due to changes in the composition of workers and job seekers over the business cycle or due to actual behavioral changes workers are making in response to changing unemployment conditions. First, I find that workers are more likely to engage in OJS when unemployment increases during their time in the panel. This result is driven by workers who decide to engage in OJS due to fear of job loss and OJS for an additional job. In contrast, workers are no more likely to engage in OJS for better pay or better amenities. In addition, I find that employed job seekers increase their search intensity when unemployment increases during their time in the panel. While all job seekers increase the intensity with which they search during a recession, workers searching due to fear of job loss and workers searching for an additional job increase their search intensity the most. These workers arguably have the most to lose if they do not find another job, as they seek to avoid the threat of unemployment and maintain financial security during a recession.

This paper adds to the small empirical literature analyzing job search behavior of workers over the business cycle. In particular, Shimer (2004) was the first to point out that the job search effort of unemployed workers appears to be countercyclical. Mukoyama et al. (2018) corroborate and expand on this finding by linking individuals' responses in the US Current Population Survey to their diary responses in the American Time Use Survey (ATUS). Similar to the results of this paper, they find that unemployed workers are more likely to engage in job search during a recession and that unemployed workers search more intensely during a recession. In addition, Ahn and Shao (2021) are the first to study the cyclicality of job search effort of *employed* workers. Using cross-sectional data from the ATUS from

2003 to 2015, these authors find suggestive evidence that OJS increases during a recession. This paper similarly finds that OJS is countercyclical, but unlike Ahn and Shao (2021), this study is able to discern whether the countercyclicality is due to a changing composition of workers or actual behavioral changes workers are making in response to changing economic conditions. Furthermore, this paper is able to track how different reasons for OJS change over the business cycle, which proves essential when explaining fluctuations in total OJS.

In addition, this study contributes to the large theoretical literature using search models to analyze the labor market. Canonical models of OJS, such as those outlined in Mortensen (1986) and that proposed by Christensen et al. (2005), have historically focused on one type of OJS: search for better pay. However, the descriptive results of this paper reveal that more workers actually search for better non-wage job attributes at any point over the business cycle, and the share of workers searching due to fear of job loss nearly matches the share of workers searching for better pay during a recession. As such, this study highlights the need for future search models to better reflect the true search motives of workers. While studies, such as those by Bonhomme and Jolivet (2009), Sullivan and To (2014), and Hall and Mueller (2018), have recently started incorporating search for better non-wage amenities into search models, few models have incorporated a precautionary motive of OJS.[2]

The finding that OJS is countercyclical is important for several reasons. First, the countercyclicality of OJS suggests that employed workers are crowding out the job search of unemployed workers during a recession. The high level of congestion in the labor market during a recession can contribute to longer unemployment spells of workers, as unemployed workers struggle to compete with employed workers for a limited number of job openings. Furthermore, congestion in the labor market affects the speed with which an economy exits from a recession, since the unemployment rate may take a longer time to fall if employed

2 Notably, Jarosch (2021) estimates a model in which jobs differ in terms of unemployment risk and pay, and workers search to improve their position in the job ladder by achieving higher pay and/or greater job security.

workers are out-competing unemployed workers when firms hire for open positions.

Second, the macro-search literature has struggled to generate high enough volatility in unemployment, vacancies, and labor productivity over the business cycle. Because of this, recent studies, such as Krause and Lubik (2010), Martin and Pierrard (2014), and Eeckhout and Lindenlaub (2019), have proposed that procyclical OJS be used as an amplification mechanism to generate higher volatility in these measures. In particular, they argue that there is a strategic complementarity between OJS by workers and vacancy posting by firms. In other words, employed workers are more likely to search for jobs when there are numerous vacancies, and firms are more likely to post vacancies when there are numerous employed workers searching for jobs. While job-to-job transitions of workers are procyclical, this study finds strong empirical evidence that OJS behavior is not.[3] Consequently, this paper's findings suggest that search models should turn toward other mechanisms (perhaps countercyclical OJS) to generate more realistic volatility in macroeconomic measures.

Finally, the results of this paper point to important considerations when setting unemployment insurance (UI) policy. In particular, I find that many workers start searching for other jobs because they fear falling into unemployment during a recession. Since the generosity of UI benefits affects the size of the threat of job loss, it is possible that generous UI benefits can discourage workers from searching for other jobs. Indeed, Light and Omori (2004) found early evidence that an increase in UI benefits was associated with a small but significant drop in job-to-job transitions motivated by quits among respondents of the 1979 National Longitudinal Survey of Youth. Moreover, Gutierrez (2016) found evidence that an increase in the potential replacement rate of UI significantly decreased the probability that older Americans at risk of job loss reported searching for another job. These studies, combined with this paper's finding that precautionary OJS represents a large fraction of

3 Fallick and Fleischman (2004) show that job-to-job transitions are highly procyclical in the US. Carrillo-Tudela et al. (2016) similarly show that job-to-job transitions are procyclical in the UK.

total OJS, underscore the potential impacts that UI can have on OJS behavior of workers and the unemployment rate during a recession.

The rest of this paper is organized as follows. Section 1.2 discusses the data and how it is used in the time series and empirical analysis. Section 1.3 shows how key OJS measures vary over the business cycle. Section 1.4 outlines the empirical strategy and Section 1.5 discusses the empirical results. Finally, Section 1.6 concludes and offers ideas for future research.

1.2 Data

The Labour Force Survey (LFS) is the largest household survey conducted in the United Kingdom and is the basis for official reporting on employment and unemployment by the Office for National Statistics (ONS). The survey consists of a rotating panel in which respondents are followed for up to five consecutive quarters and new respondents are added each quarter to replace those who have exited the survey. The LFS has been conducted on a quarterly basis since 1992: Q2 and asks respondents about employment and unemployment activities as well as job search behavior.[4] The samples used for the analysis of this paper are restricted to 18 to 64 year old respondents to focus on the job search behavior of prime, working-age individuals.

This paper makes use of two separate data sets provided by the ONS: the Quarterly Labour Force Survey data and the Two-Quarter Longitudinal Labour Force Survey data. While the Quarterly Labour Force Survey data consists of all individuals who appear at least once in the survey, the Two-Quarter Longitudinal Labour Force Survey data consists of all individuals who respond to at least two quarters up to a maximum of five quarters of the survey. The first data file contains more observations and is used for the aggregate time

4 More information about the LFS can be found in the *Labour Force Survey: User Guide* (2021). In addition, more information about the data can be found in *Labour Force Survey* (2023).

series analysis to depict time trends of job search behavior and demographic characteristics of workers with greater precision. The second data file is used in the individual-level regression analysis to take advantage of the panel structure.

Table 1.1 details the main demographic and labor market characteristics of individuals in the Quarterly Labour Force Survey and the Two-Quarter Longitudinal Labour Force Survey. Overall, there are few differences in the characteristics of respondents in each data file, suggesting that survey attrition is not leading to significant changes in the composition of employed workers or job seekers across data files. Table 1.1 does, however, point to significant differences in the characteristics of employed workers and job seekers. On average, job seekers tend to be younger, less tenured, and more educated than the average worker. They also tend to earn lower wages than workers not searching for another job.[5]

Each quarter employed respondents are asked if they looked for a different or additional paid job during the week before the survey. If the respondents answer affirmatively, respondents are then asked to indicate up to three reasons why they are searching for another job, with the reasons being recorded in the order given by respondents.[6] Table 1.2 lists the 10 possible reasons for OJS. The options indicating "change occupation" and "change sector" were added in 2008 and 2011, respectively. About 72% of respondents who provided a reason for job search listed just one reason, while the remaining respondents provided either two or three reasons. This paper chooses to use the first reason listed by respondents for the analysis because this allows the share of workers searching for each reason to sum to the total share of workers searching for another job. Figure A.1 in Appendix A shows that

5 This is consistent with Mueller (2010) and Faberman et al. (2022) who show that OJS is highly elastic with respect to a worker's wage and that individuals who earn lower wages are more likely to be searching for another job.

6 About 12% of job seekers indicate they are searching for an additional job, while 88% indicate they are searching for a job to replace their existing one. Unfortunately, respondents who indicate that they are searching for an additional job are not asked why they are searching for an additional job.

Table 1.1: LFS Sample Summary Statistics

	Quarterly LFS (*Aggregate Analysis*)		Longitudinal LFS (*Individual Analysis*)	
	Workers	Job Seekers	Workers	Job Seekers
Male	0.54	0.54	0.54	0.54
Married	0.57	0.43	0.56	0.42
Nonwhite	0.09	0.12	0.08	0.12
Degree or higher education	0.35	0.40	0.37	0.42
GCE A level or equiv.	0.24	0.24	0.25	0.24
GCSE grades A*-C or equiv	0.21	0.20	0.20	0.19
No/Other qualification	0.20	0.16	0.18	0.15
18-34 years old	0.37	0.52	0.38	0.53
35-49 years old	0.38	0.35	0.37	0.34
50-64 years old	0.25	0.14	0.25	0.13
0-2 years of tenure	0.28	0.45	0.29	0.45
2-10 years of tenure	0.41	0.42	0.40	0.42
10+ years of tenure	0.31	0.13	0.31	0.13
Full time	0.77	0.68	0.76	0.67
Mean hourly wage	12.5	10.8	12.6	11.0
Mean OJS rate	0.065	1.00	0.066	1.00
Mean no. of search methods used	–	3.15	–	3.25
Mean no. of quarters in the panel	–	–	4.1	4.0
No. observations	6,146,705	330,642	4,620,814	238,103

Notes: Samples are restricted to 18-64 year old respondents. Sample weights are used.

plotting OJS reasons using the first reason listed by respondents versus any reason listed by respondents yields qualitatively similar results, as both methods depict the same narrative of how OJS reasons vary over the business cycle.

Table 1.2 shows that the top three reasons for OJS are: (i) search for better non-wage job characteristics, (ii) search for better pay, and (iii) search due to fear of losing one's current job. For simplicity, search for a better commute, more working hours, fewer working hours, and better nonpay aspects of one's job are classified as search for better nonpay amenities. As Table 1.2 shows, there are a number of reasons for job search that are unclear in motives. For example, workers searching to change their occupation may want to change their occupation to increase their pay, improve their nonpay amenities, or decrease their risk of job loss. Because the time series analysis in this paper seeks to understand how reasons for OJS fluctuate over the business cycle, reasons with unclear motives, including "change occupation", "change sector", "current job to fill time before next job", and "other", are reapportioned to the top three job search reasons, which have very distinct, clear motives.

Table 1.2: Reasons for OJS

OJS Reason	Share of Job Seekers Listing Reason
Fear losing current job	0.15
Want better pay	0.22
Want better nonpay amenities	0.33
Improve commute to work	0.04
Want more hours	0.06
Want fewer hours	0.03
Improve nonpay aspects of job	0.19
Present job to fill time before next job	0.09
Change occupation	0.05
Change sector	0.01
Other	0.16
No. observations	328,090

Notes: Sample weights are used. First listed OJS reason is reported.

Two apportionment schemes were used to reclassify reasons with unclear motives to the top three job search reasons. In the first scheme, next quarter (clear motive) responses by individuals who listed unclear search reasons in the prior quarter were used to infer the respondents' motives for job search. In the second scheme, second or third (clear motive) reasons for job search were used to apportion individuals who listed an unclear first reason to the top three job search reasons. Figure A.2 in Appendix A shows that both schemes lead to similar qualitative results, with both yielding the same narrative of how OJS reasons fluctuate over the business cycle. Inconsequentially, this paper uses the first scheme to apportion job seekers with unclear motives to the top three job search reasons, as the sample sizes used in this scheme were much larger.

Finally, respondents are asked which methods they used to search for another job during the last four weeks. In particular, they are asked to indicate one or more methods they used from a list of 11 possible search methods. Table 1.3 reveals the proportion of employed job seekers who used each of the 11 search methods. The most common search methods were studying vacancies in newspapers, journals, or on the internet, responding to job advertisements, and asking friends and family about job openings. On average, employed job seekers used 3.25 methods in their job search efforts.

Table 1.3: Search Methods Used by Employed Job Seekers

Job Search Method	Share of Job Seekers Using Method
Visit a job center	0.15
Visit a career office	0.02
Visit a job club	0.01
Use a private employment agency	0.23
Advertise in newspapers, journals, or on the internet	0.09
Respond to ads in newspapers, journals, or on the internet	0.52
Study vacancies in newspapers, journals, or on the internet	0.83
Apply directly to employers	0.41
Ask friends or relatives about jobs	0.43
Wait for results of a job application	0.35
Do anything else to find work	0.08
Mean no. of methods used	3.25
Mean no. of active methods used	2.40
No. observations	238,103

Notes: Sample weights are used.

The total number of methods used by job seekers serves as a measure of job search intensity in this paper. This follows in the tradition of papers that have used the number of search methods used by unemployed job seekers as a measure of job search intensity, including Shimer (2004) and Mukoyama et al. (2018).[7] One concern with using the number

7 Mukoyama et al. (2018) relate the number of search methods used to time spent searching for a job by linking survey responses of individuals who participated in the Current Population Survey and the American Time Use Survey. They show a very close relationship between the two search intensity measures, with average time spent searching for a job increasing almost linearly with the number of search methods used by respondents.

of search methods is that it might not accurately reflect changes in the intensity of job search if workers substitute from more active forms of job search to more passive forms of job search at different points in the business cycle. For example, workers may be more likely to browse vacancies online but equally less likely to apply directly to employers, keeping the average number of search methods unchanged but search intensity has arguably fallen. To address this concern, this paper also uses the number of active search methods as a measure of job search intensity.[8] Nonetheless, only results using the total number of search methods are reported in this paper, as results using the number of active search methods are qualitatively similar.

1.3 Time Series Analysis

This paper studies the job search behavior of employed workers over the business cycle along two margins: the extensive margin and the intensive margin. While the extensive margin describes the share of employed workers who decide to engage in OJS, the intensive margin describes how intensely employed workers search for another job, conditional on having decided to search. Finally, this paper combines the extensive and intensive margins of OJS to create a measure of aggregate job search effort of employed workers in the UK economy.

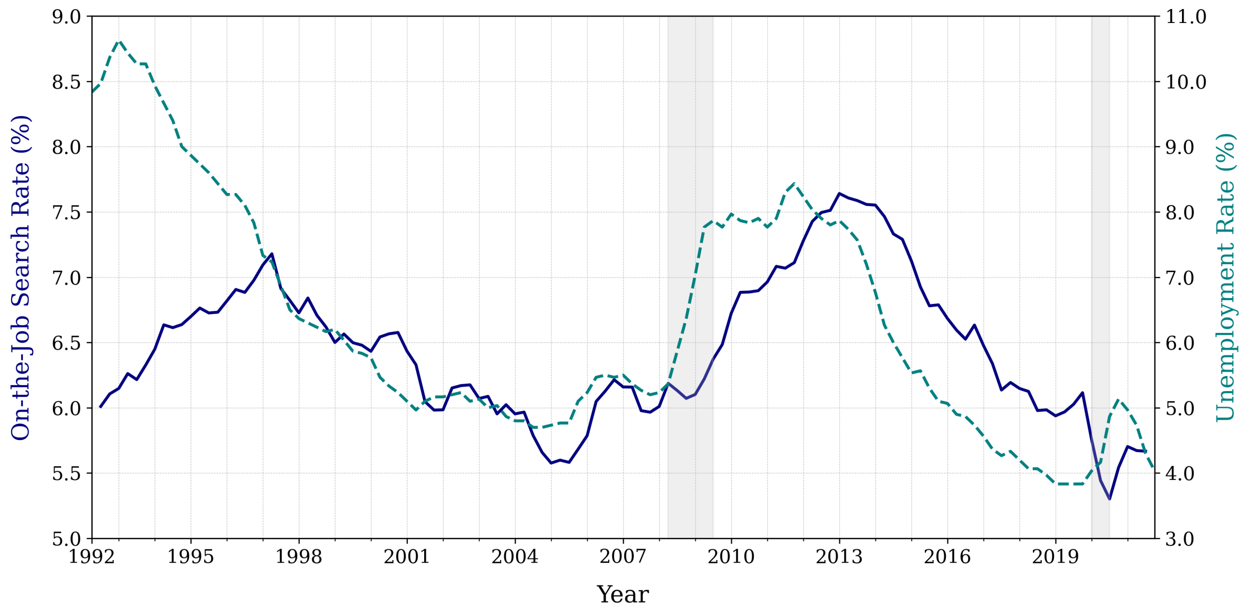
1.3.1 Extensive Margin of OJS

Figure 1.1 plots the evolution of the extensive margin of OJS along with the UK unemployment rate from 1992 to 2021. Overall, the figure shows that the share of workers searching for another job tends to fall at the beginning of a recession but then quickly rises as unemployment increases. Interestingly, the share of workers engaging in OJS continues to rise for

8 Active search methods include all listed methods, except "studying vacancies in newspapers, journals, or on the internet" and "other", which is consistent with the classification of active and passive search methods in the CPS.

three to four years after peak unemployment is reached in the early 1990's recession, while the share of workers engaging in OJS continues to rise for one year after peak unemployment is reached after the Great Recession. One to four years after unemployment peaks, the share of workers searching for another job then quickly falls as the unemployment rate falls.

Figure 1.1: On-the-Job Search Over the Business Cycle

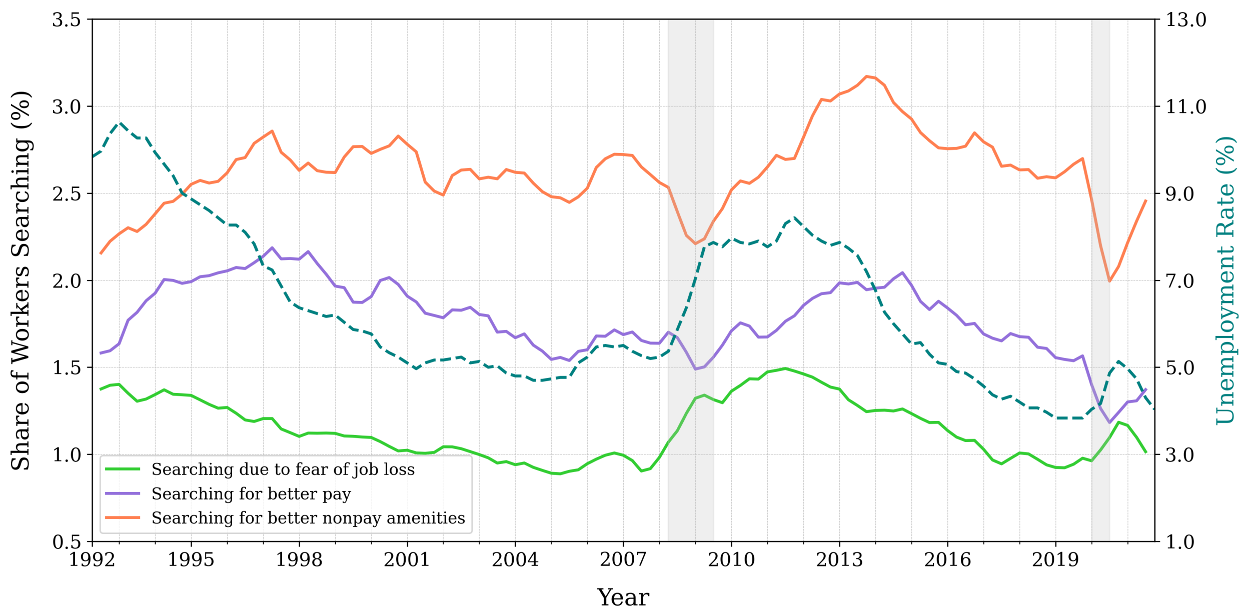


Notes: Graph starts in 1992: Q2 and ends in 2021: Q4. All tick marks reflect the first quarter of the year represented, except the first tick mark. Sample weights used. The three quarter moving average of OJS is plotted to smooth OJS seasonality.

Overall, the extensive margin of OJS appears to follow the path of the unemployment rate but with a lag. However, explanations for why the OJS rate behaves in this manner cannot be discerned from Figure 1.1 alone. This is because, by construction, the share of workers engaging in OJS at a particular time depends in part on the pool of workers who are employed during a particular time. Because unemployment risk does not uniformly affect all workers during a recession, the composition of the pool of employed workers changes over the business cycle. Thus, a rising OJS rate does not necessarily signify that workers are changing their OJS behavior over the business cycle; a rising OJS rate could simply reflect the fact that the pool of employed workers is shifting toward workers who typically have higher propensities for job search. Consequently, the empirical part of this paper seeks to discern whether the rising OJS rate during a recession is due purely to compositional changes in the pool of employed workers or if there are actual changes in job search behavior of workers in response to changing economic conditions.

Figure 1.2 further explores the extensive margin by breaking OJS down by search reason.[9] First, Figure 1.2 documents evidence of a significant precautionary motive of OJS that is highly countercyclical. While most search models assume that workers only search for better pay or better amenities, Figure 1.2 shows that the share of workers searching due to fear of job loss rises significantly during a recession to the point where the share of workers searching due to fear of job loss nearly matches the share of workers searching for better pay. This highlights the need for existing search models to incorporate precautionary OJS to better reflect the true motives of many workers seeking to change jobs over the business cycle.

Figure 1.2: On-the-Job Search by Reason Over the Business Cycle



Notes: Graph starts in 1992: Q2 and ends in 2021: Q4. All tick marks reflect the first quarter of the year represented, except the first tick mark. Sample weights used. The three quarter moving averages of OJS rates are plotted to smooth seasonality.

9 Figure 1.2 reflects only workers who are searching for a different job, as workers searching for an additional job are not asked why they are searching for another job. Figure A.3 in Appendix A plots the share of workers searching for an additional job over the business cycle, revealing that OJS for an additional job is also countercyclical.

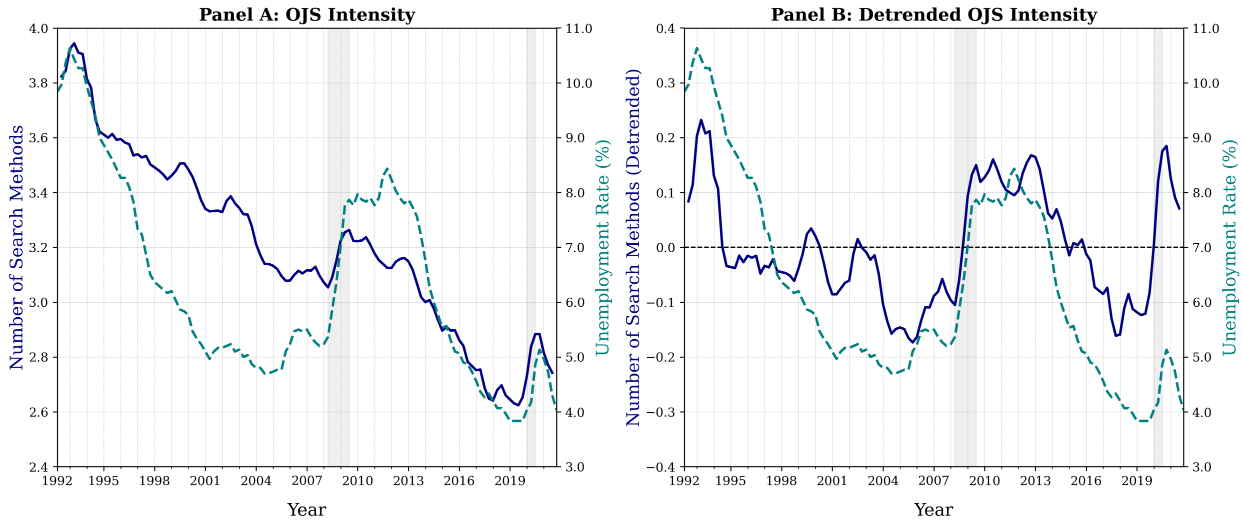
Next, Figure 1.2 illustrates that a large share of workers engage in OJS for traditional job ladder reasons over the business cycle. While the shares of workers searching for better pay and better nonpay amenities fall at the beginning of a recession, they quickly rise as more workers seek to improve their position in the job ladder. A few years after unemployment peaks, the shares of workers searching for better pay and better amenities then fall as unemployment continues to fall. Whether these time trends reflect changes in job search behavior or compositional changes in the pool of employed workers over the business cycle is explored in the empirical section of this paper.

1.3.2 Intensive Margin of OJS

While the extensive margin shows how the share of workers engaging in OJS evolves over time, the intensive margin shows how the search intensity of employed job seekers evolves over time. Figure 1.3 plots the number of search methods used by employed job seekers from 1992 to 2021 in the UK. Two observations stand out in Figure 1.3. First, the number of search methods used has steadily declined over time from about 3.8 methods to 2.8 methods. This is in large part due to workers ditching traditional in-person methods, such as visiting a job center, in favor of methods relying more on the internet, such as responding to job ads online. Indeed, Figure A.4 in Appendix A shows how the share of job seekers using each search method has changed since 1992. While use of most methods has decreased since 1992, methods relying more on the internet have experienced smaller declines or have even increased in use over time. Because there is a strong downward trend in the number of search methods used over time, Figure 1.3 also plots the cyclical component of OJS intensity over the time period under consideration. In particular, the number of search methods was regressed on a linear time trend and the residual was taken as the cyclical component of OJS intensity.

Both graphs in Figure 1.3 highlight that the number of search methods used by employed

Figure 1.3: On-the-Job Search Intensity Over the Business Cycle



Notes: Graphs start in 1992: Q2 and end in 2021: Q4. All tick marks reflect the first quarter of the year represented, except the first tick mark. Sample weights used. In Panel A, the three quarter moving average of OJS intensity is plotted to smooth seasonality. In Panel B, the number of search methods is regressed on a linear time trend and the cyclical component is plotted.

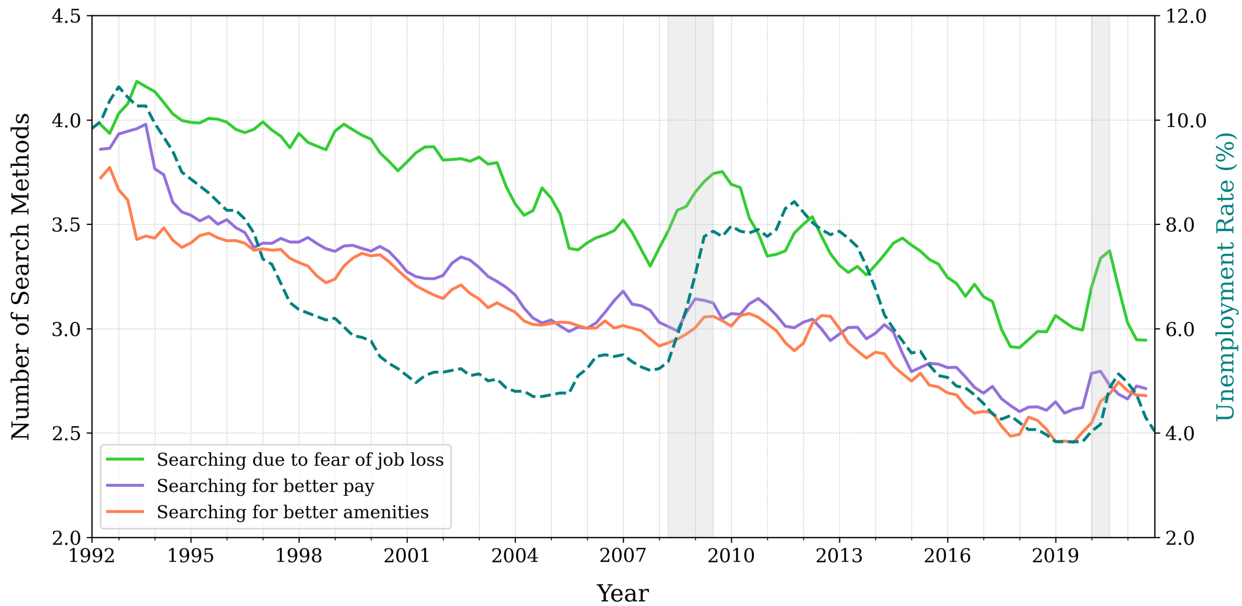
job seekers spikes during a recession.[10] Similar to the extensive margin results, it is possible that the rise in average search intensity of employed job seekers is due to compositional changes in the pool of employed job seekers over the business cycle. That is, Figure 1.3 may simply reflect the fact that the types of workers who engage in OJS during a recession have higher search intensity anyway. Consequently, the empirical section of this paper seeks to disentangle the sources of the increase in average search intensity during a recession. In particular, it seeks to discern how much of the increase reflects compositional changes in the pool of job seekers and how much of the increase reflects actual increases in search intensity by job seekers during a recession.

Figure 1.4 plots the average search intensity of workers searching for different reasons over the business cycle. Again, two observations stand out. First, the average search intensity of job seekers who fear losing their job is about 15% higher than that of job seekers who search for better pay or better amenities. The impending threat of unemployment likely creates a

10 This finding is similar to that of Mukoyama et al. (2018) who find that search intensity of unemployed job seekers increases during recessions.

sense of urgency in these workers to find a job quickly, leading them to search harder than job seekers motivated by job ladder reasons.[11] Second, while search intensity increases for all job seekers during a recession, search intensity increases most starkly for workers who search due to fear of job loss. With rising unemployment risk and fewer job openings to apply to, workers who fear losing their jobs must search harder to find a job to avoid falling into unemployment.

Figure 1.4: On-the-Job Search Intensity by Reason Over the Business Cycle



Notes: Graph starts in 1992: Q2 and ends in 2021: Q4. All tick marks reflect the first quarter of the year represented, except the first tick mark. Sample weights used. The three quarter moving average of OJS intensity is plotted to smooth seasonality.

1.3.3 Aggregate Search Effort of Employed Workers

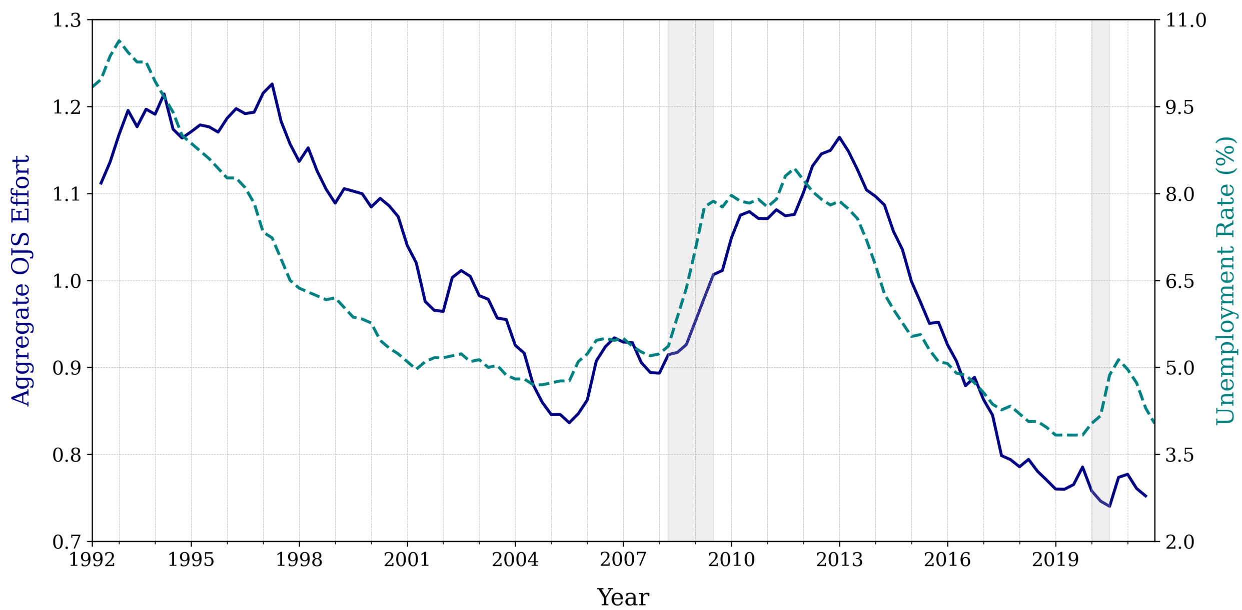
This paper defines the aggregate search effort of employed workers as the share of workers searching for another job multiplied by the average search intensity per job seeker plus the share of workers not searching for another job multiplied by the average search intensity

11 Employed job seekers who fear losing their job are about four times as likely to become unemployed the following quarter than job seekers motivated by job ladder reasons.

per non-job seeker. Since non-job seekers do not exert any search effort by definition, the aggregate search effort of employed workers reduces to the extensive margin multiplied by the intensive margin.[12]

Figure 1.5 plots the total search effort of employed workers from 1992 to 2021, with the average of the time series normalized to 1. Figure 1.5 illustrates that the aggregate search effort of employed workers closely follows the unemployment rate. When unemployment increases, aggregate search effort of employed workers tends to increase. When unemployment falls, aggregate search effort of employed workers tends to fall.[13]

Figure 1.5: Aggregate On-the-Job Search Effort Over the Business Cycle



Notes: Aggregate OJS effort is defined as the extensive margin multiplied by the intensive margin. This represents the share of workers searching multiplied by the average search intensity per searcher plus the share of workers not searching multiplied by the average search intensity per non-searcher (0). Graph starts in 1992: Q2 and ends in 2021: Q4. All tick marks reflect the first quarter of the year represented, except the first tick mark. Sample weights used. The three quarter moving average of aggregate OJS effort is plotted to smooth seasonality.

The strong countercyclical nature of aggregate OJS effort is significant because it suggests

12 This is similar to how Mukoyama et al. (2018) define aggregate search effort of unemployed workers.

13 Mukoyama et al. (2018) similarly find that aggregate search effort of unemployed workers increases during recessions.

that employed workers are crowding out the job search efforts of unemployed workers when unemployment is high. The high level of congestion in the labor market during a recession can contribute to longer unemployment spells of workers, as unemployed workers struggle to compete with employed workers for a limited number of job openings. Furthermore, congestion in the labor market affects the speed with which an economy exits from a recession, since the unemployment rate may take a longer time to fall if employed workers are out-competing unemployed workers when firms hire for open positions.

1.4 Empirical Strategy

While the extensive and intensive margins of OJS are found to be largely countercyclical, it is unclear whether the aggregate time series results are due to compositional changes in the pool of employed workers and job seekers or due to behavioral changes workers are making in response to changing economic conditions. One of the objectives of this paper is to empirically determine whether workers are changing their OJS behavior when unemployment rises and falls over the business cycle.

1.4.1 Extensive Margin of OJS

This paper estimates how an individual's probability of engaging in OJS changes with the unemployment rate. To do this, I estimate three empirical specifications.

(1.1) *OLS:* $\quad 1(\text{Engage in OJS})_{it} = \beta_0 + \beta_1(\text{UE Rate})_t + \beta_2\text{t} + \tau_q + \epsilon_{it}$

(1.2) *OLS with Controls:* $\quad 1(\text{Engage in OJS})_{it} = \beta_0 + \beta_1(\text{UE Rate})_t + \beta_2\text{X}_{it} + \beta_3\text{t} + \tau_q + \epsilon_{it}$

(1.3) *Fixed Effects:* $\quad 1(\text{Engage in OJS})_{it} = \beta_0 + \beta_1(\text{UE Rate})_t + \beta_2\text{X}_{it} + \beta_3\text{t} + \tau_q + \alpha_i + \epsilon_{it}$

First, this paper estimates a simple ordinary least squares (OLS) model with a linear time trend and quarter fixed effects to control for seasonality of job search.[14] While this specification yields a basic correlation between the unemployment rate and the decision to engage in OJS, part of the correlation will reflect changes in the composition of workers over the business cycle and part of the correlation will reflect changes in the probability of workers deciding to engage in OJS over the business cycle (if any).

This paper then estimates a second OLS model but with an extensive set of individual controls, including age, age squared, sex, ethnicity, marital status, educational attainment, job tenure, full time status, and industry. This specification controls for a changing composition of workers with respect to observable characteristics of workers. However, it is likely that the coefficient on the unemployment rate will reflect a changing composition of workers with respect to unobservable characteristics, making it impossible to say something about how higher unemployment influences individuals' probability of searching for another job. For example, suppose that less productive workers are more likely to search for other jobs than more productive workers. In as much as worker productivity is not captured by the set of controls, it is possible that the pool of employed workers becomes more productive during a recession as less productive workers are more likely to be laid off by firms. In this case, the changing composition of workers would make the coefficient on the unemployment rate smaller (or more negative). Consequently, this specification is still unable to say something about how higher unemployment influences workers' decisions to engage in OJS.

Finally, this paper leverages the panel structure of the LFS to estimate a third model that controls for individual fixed effects. This model allows us to say something more about the behavioral changes workers are making in response to changing economic conditions during their time in the panel. In particular, the fixed effects allow us to abstract from compositional changes happening in the workforce and to focus on whether workers are becoming more or

14 This paper finds that a higher share of workers search during the first quarter of the year, while a lower share of workers search during the last quarter of the year.

less likely to engage in OJS in response to a changing unemployment rate during their time in the panel.

1.4.2 Intensive Margin of OJS

Next, this paper estimates how job seekers change their search intensity in response to changing unemployment conditions. To this end, I estimate three empirical specifications to evaluate the intensive margin of OJS.[15]

(1.4) *OLS:* $\text{Search Intensity}_{it} = \beta_0 + \beta_1(\text{UE Rate})_t + \beta_2 \text{t} + \tau_q + \epsilon_{it}$

(1.5) *OLS with Controls:* $\text{Search Intensity}_{it} = \beta_0 + \beta_1(\text{UE Rate})_t + \beta_2 \text{X}_{it} + \beta_3 \text{t} + \tau_q + \epsilon_{it}$

(1.6) *Fixed Effects:* $\text{Search Intensity}_{it} = \beta_0 + \beta_1(\text{UE Rate})_t + \beta_2 \text{X}_{it} + \beta_3 \text{t} + \tau_q + \alpha_i + \epsilon_{it}$

First, this paper estimates a simple OLS model with a linear time trend and quarter fixed effects to control for the general decline in search intensity over time and to control for seasonal variation in the intensity of job search.[16] While this specification yields a basic correlation between the unemployment rate and search intensity, part of the correlation will reflect changes in the composition of job seekers over the business cycle and part of the correlation will reflect changes in the intensity with which job seekers search for another job over the business cycle (if any).

This paper then estimates a second OLS model but with the same extensive set of controls used in the second model of the extensive margin. This specification controls for a changing composition of job seekers with respect to basic observable characteristics. However, it is likely that the coefficient on the unemployment rate will reflect a changing composition of job

15 As in the time series analysis, the number of search methods used serves as a measure of a job seeker's search intensity, with a larger number of methods used signifying greater search intensity.

16 This paper finds that search intensity is typically highest during the first quarter of the year, while search intensity is lowest during the last quarter of the year.

seekers with respect to unobservable characteristics, making it impossible to say something about how higher unemployment influences job seekers' intensity of job search. For example, suppose that less productive workers search more intensely than more productive workers. If less productive workers face greater layoff risk during a recession and thus start searching for other jobs in greater numbers due to fear of job loss, it is possible that the pool of employed job seekers becomes relatively less productive during a recession. In this case, the changing composition of job seekers would make the coefficient on the unemployment rate larger (or more positive). Consequently, this specification is still unable to say something about how higher unemployment influences the intensity with which job seekers search for another job.

Finally, this paper exploits the rotating panel of the LFS to estimate a third model that controls for individual fixed effects. Similar to the third model in the extensive margin, this model allows us to say something more about the behavioral changes job seekers are making in response to changing economic conditions during their time in the panel. In particular, the fixed effects allow us to abstract from compositional changes happening in the pool of employed job seekers and to focus on whether job seekers are increasing (or decreasing) their search intensity in response to a changing unemployment rate during their time in the panel.

1.5 Empirical Results

This paper empirically estimates how unemployment conditions influence the job search behavior of employed workers. Section 1.5.1 evaluates whether a higher unemployment rate impacts workers' decisions to engage in OJS for different reasons. Section 1.5.2 assesses how higher unemployment affects the intensity with which employed workers search for another job. Finally, Section 1.5.3 explores heterogeneity in the empirical results, analyzing how different groups of workers change their job search behavior in response to changing unemployment conditions.

1.5.1 Extensive Margin of OJS

Table 1.4 summarizes the extensive margin results from the three specifications outlined in the empirical strategy section. The first column gives the relationship between the unemployment rate and the probability of engaging in OJS for any reason. Columns two through six show the relationship between the unemployment rate and the probability of engaging in OJS for specific reasons, including fear of job loss, better pay, better amenities, desire for an additional job, and other reasons.

Table 1.4: Extensive Margin Regression Results

		OJS by Reason				
Dependent variable: OJS Decision	All OJS	Fear of Job Loss	Better Pay	Better Amenities	Add'l Job	Other Reasons
OLS Regression: Basic						
UE Rate	0.00240***	0.00096***	0.00013	-0.00004	0.00080***	0.00048***
	(0.00033)	(0.00005)	(0.00010)	(0.00012)	(0.00005)	(0.00011)
OLS Regression: Controls						
UE Rate	0.00357***	0.00114***	0.00037***	0.00029**	0.00095***	0.00076***
	(0.00032)	(0.00005)	(0.00012)	(0.00014)	(0.00006)	(0.00013)
Fixed Effect Regression						
UE Rate	0.00117*	0.00159***	-0.00017	-0.00029	0.00084***	0.00026
	(0.00062)	(0.00024)	(0.00027)	(0.00034)	(0.00026)	(0.00036)
Mean OJS Rate	0.065	0.008	0.012	0.018	0.009	0.017
No. Persons	1,208,080	1,208,080	1,208,080	1,208,080	1,208,080	1,208,080
No. Observations	4,559,914	4,559,914	4,559,914	4,559,914	4,559,914	4,559,914

Notes: Standard errors are clustered by quarter in OLS regressions and individual for FE regressions. Quarter fixed effects and time trend included. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

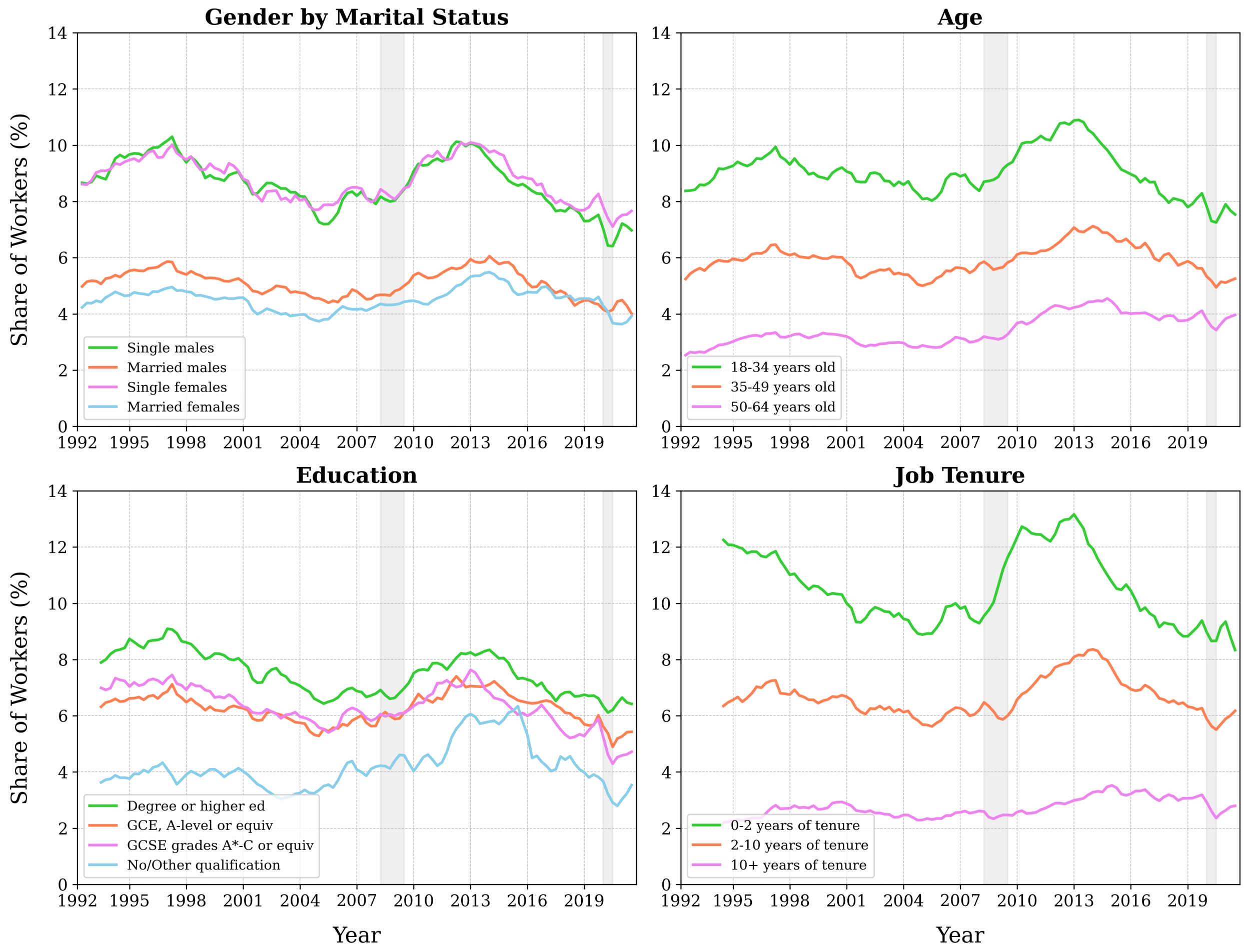
The first row reveals that the unemployment rate and decision to engage in OJS are positively related, but this result is driven by OJS due to fear of job loss and OJS for an additional job. Indeed, the correlations between the unemployment rate and search for better pay, better amenities, and other reasons are insignificant or smaller in magnitude. The second row of Table 1.4 shows that the correlation between the unemployment rate and the decision to engage in OJS is still positive after controlling for observable characteristics of workers. Finally, the fixed effect specification estimates reveal that workers are more likely to engage in OJS when unemployment increases during their time in the panel, but this result is again driven by OJS due to fear of job loss and OJS for an additional job.

The fixed effect estimates are consistent with the types of job search that we would expect to play a more prominent role during a recession. As unemployment risk and liquidity constraints tend to rise during a recession, we would expect OJS due to fear of job loss and OJS for an additional job to increase during a recession as well. In contrast, it is not clear why workers should become more likely to search for better pay or better amenities when unemployment is higher. Indeed, the fixed effect estimates show that workers are no more likely to engage in OJS for job ladder reasons when unemployment is high than they are when unemployment is low.

The differences in magnitudes of the coefficients going from the OLS regressions to the fixed effect regressions tell us about the potential role that changes in the composition of workers is playing in the time series results. Unemployment risk, of course, is not random, and different types of workers face different unemployment risks during a recession. Indeed, Figure A.5 in Appendix A illustrates that unemployment risk of workers is highly correlated with many observable characteristics of workers, including age, marital status, and job tenure. Most notably, workers who are lower tenured face significantly higher unemployment risks than other workers, consistent with many studies that have found that the last workers to join a firm are typically the first to be let go.

Figure A.6 in Appendix A depicts how the composition of workers across observable characteristics changes over the business cycle. More specifically, it shows that the pool of employed workers during a recession becomes slightly younger and substantially higher tenured. This is important because younger, lower tenured workers have much higher OJS propensities than other workers, as seen in Figure 1.6. If workers with higher propensities of job search are dropping out of the pool of employed workers during a recession, then the pool of workers remaining has a lower average propensity to engage in OJS. This puts downward pressure on the coefficients of the basic OLS regression, as the pool of workers when unemployment is higher has on average lower search propensity. As expected, when

Figure 1.6: OJS Rates by Worker Characteristics Over the Business Cycle



Notes: Graphs start in 1992: Q2 and end in 2021: Q4. All tick marks reflect the first quarter of the year represented, except the first tick mark. Sample weights used. The three quarter moving averages are plotted to smooth seasonality. Consistent education groupings are available from 1993:Q2 onward. Job tenure is available from 1994:Q2 onward.

we add the set of individual controls in the second specification, the OLS coefficients rise in magnitude as we control for compositional changes in the observable characteristics of workers that are related to both the unemployment rate and workers' probability of OJS.

Nonetheless, the coefficients in the second OLS specification are still biased because unobservable characteristics of workers, such as worker motivation or productivity, can be correlated with the unemployment rate and the decision to engage in OJS. For this reason, this paper prefers the fixed effect specification, as the fixed effect estimates tell us about the behavioral changes workers are making in response to higher unemployment. That is, they reveal that workers are more likely to engage in OJS due to fear of job loss and are more likely to start searching for an additional job when the unemployment rate increases during their time in the panel.

1.5.2 Intensive Margin of OJS

Table 1.5 summarizes the intensive margin results from the three specifications outlined in the empirical strategy section. The first column gives the relationship between the unemployment rate and search intensity for workers engaging in OJS for any reason. Columns two through six show the relationship between the unemployment rate and search intensity for workers who are searching for specific reasons, including fear of job loss, better pay, better amenities, desire for an additional job, and other reasons.

Table 1.5: Intensive Margin Regression Results

		Reason for OJS				
Dependent variable: No. of Search Methods	All OJS	Fear of Job Loss	Better Pay	Better Amenities	Add'l Job	Other Reasons
OLS Regression: Basic						
UE Rate	0.061***	0.064***	0.046***	0.045***	0.084***	0.058***
	(0.007)	(0.017)	(0.010)	(0.010)	(0.019)	(0.012)
OLS Regression: Controls						
UE Rate	0.055***	0.070***	0.036***	0.044***	0.078***	0.049***
	(0.007)	(0.017)	(0.011)	(0.011)	(0.019)	(0.013)
Fixed Effect Regression						
UE Rate	0.134***	0.242***	0.099	0.136**	0.269***	0.075
	(0.027)	(0.092)	(0.069)	(0.054)	(0.097)	(0.067)
Mean No. of Methods	3.39	3.72	3.31	3.17	3.23	3.40
No. Persons	53,783	4,867	8,933	13,477	4,162	10,169
No. Observations	134,804	11,392	21,809	32,364	9,776	23,868

Notes: Standard errors are clustered by quarter in OLS regressions and individual for FE regressions. Quarter fixed effects and time trend included. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

The first row reveals that the unemployment rate and search intensity are positively related for all job seekers, but the correlation is strongest for workers searching due to fear of job loss and workers searching for an additional job. The second row of Table 1.5 shows that the correlation between the unemployment rate and search intensity of job seekers is still positive after controlling for observable characteristics of job seekers. Finally, the fixed effect estimates reveal that job seekers increase their search intensity when unemployment increases during their time in the panel. In particular, job seekers increase the number of search methods that they use by 0.13 methods on average when the unemployment rate increases by 1 percentage point. This represents a 4% increase in search intensity for each percentage point increase in the unemployment rate, since the average number of search methods used by job seekers is 3.39 methods.

Unsurprisingly, the fixed effect estimates reveal that workers searching due to fear of job loss and workers searching for an additional job increase their search intensity the most during a recession. More specifically, workers searching due to fear of job loss increase their search intensity by 6.5% and workers searching for an additional job increase their search intensity by 8.3% for each percentage point increase in the unemployment rate. Given that unemployment risk rises during a recession, workers who fear losing their jobs face greater urgency in finding another job before they are let go by their firms, motivating these workers to search harder to avoid the threat of unemployment. While it is unspecified why workers search for additional jobs, it is likely that workers search for additional jobs because their current job does not provide sufficient income. Because liquidity constraints are more prevalent in a recession, heightened financial stress likely motivates these workers to search harder for a second job to obtain greater financial security.

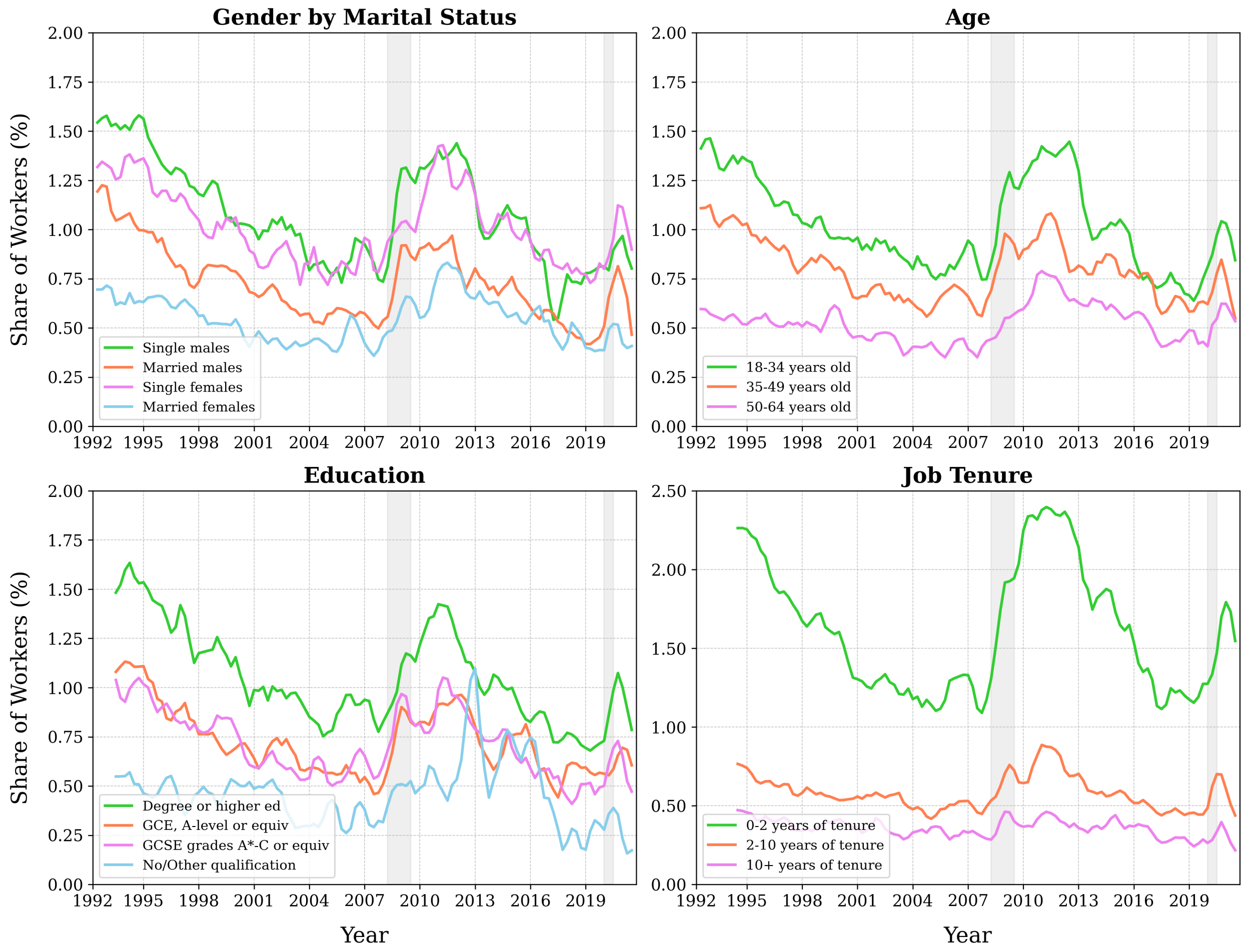
The differences in magnitudes of the coefficients going from the OLS regressions to the fixed effect regressions tell us about the potential role that changes in the composition of job seekers is playing in the time series results. As Figure A.5 in Appendix A shows, unemployment risk is highly correlated with observable characteristics of workers, with younger and lower tenured workers facing much higher layoff risks. Therefore, the pool of employed workers becomes relatively older and longer-tenured during a recession. However, the pool of employed job seekers does not change as starkly as the pool of employed workers over the business cycle. While the pool of employed workers is higher tenured during a recession, lower-tenured workers are much more likely to engage in OJS during a recession because they are the most at risk of unemployment. Thus, their share in the pool of job seekers during a recession remains similar to their share in the pool of job seekers during a boom, even though they represent a much smaller share of workers during a recession. Indeed, Figure A.7 in Appendix A shows that the pool of employed job seekers changes little in terms of observable characteristics during a recession, with lower tenured workers representing a slightly larger share of job seekers when unemployment is higher.

Because the composition of job seekers does not change significantly with respect to observable characteristics, adding the set of individual controls in the second OLS specification does not alter the magnitudes of the coefficients much. Nonetheless, the coefficients on the second OLS specification are still biased because unobservable characteristics of workers, such as worker motivation or productivity, can be correlated with the unemployment rate and search intensity. For this reason, this paper prefers the fixed effect specification, as the fixed effect estimates tell us about the behavioral changes workers are making in response to higher unemployment. That is, they reveal that most workers who engage in OJS increase their search intensity when the unemployment rate increases during their time in the panel, and this result becomes larger when workers are searching due to fear of job loss or for an additional job.

1.5.3 Heterogeneity Analysis

In the empirical analysis of the extensive margin, this paper finds that workers are more likely to engage in OJS due to fear of job loss when unemployment increases during their time in the panel. This section explores the heterogeneous impact of the unemployment rate on the decision to engage in OJS due to fear of job loss among different groups of workers.

Figure 1.7: OJS due to Fear of Job Loss by Worker Characteristics Over the Business Cycle



Notes: Graphs start in 1992: Q2 and end in 2021: Q4. All tick marks reflect the first quarter of the year represented, except the first tick mark. Sample weights used. The three quarter moving averages are plotted to smooth seasonality. Consistent education groupings are available from 1993:Q2 onward. Job tenure is available from 1994:Q2 onward.

Figure 1.7 shows the share of workers engaging in OJS due to fear of job loss across several observable characteristics of workers. From the figure, we see that higher educated workers, younger workers, and shorter-tenured workers are more likely to search for another job due to fear of job loss at any point over the business cycle. The fact that younger and lower-tenured workers are more likely to engage in precautionary OJS is unsurprising given that these workers face much higher unemployment risks. In addition, the finding that educated workers are also more likely to engage in precautionary OJS is consistent with educated workers engaging more frequently in similar behaviors, such as precautionary saving.[17] While these workers are more likely to engage in precautionary OJS in general, they are also the most likely to start searching for another job due to fear of job loss during a recession. Most strikingly, the share of low tenured workers searching due to fear of job loss jumps from about 1% in early 2008 to a peak of nearly 2.5% during the Great Recession.

Table 1.6: Heterogeneity Analysis: Extensive Margin Regression Results

Dependent variable: OJS Decision	(1)	(2)	(3)	(4)	(5)	(6)
UE Rate	0.00159***	0.00127***	0.00158***	0.00108**	0.00118***	0.00051
UE Rate Interactions						
Male		0.00064				0.00073*
Married		-0.00000				-0.00001
Degree or higher ed.			0.00080*			0.00079*
GCE, A level			0.00032			0.00031
GCSE grades A-C*			0.00044			0.00044
No/Other qualification			0.00022			0.00022
18-34 yrs old				0.00075*		0.00040
35-49 yrs old				0.00039		0.00026
0-2 yrs of tenure					0.00057	0.00056
2-10 yrs of tenure					0.00017	0.00016
10+ yrs of tenure					-0.00085***	-0.00084***
R-squared	0.45242	0.45242	0.45280	0.45242	0.45242	0.45281
No. Persons	1,208,080	1,208,080	1,208,080	1,208,080	1,208,080	1,208,080
No. Observations	4,559,914	4,559,914	4,559,914	4,559,914	4,559,914	4,559,914

Notes: Standard errors are clustered by individual. Quarter fixed effects and linear time trend included. Sample weights are used. The excluded category for education consists of individuals with missing education information. The excluded category for age consists of 50-64 year old respondents. The excluded category for tenure consists of individuals with missing tenure information. *, **, and *** show significance at the 1%, 5%, and 10% levels.

Table 1.6 further explores the heterogeneous responses of workers to higher unemployment by interacting observable characteristics of workers with the unemployment rate in the fixed effect specification. When we interact education levels with the unemployment rate, we see that higher educated workers are significantly more likely to start searching on-the-job due to fear of job loss. Moreover, younger workers and lower tenured workers are also more likely

17 Kennickell and Lusardi (2004) find that individuals with higher levels of education are more likely to report higher desired levels of precautionary savings after controlling for wealth, income levels, and demographic characteristics of workers.

to engage in OJS due to fear of job loss in response to higher unemployment. These results highlight the fact that workers who are most likely to be concerned about job security are the most responsive to changes in unemployment risk. In particular, educated and lower tenured workers are more likely to engage in precautionary OJS when the unemployment rate increases during their time in the panel.

1.6 Conclusion

This paper studies the cyclicality of OJS using data from the UK Labour Force Survey (LFS). First, I find that a higher share of workers tends to engage in OJS when unemployment is higher. Next, I find that average search intensity of employed job seekers rises during a recession. I then combine the extensive and intensive margins of OJS to create an aggregate measure of job search effort. Results show that aggregate search effort of employed workers is highly countercyclical, closely following the unemployment rate.

While this paper finds aggregate search effort to be countercyclical, it is not immediately clear whether the countercyclicality is due to compositional changes in the pool of employed workers and job seekers or due to behavioral changes workers are making in response to changing economic conditions. To this end, I exploit the panel structure of the LFS to estimate how changing unemployment conditions influence OJS behavior of workers during their time in the panel. Most notably, I find that a higher unemployment rate increases the probability that a worker engages in OJS due to fear of job loss and OJS for an additional job. In addition, I find that a higher unemployment rate increases the intensity with which employed job seekers search for another job.

Lastly, the findings of this paper open up new doors for future research. First, this paper documents the large presence of a precautionary motive of OJS and shows that this motive plays a heightened role in motivating job search during a recession. Future work can incorporate the precautionary motive of OJS into search models to better reflect motives for job mobility and to quantify the impacts that the precautionary motive has on the evolution of the unemployment rate over the business cycle. Second, the findings of this paper suggest that unemployment benefits can potentially influence the OJS behavior of workers, especially during a recession. More specifically, it is possible that UI benefits can reduce the threat of job loss, leading some workers to not search for another job and become unemployed. While Gutierrez (2016) finds that an increase in the UI replacement rate indeed decreases the probability of OJS among older Americans nearing retirement, future work is needed to determine if these results are generalizable to the broader population.

Chapter 2

The Value of Non-Wage Job Attributes and Their Impact on Compensation Inequality: Evidence from Germany

2.1 Introduction

Economists have long understood that workers care about non-wage job characteristics. However, researchers have faced several challenges when trying to estimate the value of non-wage job attributes and their impact on wage inequality. First, there are few nationally representative surveys containing detailed information on both wages and non-wage job characteristics (Maestas et al., 2018; Sockin, 2022). In addition, studies using observational data are typically unable to account for worker and firm selection and suffer from omitted variable bias. Indeed, traditional hedonic wage regressions are known to produce attribute valuations that are incorrectly-signed and unrealistic in magnitude (Brown, 1980). Third, studies using data on job transitions are often unable to specify which job attributes workers value and they rely on a strong assumption that job transitions characterized by wage losses signify transitions to jobs with better attributes (Sullivan and To, 2014; Sorkin, 2018). Finally, studies evaluating the impact of non-wage job characteristics on compensation inequality have often led to mixed conclusions. While some studies have found that adjusting wages for the monetary value of job attributes decreases compensation inequality (Brown, 1980; Filer, 1985), other studies have found that accounting for job attributes increases compensation inequality (Hall and Mueller, 2018; Sorkin, 2018; Maestas et al., 2018; Nagler et al., 2022).

This paper overcomes the usual difficulties of estimating the values of job attributes by analyzing a stated-preference experiment from the German panel study *Labour Market and Social Security* (PASS). In 2018, PASS survey respondents were asked to complete a vignette module in which they were presented with three hypothetical job vacancies. In particular, respondents were asked to rate their willingness to accept hypothetical jobs that contained eight randomly varied attributes. Fortunately, the PASS survey also asks respondents about the quality of their employment each year, and four of the job attributes asked in the survey relate directly to the attributes presented in the experiment. To the best of my knowledge, I am the first to analyze the 2018 vignette module to estimate the monetary value of key non-wage job attributes and quantify their impact on German compensation inequality.[1]

This paper first evaluates the incidence of four key job attributes in Germany: (i) overtime work requirements, (ii) permanent employment contracts, (iii) good promotion opportunities, and (iv) schedule flexibility. Overall, I find that there are large disparities in the prevalence of these attributes in the German working population. Most notably, women are less likely than men to have good promotion opportunities and schedule flexibility; workers at the top

1 In 2011, PASS survey respondents completed a similar vignette module that focused on which non-wage job attributes and regional characteristics influence workers' decisions to move to a different region for a job. Abraham et al. (2013), Auspurg and Gundert (2015), and Abraham et al. (2019) analyze the 2011 vignette module to determine which job attributes are important when considering accepting a job that is 1, 4, or 6 hours away from workers' place of residence.

of the wage distribution are more likely to have flexibility to set their own schedule; workers with greater education are more likely to work overtime in their jobs; and older workers are more likely to have permanent employment contracts.

Next, this paper estimates the value that workers place on the eight non-wage job attributes that are experimentally varied in the vignette module. The eight job attributes include the four previously mentioned job attributes along with four others: (i) weekly work hours, (ii) provision of child care by the employer, (iii) the ability to work from home, and (iv) the popularity of the employer in receiving job applications. Overall, I find significant willingness to pay for several job attributes. Most notably, I find that workers are willing to pay 31% of their wage to have a permanent employment contract, 13% of their wage for good promotion opportunities, 10% of their wage for schedule flexibility, and 8% of their wage to avoid overtime work requirements. In addition, this study finds that valuations of job attributes vary meaningfully by gender, education, and age. In particular, women value schedule flexibility more than men; highly educated workers value schedule flexibility more than less educated workers; and older workers value permanent employment contracts more than their younger counterparts. Interestingly, this paper finds evidence that workers sort into jobs with their preferred non-wage attributes. That is, individuals working in jobs with certain non-wage characteristics tend to value those characteristics more than individuals in jobs without them, corroborating a central prediction of theories of compensating differentials (Rosen, 1986).

Finally, this paper constructs a measure of compensation that adds the monetary value of four job attributes to workers' wages. In general, I find that accounting for both the incidence and valuation of non-wage job characteristics widens compensation inequities by gender, education, and age. For example, workers aged 18 to 29 earn 25.7% lower wages than workers aged 45 to 60, but this differential increases to 28.4% when wages are adjusted to account for non-wage job characteristics. Furthermore, I find that overall measures of German inequality increase when accounting for job attributes. For example, the 90/10 wage ratio widens when accounting for job characteristics, highlighting that workers at the top of the wage distribution tend to have jobs with more desirable characteristics.

This paper makes several contributions to the literature. First, it adds to the growing literature that estimates the value of non-wage job attributes through stated-preference experiments. On the one hand, my results confirm willingness to pay estimates for job attributes analyzed by previous studies. For example, I compute valuations of schedule flexibility that are comparable to those found by Maestas et al. (2018) in the United States and those found by Nagler et al. (2022) in Germany. In addition, I find that German workers place similar value on the ability to work from home as workers in the United States (Maestas et al., 2018). On the other hand, I also compute willingness to pay estimates for job attributes that are *new* for Germany. In particular, I provide novel estimates of workers' valuations of overtime work requirements and permanent employment contracts. While previous studies have estimated the value of permanent employment contracts in the context of moving to a different region (Abraham et al., 2013; Auspurg and Gundert, 2015; Abraham et al., 2019) or when looking at workers in the German health care sector (Kroczek and Späth, 2022), this paper quantifies the value of permanent employment contracts in a broader job choice context and for a nationally representative sample of employed workers in Germany.

Indeed, one of this paper's main findings is that German workers value permanent employment contracts more than any other job attribute. More specifically, workers are willing to give up nearly a third of their wage to have a permanent employment contract rather than a one year fixed-term contract. In the context of the German labor market, this result is significant. Since the Hartz reforms of 2003, the German government has provided more flexibility to firms to hire workers under fixed-term contracts, which allow firms to hire workers for six months to two years without requiring them to extend a permanent contract. Since 2003, the fraction of workers employed under fixed-term contracts has risen to over 8%. While fixed-term contracts offer firms the ability to dismiss workers more easily, I find that workers value job security and would accept significantly lower wages for a permanent employment contract. Consequently, this study adds to the literature that highlights the important role that job security plays in job choice and job mobility (Bonhomme and Jolivet, 2009; Datta, 2019; Jarosch, 2021).

Finally, this paper contributes to the literature evaluating the impact of non-wage job attributes on compensation inequality. While many early studies find evidence that accounting for non-wage job attributes decreases wage inequality, this study adds support to the recent experimental literature that finds that accounting for non-wage job characteristics exacerbates wage inequality. For example, Maestas et al. (2018) conduct a stated-preference experiment in the United States and find that accounting for the value of nine job attributes widens compensation inequality. Likewise, Nagler et al. (2022) administer a job choice experiment in Germany and find that accounting for the ability to work from home, schedule flexibility, paid time off, and commuting time increases compensation inequality. Notably, this paper finds that adjusting compensation to include the monetary values of three *new* job attributes not considered by Nagler et al. (2022) (i.e. overtime work requirements, employment contract duration, and promotion opportunities) increases measures of compensation inequality in Germany.

The remainder of this paper is organized as follows. Section 2.2 describes the data and summarizes the incidence of non-wage job attributes in the German working population. Section 2.3 outlines the empirical strategy used to estimate workers' willingness to pay for job attributes and their impact on German inequality. Section 2.4 presents the results and Section 2.5 concludes.

2.2 Data

2.2.1 Survey Design and Sample

The panel study *Labour Market and Social Security* (PASS) is an annual survey conducted by the German Institute for Employment Research (IAB). The survey has been fielded since December 2006 and the sample consists of two separate subgroups. The first subgroup consists of a random sample of households that receive unemployment benefits II in Germany. Individuals on unemployment benefits II are typically long-term unemployed and no longer eligible for unemployment benefits I or they are employed but unable to meet their family's living expenses. The second subgroup consists of a random sample of private households living in Germany and over-samples households from lower socioeconomic backgrounds. Due to the unique structure of the survey and composition of the two subgroups, the IAB provides sample weights so that the total sample containing both subgroups reflects the German population. These sample weights are used to make inferences about the prevalence of job attributes in the German workforce and to derive conclusions about the impact of the attributes on German compensation inequality.[2]

In 2018, the IAB administered a vignette module within the PASS survey in which respondents were presented with three hypothetical job vacancies. At the beginning of the module, each respondent was asked what a realistic gross monthly salary for a full-time job with a 40 hour work week would be for someone in *their* occupational field with *their* qualifications and professional experience. Respondents were then told that they would be shown three job vacancies.[3] Respondents were instructed to evaluate each presented vacancy

2 For more information concerning the PASS survey, please see Bähr et al. (2021) and Berg et al. (2021). Data access for this project was provided via a scientific use file supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

3 Respondents were told to assume that they had the necessary qualifications for the presented vacancies.

in terms of: (i) how likely they would be to apply for the job and (ii) how likely they would be to take the job if it was offered to them without applying.

Vacancies were presented as vignettes to respondents and consisted of eight experimentally varied job attributes. More specifically, respondents observed job vacancies that varied in: (i) the number of hours required by the position, (ii) the overtime work requirements of the position, (iii) the employment contract duration, (iv) the opportunities for promotion, (v) the provision of child care by the firm, (vi) the ability to work from home, (vii) the ability to set one's working hours, and (viii) the number of job applications that the employer receives regularly. The gross monthly salary for each position was also randomly varied. Table 2.1 lists the eight job attributes given by the vignettes as well as the values that each job attribute can take. After observing a vacancy on the screen, each respondent indicated their willingness to (i) apply for the job and (ii) accept the job if it was offered to them on an 11-point scale from 0 to 10. Figure B.1 in Appendix B provides an example of a vignette posed to a respondent.

Table 2.1: Vignette Variable Overview

	Dimension						
Vignette Variable	1	2	3	4	5	6	Total
Hours	20	30	40	–	–	–	3
Overtime work	Required	Blank	–	–	–	–	2
Employment duration	Indefinite	1 year	3 years	–	–	–	3
Salary	-10%	+0%	+10%	+20%	+30%	+40%	6
Promotion opportunities	Poor	Good	Very good	–	–	–	3
Child care	Available	Blank	–	–	–	–	2
Work location	WFH possible	Required presence	Blank	–	–	–	3
Work hours	Self-determined	Fixed	–	–	–	–	2
Number of applications	Very few	A large number	Blank	–	–	–	3

Notes: The first level of the overtime work dimension states that readiness to work overtime is required during peak business periods. The first level of the child care dimension states that the employer provides internal child care at customary local costs. WFH signifies work from home is feasible.

Survey respondents observed vignettes with job attributes that were randomly varied

They were also told that the activities implied by the jobs basically appealed to them and that all jobs could be easily reached with a short commute.

within the computer-assisted personal interview (CAPI) software that respondents used to complete the survey. Random variation of job attributes ensures that all workers are equally likely to observe job vacancies with different levels of job attributes. To verify successful randomization, dummy variables were created for each job attribute level and then regressed on demographic and labor market characteristics of workers, including gender, marital status, age, education, region, salary, and employment status. Table B.1 in Appendix B reports the p-value of the F-tests for joint significance of the regression coefficients. Nearly all of the F-tests yielded a p-value greater than the 10% threshold, suggesting that job attributes were successfully randomized across workers in the survey.

Survey respondents between the ages of 18 and 60 completed the vignette module. Individuals completing the module could be employed, unemployed, or nonemployed, but individuals who were nonemployed for reasons other than health problems, upcoming retirement, or training were excluded from the experiment. Table 2.2 provides summary statistics for the full sample of 5,107 respondents as well as the employed sample of 2,732 respondents.[4] 64% of individuals who completed the vignette module were employed, while 18% were unemployed and 18% were nonemployed. While estimates of job attribute valuations are provided for the full sample, this paper focuses on the valuations of employed workers to better understand the preferences of workers who sort into jobs with certain attributes as well as to understand the implications of job attribute valuations on the German wage structure.

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4 The full sample consists of individuals who rated all three job vacancies in the vignette module and did not having missing information concerning their demographic and labor market characteristics. The employed sample is a subsample of the full sample and consists of workers who provided information about the four job attributes measured in the PASS survey. In particular, workers who failed to answer the survey questions regarding overtime work requirements, employment contract duration, promotion prospects, and schedule flexibility were not included in the employed sample.

Table 2.2: Sample Summary Statistics

	Employed Sample		Full Sample	
Mean Characteristic	Nonweighted	Weighted	Nonweighted	Weighted
Male	0.49	0.55	0.48	0.51
Married	0.47	0.65	0.44	0.63
Lower secondary school degree or less	0.24	0.25	0.28	0.27
Intermediate or upper secondary school degree	0.54	0.51	0.50	0.48
University degree	0.22	0.23	0.21	0.25
Age	41.4	41.4	39.9	40.3
West Germany	0.71	0.83	0.73	0.83
Employed	–	–	0.64	0.79
Unemployed	–	–	0.18	0.05
Nonemployed	–	–	0.18	0.16
No. observations	2,732	2,732	5,107	5,107

Notes: Both samples consist of individuals aged 18 to 60 who completed the 2018 PASS vignette module. The employed sample consists of workers with non-missing job attribute information. The full sample consists of employed, unemployed, and nonemployed individuals. Sample weights are used for the weighted statistics.

2.2.2 Prevalence of Job Attributes in Germany

Fortunately, survey respondents are asked about the quality of their employment each year in the PASS survey, and four of the questions asked relate directly to the job attributes presented in the vignette module. First, respondents are asked how often they work overtime in their job. Second, respondents are asked if they are employed through a temporary work agency or if they are employed on a fixed-term contract.[5] Third, respondents are asked about promotion prospects at their firm. Finally, respondents are asked to what extent they are able to set their own work hours. Table 2.3 describes the prevalence of the four job attributes in the employed sample as well as the prevalence of the four job attributes in the German employed population, estimated using the sampling weights.

As Table 2.3 reveals, approximately 71% of German workers between the ages of 18 and 60

5 This paper assumes that workers who are not employed on temporary or fixed-term contracts are employed under a permanent contract.

Table 2.3: Employed Sample Job Attributes

Job Attribute	Nonweighted	Weighted
Hours worked	34.3	34.8
Hourly wage	16.2	18.7
<u>Percent with each attribute</u>		
Work overtime	0.69	0.71
Temporary employment contract	0.03	0.02
Fixed-term employment contract	0.14	0.10
Permanent employment contract	0.83	0.88
Good promotion opportunities	0.39	0.41
Flexibility to set working hours	0.29	0.36
No. observations	2,732	2,732

Notes: The employed sample consists of workers aged 18 to 60 who completed the 2018 PASS vignette module and had non-missing job attribute information. Sample weights are used for weighted statistics.

report working overtime in their job at least once per month. As overtime work is not defined by the survey question, this estimate likely includes individuals who complete both formal and informal overtime work for their employer. Notably, this estimate is consistent with the finding that 71% of German workers reported working unpaid overtime regularly in 2018 (*The Workforce View in Europe*, 2019). Furthermore, Table B.2 in Appendix B shows how the incidence of overtime work varies across demographic groups and position in the wage distribution. In particular, men are more likely to work overtime than women, and higher educated workers are more likely to work overtime than their less educated counterparts.

In addition to overtime work, Table 2.2 shows the different types of employment contracts that German workers are employed under. In general, firms may offer workers one of three types of employment contracts in Germany. First, firms may offer an indefinite employment contract. This type of employment relationship is often referred to as "permanent", as it is difficult for a firm to dismiss an employee after they have completed a short probationary period. Second, firms may offer workers a fixed-term contract that typically ranges in duration from six months to two years. The prevalence of fixed-term contracts grew after the Hartz reforms in 2003 and peaked in popularity in 2017, when approximately 8.5% of workers in Germany were employed under a fixed-term contract. Finally, firms may hire workers through a temporary work agency for a limited duration of time ranging from a few weeks to 18 months. In many cases, firms hire temporary workers to satisfy short-term personnel needs (e.g. backfilling an employee who is on leave). In other cases, workers may seek employment through a temporary work agency to explore jobs in different occupations or regions.

Table 2.2 reveals that 88% of German workers between the ages of 18 and 60 are employed in a permanent employment contract, while 10% of workers are employed in a fixed-term contract and 2% of workers are employed through a temporary work agency. These statistics are consistent with what has been published by the IAB and Federal Statistics Office of Germany (Destatis).[6] Moreover, Table B.2 in Appendix B highlights that permanent employment contracts are highly correlated with age and income of workers. Older workers and higher income workers are much more likely to be employed under permanent employment contracts than their younger and lower income counterparts.

Next, Table 2.2 reveals that 41% of German workers state that they have good promotion prospects. Men are more likely than women to report having good promotion prospects, highlighting a disadvantage that women face in the German labor market on top of lower wages. In addition, promotion prospects are correlated with workers' education and income levels. Workers with university degrees and workers in higher wage quintiles are more likely to report having good promotion prospects than workers with less education and workers in

6 The weighted percent of workers in a permanent employment contract given by this paper is slightly lower than typical German workforce estimates of around 90% due to the age restrictions of the vignette module. In particular, older workers are much more likely to be in permanent employment contracts, and workers over 60 years of age do not participate in the vignette module.

lower wage quintiles. Furthermore, younger workers are more likely to report having good promotion prospects, due in part to the fact that they stand the most to grow in their careers than older workers.

Lastly, Table 2.2 reveals that 36% of workers are able to set their own work hours in Germany. This is similar to Destatis' finding that 39% of German workers were able to influence their work hours in 2017. Furthermore, this is also consistent with the finding by Nagler et al. (2022) that 36% of German private sector workers had flexibility to determine their work hours in 2022. Table B.2 in Appendix B underscores that schedule flexibility is highly correlated with demographic and labor market characteristics of workers. In particular, men have more flexibility to set their own work hours than women, and workers with higher education levels are more likely to have schedule flexibility than workers with lower levels of education.

2.3 Empirical Strategy

A long line of literature has sought to estimate the value that workers place on non-wage job attributes. While early studies implemented a hedonic pricing approach, the literature has since recognized that several biases arise from estimating hedonic wage regressions. For example, omitted variable bias arises when unobserved worker skills that determine earnings are correlated with workers' willingness to pay for job attributes. In addition, omitted variable bias occurs when desirable (undesirable) job attributes are bundled with other desirable (undesirable) attributes, and measures of all attributes are not included in the wage regressions. Third, wage and job attribute correlations are biased in the presence of search frictions in the labor market (Hwang et al., 1998; Bonhomme and Jolivet, 2009). Finally, coefficients in hedonic wage regressions may partially reflect firm personnel policies rather than workers' valuations of job attributes, as high-wage firms may offer desirable job attributes as a tool to reduce worker turnover (Dale-Olsen, 2006). As a result of these biases, studies estimating the value of job attributes through a hedonic wage approach often yield estimates that are incorrectly signed, statistically insignificant, or unrealistic in magnitude (Brown, 1980).

As such, recent studies have turned toward using experiments to elicit workers' willingness to pay for job attributes. These studies present vignettes containing job descriptions to workers and exploit random variation in job attributes to estimate workers' willingness to pay for the attributes. Most studies using vignettes, such as those by Wiswall and Zafar (2018), Maestas et al. (2018), Nagler et al. (2022), and Non et al. (2022), present vacancies alongside one another and ask respondents to choose their preferred job vacancy. These studies typically estimate logistic regressions to quantify workers' valuations of job attributes.

In contrast, the PASS vignette module is unique in that it does not force respondents to choose between side-by-side job vacancies. Instead, it asks workers to rate their willingness to take each job on an 11 point scale. As a result, this paper leverages the variation in respondents' ratings to back out workers' valuations of key job attributes. More specifically, this paper estimates the impact of each job attribute on a worker's willingness to take a job using the specification given by Equation 2.1. In this specification, the dependent variable is individual i's likelihood of accepting job j; X_j represents a vector of job attributes given for job j, including the wage; α_i represents an individual fixed effect, which controls for time-invariant unobserved heterogeneity of workers that is correlated with a worker's propensity to take another job; and ϵ_{ij} represents a normally distributed error term.[7]

$$(\text{Likelihood of taking job})_{ij} = \beta_0 + \beta' \mathrm{X}_j + \alpha_i + \epsilon_{ij} \tag{2.1}$$

The regression coefficients estimated from the fixed effect specification are then used to

7 This paper also estimates a model using an ordinary least squares (OLS) specification that controls for demographic and labor market characteristics of workers. Results are similar to the fixed effect specification, so only the fixed effect results are reported.

back out workers' willingness to pay for each job attribute. For example, suppose that an individual is indifferent between a job not having a particular attribute k with wage w and a job having the attribute k but with a corresponding wage decrease equal to WTP_k. Then the indifference condition given by Equation 2.2 must hold.

$$\beta_{wage} ln(w) = \beta_k + \beta_{wage} ln[w - WTP_k] \tag{2.2}$$

That is, the wage must adjust in the job containing attribute k in order for the two jobs to be equally ranked by the individual. The willingness to pay for job attribute k as a fraction of a worker's wage can then be easily computed by rearranging terms, as seen in Equation 2.3.

$$\frac{WTP_k}{w} = 1 - e^{-\frac{\beta_k}{\beta_{wage}}} \tag{2.3}$$

This paper follows Maestas et al. (2018) and presents all willingness to pay estimates as fractions of workers' wages. More specifically, I estimate that gaining attribute k is equivalent to a $100 * [1 - e^{-\frac{\beta_k}{\beta_{wage}}}]\%$ wage increase (decrease) if the job attribute is desirable (undesirable). Standard errors of estimates are clustered at the individual level and are computed using the delta method.

Finally, this paper uses willingness to pay estimates of four job attributes measured in the PASS survey to evaluate the impact of accounting for job attributes on German compensation inequality. Like Maestas et al. (2018), I create a measure of total compensation that adjusts workers' wages to include the monetary value of the four job characteristics. The computation of total compensation for each individual i is given by Equation 2.4, where

A_{ik} indicates whether individual i possesses job attribute k at the time of interview in 2018.[8]

$$\text{Total Compensation}_i = \ln\left(w_i + w_i\left[1 - e^{\left(-\frac{\sum_k A_{ik}\beta_k}{\beta_{wage}}\right)}\right]\right) \tag{2.4}$$

Next, I quantify compensation differentials between worker subgroups by estimating a regression of the logarithm of total compensation on indicator variables for gender, educational attainment, age group, and industry, which are aggregated into supersectors.[9] In addition, I estimate log compensation differences between the 90th, 50th, and 10th percentiles to assess overall compensation inequality in Germany. By comparing compensation differentials to similarly estimated wage differentials, this paper is able to determine whether accounting for job attributes increases or decreases inequality in Germany.

2.4 Empirical Results

2.4.1 Main Estimates of Willingness to Pay for Job Attributes

Table 2.4 provides the main estimates of workers' willingness to pay for the job attributes varied in the vignette module. Column 1 lists the results for the main employed sample, column 2 gives estimates for nonemployed individuals, and column 3 provides estimates for the full sample of individuals, which includes unemployed workers.[10]

Table 2.4 reveals that German workers are willing to pay for a variety of non-wage job

8 The four job attributes measured by the PASS survey include: (i) frequency of work overtime, (ii) employment contract duration, (iii) promotion opportunities, and (iv) schedule flexibility.

9 This paper aggregates industries into economic supersectors using the same method of Maestas et al. (2018).

10 As only 6% of unemployed individuals who completed the vignette module are from the second sample subgroup (i.e. the general population subsample), this paper does not present willingness to pay results for unemployed workers separately, as they are likely not generalizable to the German unemployed population even when sample weights are used.

Table 2.4: Estimates of Willingness to Pay for Job Attributes

Job Attribute	Employed	Nonemployed	Full Sample
Overtime work	-0.079**	-0.017	-0.058**
[Blank]	(0.035)	(0.058)	(0.027)
3 year employment contract	0.210***	0.083	0.172***
[1 year employment contract]	(0.041)	(0.063)	(0.031)
Permanent employment contract	0.314***	0.205***	0.278***
[1 year employment contract]	(0.041)	(0.058)	(0.032)
Good promotion opportunities	0.128***	0.195***	0.126***
[Poor promotion opportunities]	(0.035)	(0.070)	(0.029)
Very good promotion opportunities	0.139***	0.093	0.133***
[Poor promotion opportunities]	(0.036)	(0.070)	(0.029)
Childcare	0.007	0.116**	0.023
[Blank]	(0.033)	(0.054)	(0.025)
Work from home possible	0.046	0.044	0.038
[Blank]	(0.041)	(0.058)	(0.032)
Work from home not possible	-0.018	0.039	-0.003
[Blank]	(0.039)	(0.049)	(0.030)
Schedule flexibility	0.097***	0.133**	0.104***
[Fixed schedule]	(0.034)	(0.060)	(0.028)
Firm receives few applications	-0.022	-0.063	-0.023
[Blank]	(0.044)	(0.069)	(0.035)
Firm receives many applications	0.041	0.050	0.035
[Blank]	(0.039)	(0.057)	(0.030)
Observations	8,196	2,751	15,321

Notes: Omitted job attribute dimensions are italicized and expressed in brackets. Regressions include individual fixed effects. Standard errors are clustered by individual. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

attributes. Most strikingly, employed workers place the highest value on job security. In particular, employed workers are willing to pay 21.0% of their wage to have a three year fixed-term contract compared to a one year fixed-term contract, and workers are willing to pay 31.4% of their wage for a permanent contract compared to a one year fixed-term contract. These estimates are comparable to those found in other experimental studies. For example, Kroczek and Späth (2022) find that workers in the German health care sector are willing to pay 36% for a permanent employment contract.[11] In addition, Auspurg and Gundert (2015) find that Germans are willing to pay 33% for a permanent employment contract when deciding to accept a job in another region.[12] Unsurprisingly, this paper finds that nonemployed workers place less value on longer term contracts, likely due in part to their weaker attachment to the labor market.

Second, workers significantly value promotion opportunities at work. While employed workers are willing to pay 12.8% of their wage for good promotion opportunities, they are willing to pay slightly more for *very* good promotion opportunities. These estimates are consistent with the findings of Abraham et al. (2013), which show that promotion opportunities are significant determinants of German workers' decisions to accept a job in another region. Overall, the results of this paper suggest that German workers are willing to accept lower wages as long as there is promise for future career advancement.[13]

Next, workers place a high value on the ability to set work hours. More specifically, employed workers are willing to pay 9.7% of their wage to have schedule flexibility. On the one hand, this is consistent with the findings of Maestas et al. (2018), which find that Americans are willing to pay 8.8% of their wage for schedule flexibility. On the other hand, this is somewhat larger than the results of Nagler et al. (2022), which find that German private sector workers are willing to pay 5.4% of their wage for schedule flexibility. Interestingly,

11 This is based on my own calculations from the authors' reported regression coefficients.

12 Permanent employment contracts have also been shown to be important components of jobs for workers in other countries, including individuals living in the UK (Datta, 2019), individuals living in the Netherlands (Non et al., 2022), and individuals living in Bangladesh (Mahmud et al., 2021).

13 If promotion opportunities reflect opportunities for future wage growth, then this finding is consistent with the results of Wiswall and Zafar (2018), which find that students from New York University (NYU) are willing to give up 3.4% of current earnings for each percentage point increase in future annual earnings growth.

nonemployed workers value schedule flexibility more than their employed counterparts. They are willing to pay 13.3% of their wage to have the ability to set work hours, suggesting that schedule flexibility may be used as a personnel instrument by firms to attract workers into the labor force.

While German workers place a high value on schedule flexibility, they do not place a high value work location flexibility. In particular, employed workers are only willing to pay 4.6% of their wage for the ability to work from home (and the result is insignificant). This is consistent with the finding by Maestas et al. (2018) that Americans are willing to pay 4.4% of their wage for the ability to work from home and is smaller than the finding by Nagler et al. (2022) that German workers are willing to pay 5.4% of their wage for the ability to work from home two days per week. One explanation for this paper's smaller result is the fact that the PASS experiment was conducted in 2018 before the Covid-19 pandemic, while the experiment conducted by Nagler et al. (2022) was conducted after the pandemic in 2022.

In addition, workers appear to significantly dislike overtime work requirements. Indeed, employed workers are willing to give up 7.9% of their wage to avoid working overtime during peak business periods. This suggests that firms in industries in which overtime work is prevalent may be able to attract workers with lower wages if they assert that overtime work is not required for the position.

Finally, like Maestas et al. (2018), this paper analyzes valuations of weekly work hours by estimating a separate model including indicator variables for weekly work hours and using total earnings instead of hourly wages. This is because accepting a lower wage for more work hours does not necessarily signal that workers have preferences for reduced leisure time, as expanding work hours increases total earnings at the same time that accepting a lower wage reduces them. Table B.3 in Appendix B displays willingness to pay estimates for weekly work hours and other job attributes. First, Table B.3 shows that estimates of willingness to pay remain largely the same for other job attributes, showing that job attribute valuations are robust to other specifications. Second, Table B.3 shows that workers are willing to give up 26.1% of earnings for a 20 hour work week and 20.3% of earnings for a 30 hour work week. These findings are broadly consistent with the findings of Maestas et al. (2018), which show that workers are willing to give up approximately 40% of earnings for a 20 hour work week and 20% of earnings for a 30 hour work week. Interestingly, nonemployed individuals are willing to give up more earnings to work fewer hours, suggesting that firms can offer shorter work weeks to entice nonemployed individuals to enter the labor force.

Overall, this paper finds job attribute valuations that are of the expected sign and similar in magnitude to those found in the experimental literature. For comparison purposes, I also estimate job attribute valuations using a hedonic pricing approach. Since four job attributes of workers are measured in the PASS survey, this paper estimates hedonic wage regressions with the logarithm of wage as the dependent variable and the four job attributes as independent variables. In particular, two specifications are estimated: (i) a simple ordinary least squares (OLS) specification with controls for demographic and labor market characteristics of workers and (ii) a fixed effect specification that uses data on workers' wages and job attributes from 2018 to 2020. As Table B.4 in Appendix B shows, both specifications produce valuations of the wrong sign for three of the four job attributes, similar to the majority of the literature using hedonic wage methods.[14] As such, this paper adds to the growing literature that finds that experimental estimates of willingness to pay are more reliable and realistic than those produced by traditional hedonic wage methods.

2.4.2 Sorting of Workers into Jobs with Preferred Attributes

Theories of compensating differentials predict that workers with higher valuations of certain job attributes will sort into jobs containing those attributes (Rosen, 1986). Since PASS respondents are asked about four of the job attributes presented in the vignette module, this

14 After estimating the hedonic wage regressions, I estimate willingness to pay for each job attribute using the following equation: $(-1)*(1-\mathrm{e}^{-\beta})$, where β represents the regression coefficient on the job attribute.

paper estimates valuations for individuals working in jobs *with* the attributes and individuals working in jobs *without* the attributes. In general, this paper finds that workers indeed sort into jobs that align with their job attribute preferences.

Table B.5 in Appendix B presents willingness to pay estimates of individuals working in jobs with and without the four job attributes. Workers in jobs requiring overtime at least once per month dislike working overtime less than those who do not work overtime hours. In addition, workers in permanent employment contracts are willing to pay 32.5% of their wage for a permanent contract, while workers in temporary and fixed-term contracts are only willing to pay 20.7% of their wage for a permanent contract. Furthermore, workers employed at firms where promotion opportunities are described as good place a higher value on promotion opportunities than workers employed at firms where promotion opportunities are described as bad. Lastly, workers in jobs with schedule flexibility are willing to pay 14.8% of their wage to determine their work hours, while workers lacking schedule flexibility are only willing to pay 7.1% of their wage to determine their work hours. Overall, while differences in coefficients are generally not statistically significant, results support the notion that workers indeed sort into jobs that reflect their job attribute preferences.

2.4.3 Heterogeneity in Willingness to Pay for Job Attributes

This section seeks to understand how valuations of job attributes vary by worker characteristics, paying close attention to how preferences vary by gender, education, age, and position in the wage distribution.

First, Table B.6 in Appendix B reveals that women and men have different preferences over many job attributes. In particular, women are willing to pay more for job security, as they value longer, more stable employment contracts more than their male counterparts. While women are willing to pay 34.9% of their wage for a permanent employment contract, men are only willing to pay 29.5% of their wage for a permanent employment contract, consistent with the common finding that women are more risk-averse than men. Second, women place a much higher value on schedule flexibility than their male counterparts, perhaps due to their oversized role in family caretaking and their weaker attachment to the labor market. While women are willing to pay 15.5% of their wage to obtain schedule flexibility, men are only willing to pay 5.8% of their wage. Finally, women tend to dislike overtime work less than their male counterparts. While men are willing to give up 9.3% of their wage to not work overtime, women are willing to give up 6.1% of their wage to not work overtime. Although this study finds differences in willingness to pay by gender for three key job attributes, it is important to keep in mind that differences are not statistically significant.

Next, Table B.7 in Appendix B shows that there are differences in job attribute valuations by educational attainment. Workers with lower secondary school degrees as well as workers with university degrees tend to dislike overtime work more than individuals with intermediate and upper secondary school degrees. In addition, workers with lower secondary school degrees as well as workers with university degrees tend to place higher values on permanent employment contracts than workers with intermediate or upper secondary school degrees. Finally, workers with higher educational attainment place higher value on schedule flexibility, consistent with the finding that workers with higher education sort into jobs that allow for schedule flexibility.

Moreover, this paper finds that job attribute valuations vary by age, as seen in Table B.8 in Appendix B. Most notably, the value of a permanent employment contract increases significantly with age, suggesting that individuals tend to value job security more as they get older. Interestingly, workers between 18 and 29 years of age and workers between 45 and 60 years of age dislike overtime work more than their 30 to 44 year old counterparts. Lastly, younger and older workers tend to value schedule flexibility the most, although differences between coefficients are statistically insignificant.

Finally, job attribute valuations are estimated by wage quintile. Table B.9 in Appendix B shows how job attribute valuations change as workers move up the wage distribution. In particular, workers in higher wage quintiles value schedule flexibility more than workers in the lowest wage quintile, consistent with the finding that workers in higher wage quintiles are more likely to work in jobs that offer schedule flexibility. In addition, Table B.9 shows that workers at the top of the wage distribution tend to place higher value on jobs with good promotion opportunities, consistent with the finding that workers at the top of the wage distribution enjoy jobs with better promotion opportunities.

2.4.4 Impact of Job Attributes on Compensation Inequality

While Section 2.2 reviews the incidence of four job attributes in Germany, this section examines how the incidence and valuations of the four job attributes impact compensation inequities by gender, education, and age group. After analyzing inequities between subgroups, this paper then quantifies the impact of accounting for job attributes on overall compensation inequality in Germany.

First, this paper measures pay inequities by gender. Table 2.5 reveals that when we strictly look at hourly wage, the log wage differential between men and women is equal to -0.129, signifying that women earn approximately 12.1% lower wages. In contrast, when we account for gender differences in the prevalence of job attributes, the log compensation differential increases to -0.135, signifying that women earn approximately 12.6% lower pay. In short, the gender pay differential increases because women are less likely than men to have schedule flexibility and good promotion opportunities, two non-wage attributes that are highly valued in the labor market.

Next, Table 2.5 reveals that pay inequities widen between education groups when job attributes are accounted for. More specifically, workers with the lowest education earn approximately 37.3% (-0.467 log points) lower wages than workers with university degrees, but when job attributes are accounted for the pay differential increases to 38.8% (-0.491 log points). The pay differential between workers with upper secondary school degrees and

Table 2.5: Log Wage and Compensation Differentials After Adjusting for Job Attributes

Demographic Subgroup	Log Wage	Log Compensation	Difference
Women	-0.129	-0.135	-0.006
[Men]	(0.027)	(0.028)	[-0.020,0.009]
Lower secondary school or less	-0.467	-0.491	-0.023
[University degree]	(0.039)	(0.043)	[-0.047,0.000]
Intermediate/Upper secondary school	-0.296	-0.300	-0.003
[University degree]	(0.029)	(0.033)	[-0.023,0.016]
Ages 18-29	-0.297	-0.334	-0.038
[Ages 45-60]	(0.034)	(0.039)	[-0.063,-0.013]
Ages 30-44	-0.113	-0.127	-0.014
[Ages 45-60]	(0.028)	(0.031)	[-0.028,-0.000]

Notes: Column 1 gives estimates of coefficients from regressions of log wage on gender, education, age, and industry. Column 2 gives estimates of coefficients from regressions of log compensation on the same variables. Column 3 gives the differences in the coefficients between columns 2 and 1. Standard errors of regression coefficients are in parentheses. 95% confidence intervals for the coefficient differences are in brackets in column 3. Sample weights are used.

university degrees similarly widens when we account for job characteristics, albeit by a smaller amount. Like the gender pay differential, the education pay differential increases due to differences in the incidence of schedule flexibility and good promotion opportunities among education groups. While these job attributes are highly valued, less educated workers are significantly less likely to work in jobs with these two attributes.

In addition, Table 2.5 shows that pay inequities widen the most between age groups when we account for job attributes. In particular, workers aged 18 to 29 earn 25.7% (-0.297 log points) lower wages than workers aged 45 to 60, but this pay differential increases to 28.4% (-0.334 log points) when we account for job characteristics of workers. Similarly, workers aged 30 to 44 earn 10.7% (-0.113 log points) lower wages than workers aged 45 to 60, but this differential increases to 11.9% (-0.127 log points) when incorporating the value of job characteristics of workers. Interestingly, pay inequities by age group increase largely due to differences in the incidence of permanent employment contracts. Younger workers are the least likely to be employed under permanent employment contracts, and permanent employment contracts are highly valued in the German labor market.

Table 2.6: Log Wage and Compensation Inequality After Adjusting for Job Attributes

Percentile Inequality	Log Wage	Log Compensation
90th - 50th Percentile	0.508	0.562
	[0.451,0.565]	[0.511,0.613]
50th - 10th Percentile	0.525	0.586
	[0.484,0.567]	[0.535,0.639]
90th - 10th Percentile	1.034	1.149
	[0.968,1.100]	[1.081,1.217]

Notes: 95% confidence intervals are in brackets. Sample weights are used.

Finally, this paper measures the overall impact of accounting for the incidence and valuation of job attributes on the German wage structure. More specifically, I compute pay differences between the 90th, 50th, and 10th percentiles of the wage distribution before and after accounting for job attributes. In particular, the 90/10 pay ratio increases from 64.4% (1.034 log points) to 68.3% (1.149 log points) once we account for job characteristics of workers. As Table 2.6 shows, the 90/50 and 50/10 pay ratios similarly increase when accounting for job characteristics of workers. Consequently, accounting for the incidence and valuation of job attributes widens compensation inequality in Germany. As workers move up the wage distribution, their jobs tend to have better amenities, leading economists to understate inequality when job attributes are not accounted for.

2.5 Conclusion

A long literature has sought to quantify the value that workers place on non-wage job characteristics. As hedonic wage regressions have produced valuations that are often the wrong sign or unrealistic in magnitude, the literature has recently turned toward experimental methods to elicit workers' willingness to pay for non-wage characteristics of jobs. This paper adds to the growing experimental literature by analyzing a vignette module from a nationally representative survey of German households (PASS) that was administered in 2018.

First, I find that there are large disparities in the incidence of key job attributes in the German working population. In particular, workers differ markedly in whether their job contains the following four attributes: (i) overtime work requirements, (ii) a permanent employment contract, (iii) good promotion opportunities, and (iv) schedule flexibility. Among these four attributes, I find that employment contract duration and schedule flexibility vary the most across gender, education, age group, and position in the wage distribution.

Next, this paper estimates the value that workers place on eight job attributes that are experimentally varied in the vignette module. The eight job attributes include the four previously mentioned attributes along with four others: (i) weekly work hours, (ii) provision of child care by the employer, (iii) the ability to work from home, and (iv) the popularity of the employer in receiving job applications. Overall, results show significant willingness to pay for several job attributes. In particular, results reveal that workers are willing to pay 31% of their wage to have a permanent employment contract, 13% of their wage for good promotion opportunities, 10% of their wage for schedule flexibility, and 8% of their wage to avoid overtime work requirements. Valuations of job attributes vary meaningfully by gender, education, age group, and wage quintile. More specifically, women and highly educated workers value schedule flexibility more than men and less educated workers, respectively. Moreover, older workers place higher value on permanent employment contracts than their younger counterparts.

Finally, this paper constructs a measure of compensation that accounts for the monetary values of four job attributes in the German working population. Most notably, I find that accounting for the incidence and valuation of non-wage job characteristics widens compensation inequities by gender, education, and age. Moreover, this paper finds that overall measures of German inequality increase when accounting for job attributes. For example, the 90/10 pay ratio widens when accounting for non-wage job characteristics, highlighting that workers at the top of the wage distribution tend to work in jobs with better characteristics.

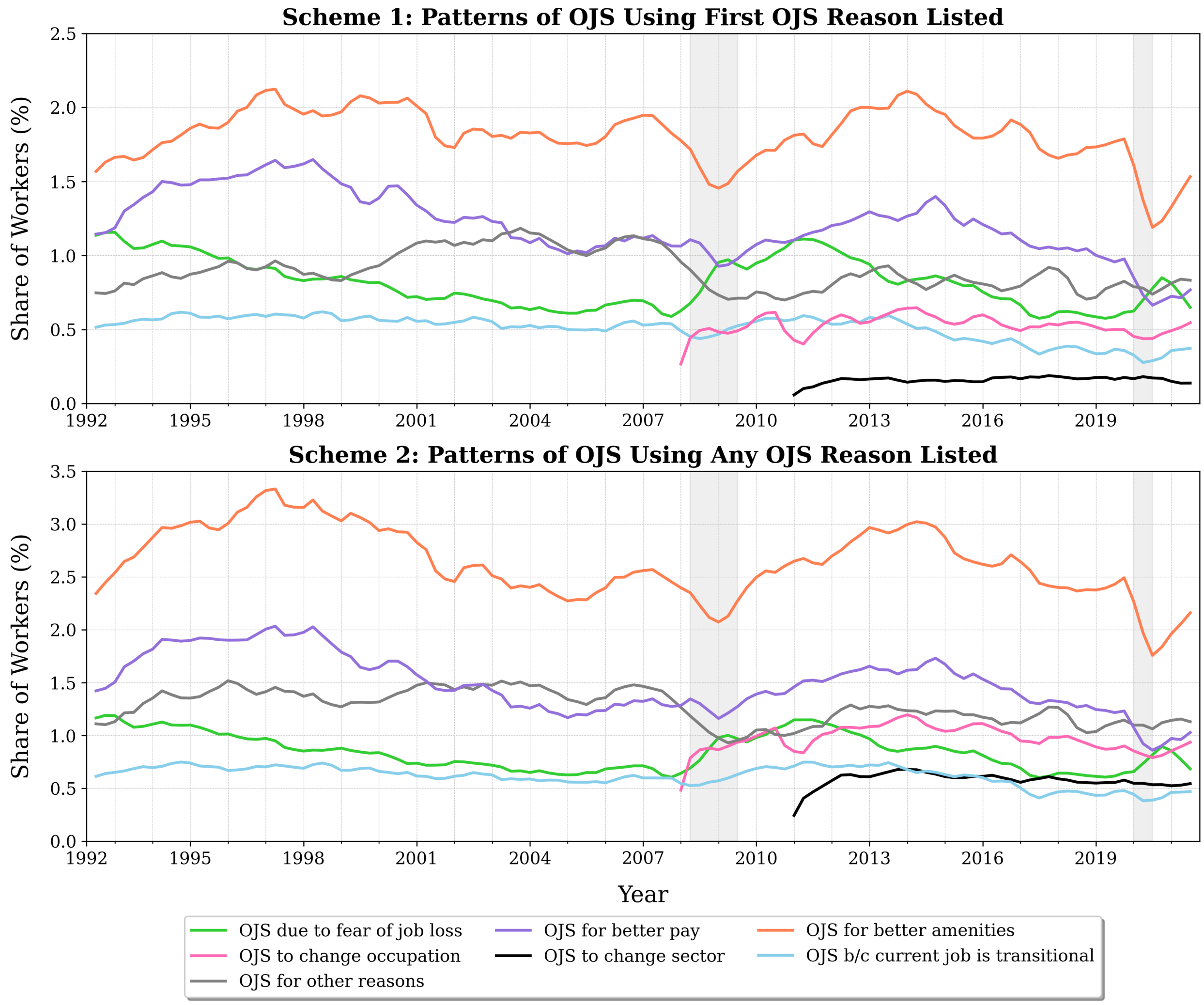
While this paper adds to the experimental literature estimating workers' willingness to pay for job attributes, this paper also highlights promising avenues for future research. In particular, most experimental studies focus on estimating the value of job attributes for employed workers. While I report valuations of job attributes for nonemployed individuals, the sample size is not large enough to examine this important subgroup in greater detail. It would be valuable for future surveys to ask unemployed and nonemployed individuals to participate in experimental modules so we can better understand the attributes that influence unemployed workers' decisions to accept a job as well as the attributes that can encourage nonemployed individuals to enter the labor force. In addition, future studies should seek to connect stated preferences in experiments to actual job transitions of workers. While Mas and Pallais (2017) show that actual behavior of workers applying to work in US call centers is consistent with experimental findings, more work is needed to solidify the link between stated preferences in experiments and actual behavior of workers in the labor market.

Appendix A

Chapter 1 Appendix

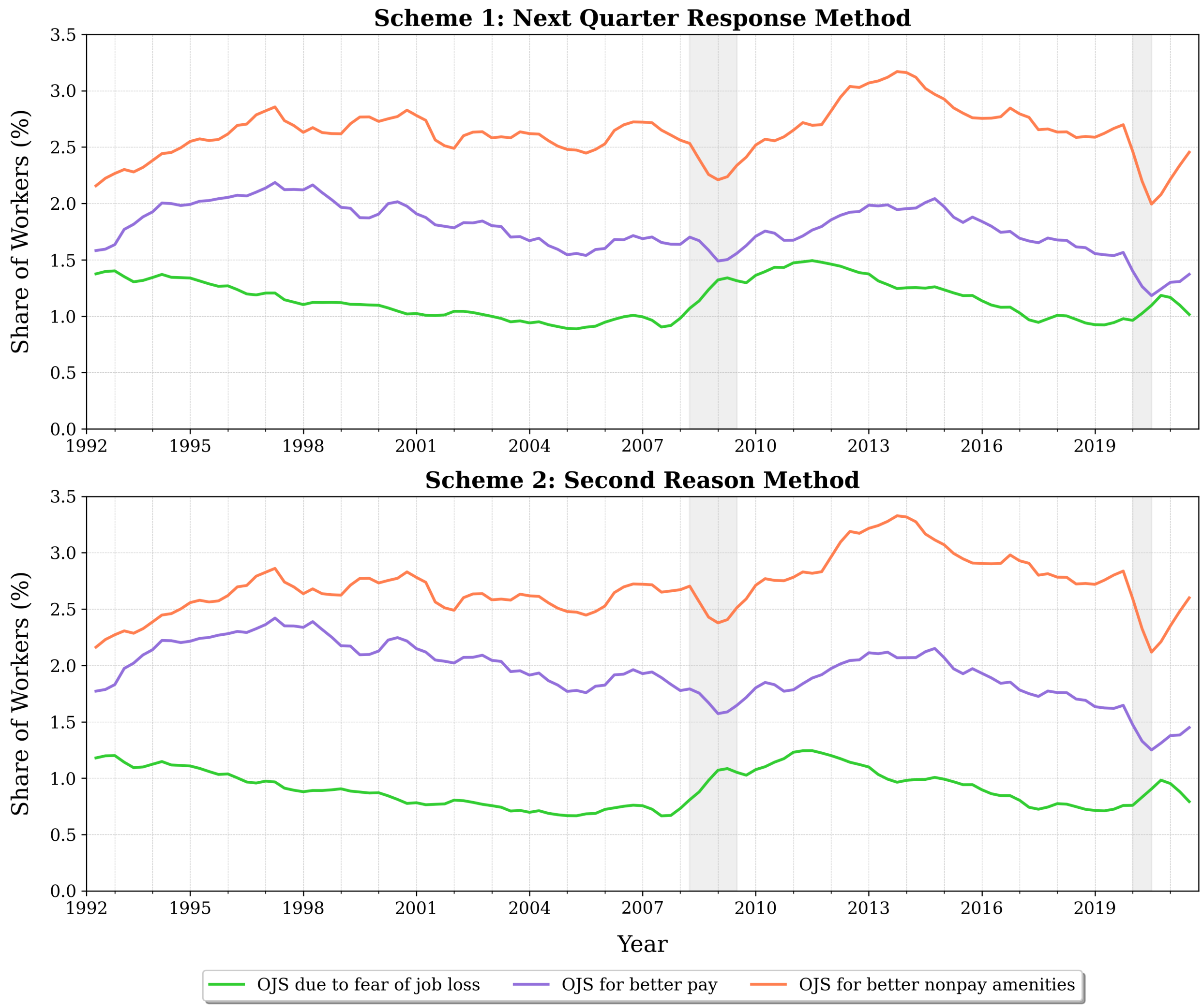
A.1 Figures

Figure A.1: OJS Over the Business Cycle: First Listed Reason vs Any Listed Reason



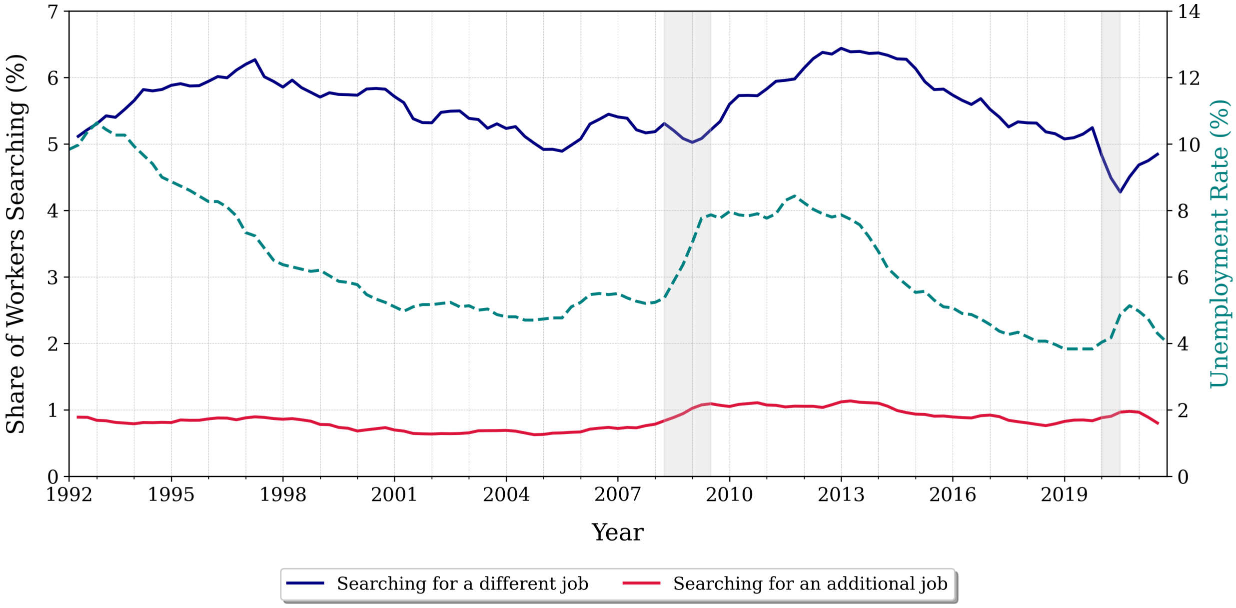
Notes: Graphs start in 1992: Q2 and end in 2021: Q4. All tick marks reflect the first quarter of the year represented, except the first tick mark. Sample weights used. The three quarter moving averages are plotted to smooth seasonality. Scheme 1 plots OJS by reason using the first OJS reason listed by respondents. Scheme 2 plots OJS by reason using any OJS reason indicated by respondents (i.e. second and third reasons listed).

Figure A.2: Top Three Reasons for OJS Under Different Apportionment Schemes



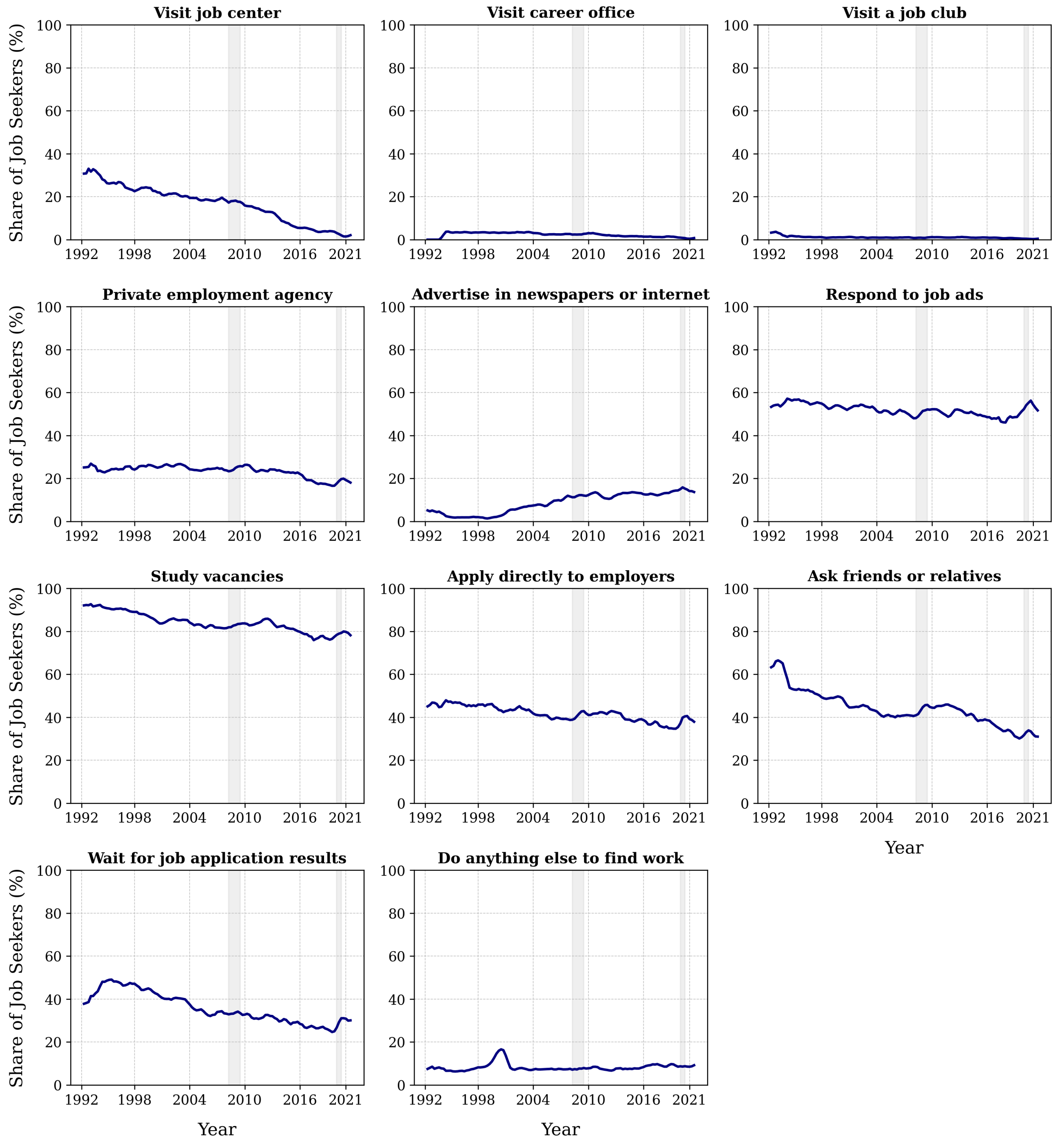
Notes: Graphs start in 1992: Q2 and end in 2021: Q4. All tick marks reflect the first quarter of the year represented, except the first tick mark. Sample weights used. The three quarter moving averages are plotted to smooth seasonality. Scheme 1 apportions individuals who list change occupation, change sector, transitional jobs, and other reasons as their first OJS reason by using the OJS reason breakdown of these individuals the next quarter. Scheme 2 apportions individuals who list change occupation, change sector, transitional jobs, and other reasons as their first OJS reason by using the second OJS reason listed by these individuals who list multiple OJS reasons.

Figure A.3: OJS for a Different or Additional Job Over the Business Cycle



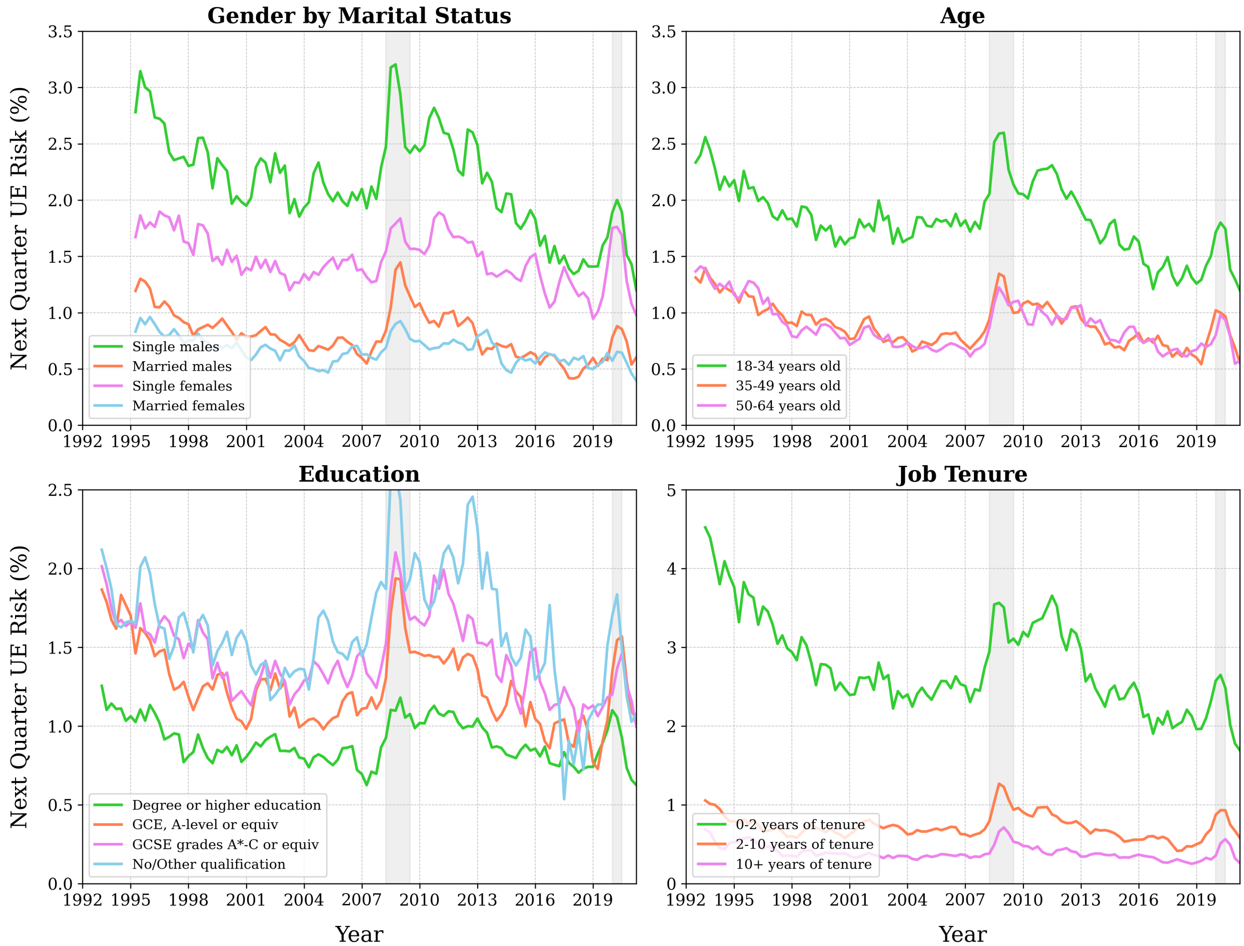
Notes: Graph starts in 1992: Q2 and ends in 2021: Q4. All tick marks reflect the first quarter of the year represented, except the first tick mark. Sample weights used. The three quarter moving averages of OJS rates are plotted to smooth seasonality.

Figure A.4: Prevalence of OJS Methods Over the Business Cycle



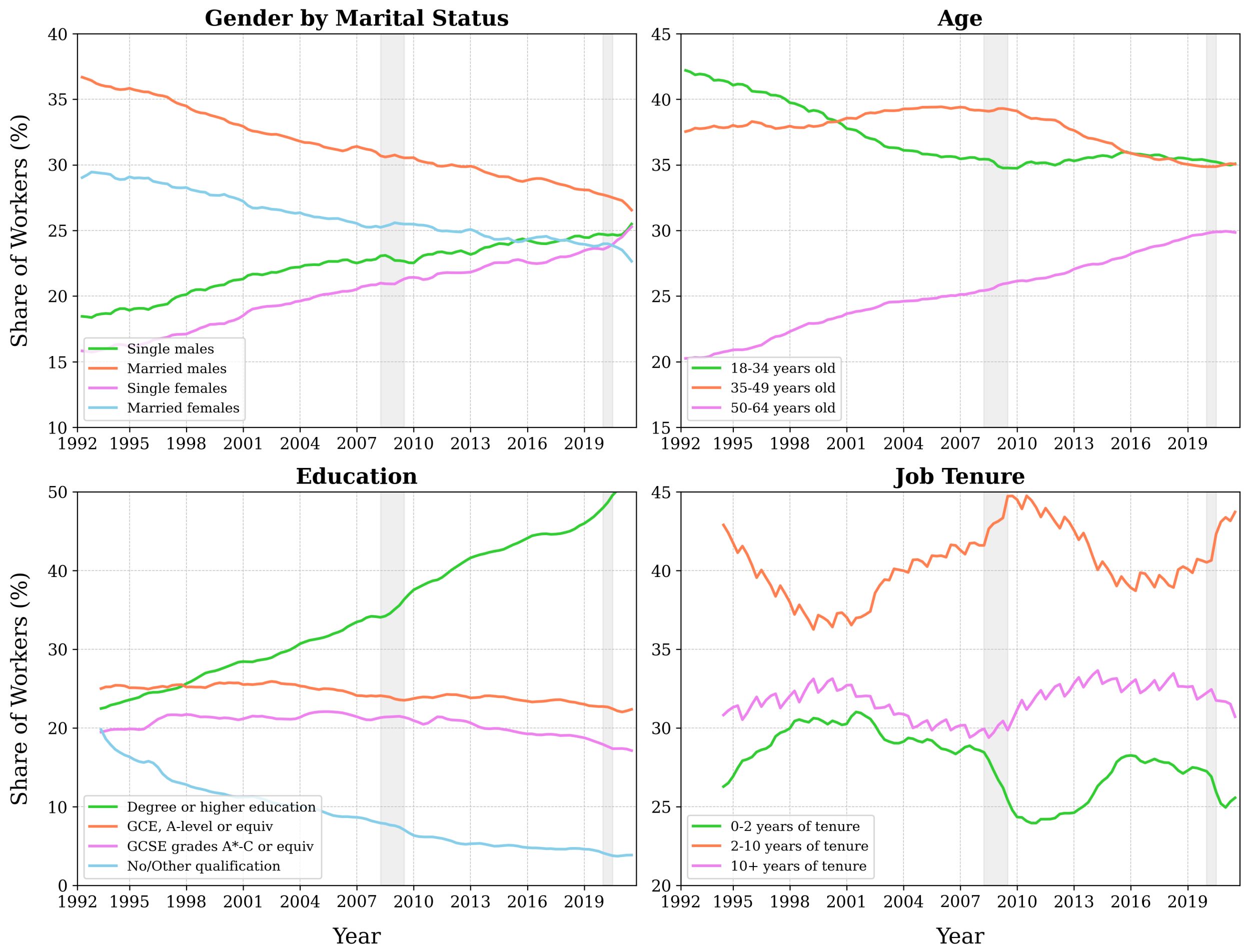
Notes: Graphs start in 1992: Q2 and end in 2021: Q4. All tick marks reflect the first quarter of the year represented, except the first tick mark. Sample weights used. The three quarter moving averages are plotted to smooth seasonality.

Figure A.5: Next Quarter Unemployment Risk by Worker Characteristics



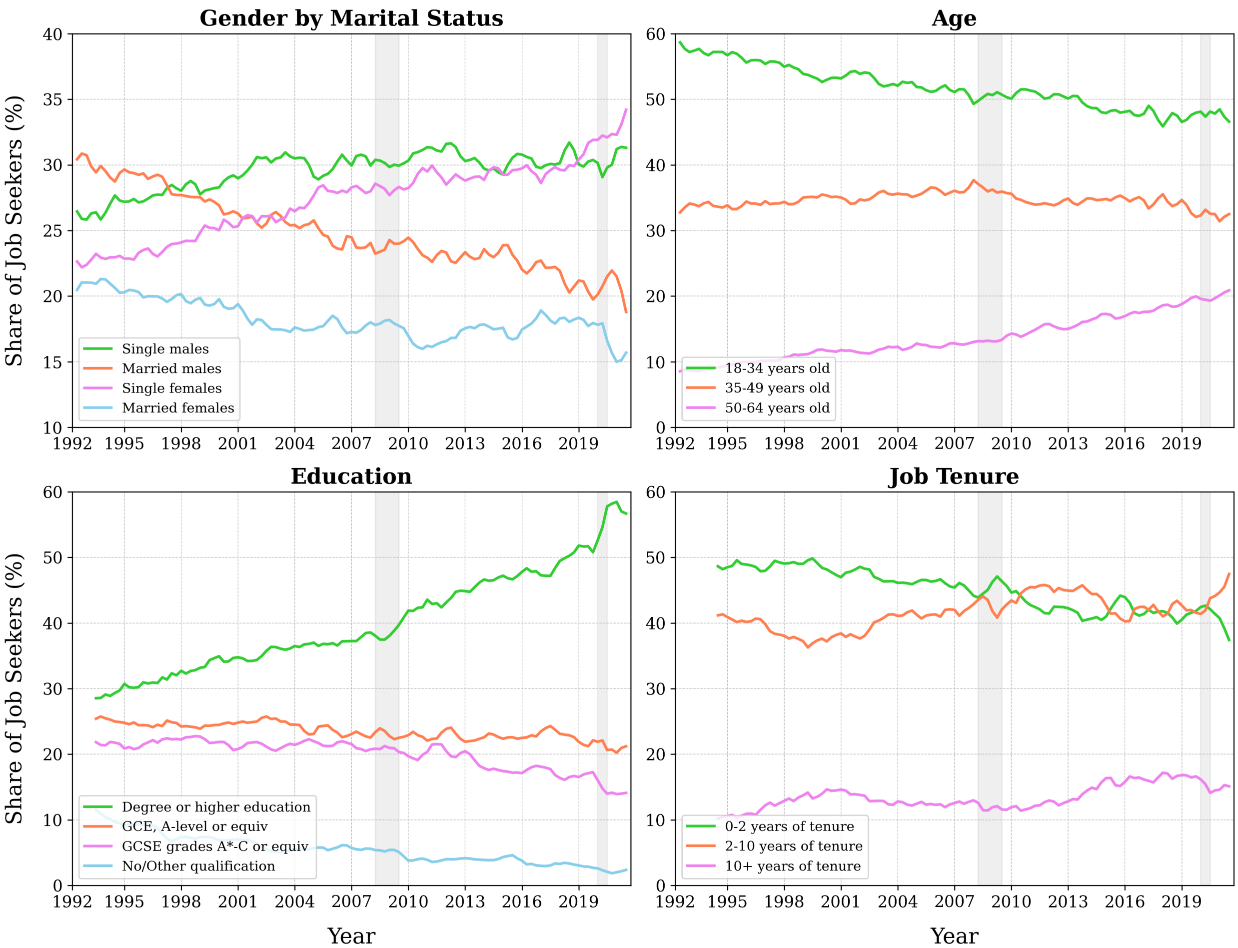
Notes: Graphs start in 1992: Q2 and end in 2021: Q4. All tick marks reflect the first quarter of the year represented, except the first tick mark. Quarter Sample weights used. The three quarter moving averages are plotted to smooth seasonality. Data for the time series comes from the Two Quarter Longitudinal Labour Force Survey. Marital status is available from 1995:Q1 onward. Consistent education groupings are available from 1993:Q2 onward. Job tenure is available from 1993:Q2 onward.

Figure A.6: Worker Characteristics Over the Business Cycle



Notes: Graphs start in 1992: Q2 and end in 2021: Q4. All tick marks reflect the first quarter of the year represented, except the first tick mark. Sample weights used. The three quarter moving averages are plotted to smooth seasonality. Consistent education groupings are available from 1993:Q2 onward. Job tenure is available from 1994:Q2 onward.

Figure A.7: Job Seeker Characteristics Over the Business Cycle



Notes: Graphs start in 1992: Q2 and end in 2021: Q4. All tick marks reflect the first quarter of the year represented, except the first tick mark. Sample weights used. The three quarter moving averages are plotted to smooth seasonality. Consistent education groupings are available from 1993:Q2 onward. Job tenure is available from 1994:Q2 onward.

A.2 Tables

Table A.1: Extensive Margin: Basic OLS Regression Results

Dependent variable: OJS Decision	All OJS	OJS by Reason: Fear of Job Loss	Better Pay	Better Amenities	Add'l Job	Other Reasons
UE Rate	0.00240***	0.00096***	0.00013	-0.00004	0.00080***	0.00048***
	(0.00033)	(0.00005)	(0.00010)	(0.00012)	(0.00005)	(0.00011)
Time	0.00005***	0.00001***	-0.00005***	-0.00003***	0.00005***	0.00007***
	(0.00002)	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00001)
Constant	0.04756***	0.00181***	0.01430***	0.02020***	0.00094**	0.01041***
	(0.00258)	(0.00042)	(0.00086)	(0.00099)	(0.00045)	(0.00092)
R-squared	0.00020	0.00029	0.00025	0.00005	0.00022	0.00020
No. Observations	4,559,914	4,559,914	4,559,914	4,559,914	4,559,914	4,559,914

Notes: Standard errors are clustered by quarter. Quarter fixed effects and linear time trend included. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

Table A.2: Extensive Margin: OLS with Controls Regression Results

		OJS by Reason				
Dependent variable: OJS Decision	All OJS	Fear of Job Loss	Better Pay	Better Amenities	Add'l Job	Other Reasons
UE Rate	0.00357***	0.00114***	0.00037***	0.00029**	0.00095***	0.00076***
	(0.00032)	(0.00005)	(0.00012)	(0.00014)	(0.00006)	(0.0001)
Male	0.01924***	0.00102***	0.00502***	0.00210***	0.00468***	0.00601***
	(0.00052)	(0.00014)	(0.00020)	(0.00021)	(0.00018)	(0.00021)
Nonwhite	0.02024***	0.00084***	0.00402***	0.00071**	0.00908***	0.00519***
	(0.00078)	(0.00023)	(0.00033)	(0.00034)	(0.00033)	(0.00045)
Age	0.00061***	0.00046***	0.00030***	0.00086***	0.00042***	-0.00147***
	(0.00014)	(0.00003)	(0.00006)	(0.00006)	(0.00005)	(0.00006)
Age Squared	-0.00002***	-0.00001***	-0.00001***	-0.00001***	-0.00001***	0.00001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Married	-0.02174***	-0.00222***	-0.00426***	-0.00451***	-0.00451***	-0.00591***
	(0.00048)	(0.00013)	(0.00019)	(0.00020)	(0.00017)	(0.00017)
Full time	-0.03668***	0.00048***	0.00076***	-0.00805***	-0.01870***	-0.00991***
	(0.00117)	(0.00015)	(0.00024)	(0.00040)	(0.00043)	(0.00032)
0-2 years of tenure	0.03592***	0.00845***	0.00661***	0.00696***	0.00520***	0.00809***
	(0.00246)	(0.00040)	(0.00073)	(0.00075)	(0.00044)	(0.00099)
2-10 years of tenure	0.00926***	-0.00130***	0.00478***	0.00468***	0.00004	0.00086
	(0.00238)	(0.00032)	(0.00069)	(0.00077)	(0.00040)	(0.00096)
10+ years of tenure	-0.01538***	-0.00373***	-0.00269***	-0.00402***	-0.00199***	-0.00293***
	(0.00233)	(0.00033)	(0.00068)	(0.00075)	(0.00040)	(0.00094)
Degree or higher ed.	0.01821***	0.00210***	0.00126	0.00213	0.00223*	0.00985***
	(0.00608)	(0.00075)	(0.00152)	(0.00150)	(0.00114)	(0.00156)
GCE, A-level or equiv.	0.00274	-0.00056	0.00119	-0.00014	0.00160	0.00010
	(0.00603)	(0.00073)	(0.00151)	(0.00151)	(0.00111)	(0.00152)
GCSE, A*-C or equiv.	0.00197	-0.00048	0.00163	0.00074	0.00101	-0.00149
	(0.00604)	(0.00075)	(0.00151)	(0.00149)	(0.00112)	(0.00153)
No/Other qualification	-0.00422	-0.00151**	0.00064	-0.00176	0.00090	-0.00301**
	(0.00604)	(0.00074)	(0.00152)	(0.00150)	(0.00113)	(0.00151)
Time	-0.00001	0.00000	-0.00005***	-0.00004***	0.00003***	0.00004***
	(0.00002)	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00001)
Constant	0.06226***	-0.00919***	0.00430*	0.01141***	0.00508***	0.05113***
	(0.00742)	(0.00123)	(0.00230)	(0.00227)	(0.00144)	(0.00239)
R-squared	0.02403	0.00444	0.00452	0.00434	0.01065	0.01100
No. Observations	4,559,914	4,559,914	4,559,914	4,559,914	4,559,914	4,559,914

Notes: Standard errors are clustered by quarter. Quarter fixed effects and linear time trend included. Industry dummies excluded from table. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

Table A.3: Extensive Margin: Fixed Effect Regression Results

Dependent variable: OJS Decision	All OJS	OJS by Reason: Fear of Job Loss	Better Pay	Better Amenities	Add'l Job	Other Reasons
UE Rate	0.00117*	0.00159***	-0.00017	-0.00029	0.00084***	0.00026
	(0.00062)	(0.00024)	(0.00027)	(0.00034)	(0.00026)	(0.00036)
Age	-0.00850***	-0.00123***	-0.00282***	-0.00169***	0.00003	-0.00259***
	(0.00110)	(0.00035)	(0.00051)	(0.00059)	(0.00043)	(0.00062)
Age Squared	0.00009***	0.00001***	0.00003***	0.00002**	0.00000	0.00003***
	(0.00001)	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00001)
Married	-0.00350	0.00055	-0.00045	-0.00342***	-0.00100	0.00060
	(0.00216)	(0.00074)	(0.00114)	(0.00116)	(0.00076)	(0.00111)
Full time	-0.07338***	-0.00131**	-0.00515***	-0.01796***	-0.02268***	-0.02454***
	(0.00159)	(0.00061)	(0.00061)	(0.00086)	(0.00078)	(0.00104)
0-2 years of tenure	-0.03881***	-0.00900***	-0.00579***	-0.01328***	-0.00053	-0.01006***
	(0.00130)	(0.00055)	(0.00060)	(0.00072)	(0.00053)	(0.00074)
2-10 years of tenure	0.01929***	0.00002	0.00584***	0.00804***	0.00006	0.00511***
	(0.00107)	(0.00044)	(0.00050)	(0.00060)	(0.00045)	(0.00059)
10+ years of tenure	0.02279***	0.00616***	0.00419***	0.00795***	-0.00059	0.00498***
	(0.00114)	(0.00050)	(0.00050)	(0.00064)	(0.00047)	(0.00063)
Time	-0.00307***	-0.00030***	-0.00057***	-0.00122***	-0.00012**	-0.00078***
	(0.00014)	(0.00005)	(0.00006)	(0.00008)	(0.00005)	(0.00008)
Constant	0.47683***	0.04466***	0.11177***	0.13776***	0.03109***	0.13218***
	(0.02495)	(0.00832)	(0.01167)	(0.01349)	(0.00946)	(0.01442)
No. Observations	4,559,914	4,559,914	4,559,914	4,559,914	4,559,914	4,559,914
R-squared	0.52525	0.45289	0.47791	0.45973	0.45197	0.47077

Notes: Standard errors are clustered by individual. Quarter fixed effects and linear time trend included. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

Table A.4: Intensive Margin: Basic OLS Regression Results

		OJS by Reason				
Dependent variable: *No. of search methods*	All OJS	Fear of Job Loss	Better Pay	Better Amenities	Add'l Job	Other Reasons
UE Rate	0.061***	0.064***	0.046***	0.045***	0.084***	0.058***
	(0.007)	(0.017)	(0.010)	(0.010)	(0.019)	(0.012)
Time	-0.005***	-0.007***	-0.005***	-0.006***	-0.002*	-0.007***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	3.301***	3.709***	3.288***	3.219***	2.947***	3.459***
	(0.054)	(0.128)	(0.078)	(0.079)	(0.135)	(0.093)
R-squared	0.012	0.016	0.013	0.014	0.008	0.016
No. Persons	53,783	4,867	8,933	13,477	4,162	10,169
No. Observations	134,804	11,392	21,809	32,364	9,776	23,868

Notes: Standard errors are clustered by quarter. Quarter fixed effects and linear time trend included. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

Table A.5: Intensive Margin: OLS with Controls Regression Results

		OJS by Reason				
Dependent variable: No. of search methods	All OJS	Fear of Job Loss	Better Pay	Better Amenities	Add'l Job	Other Reasons
UE Rate	0.055***	0.070***	0.036***	0.044***	0.078***	0.049***
	(0.007)	(0.017)	(0.011)	(0.011)	(0.019)	(0.013)
Male	0.181***	0.205***	0.139***	0.142***	0.223***	0.210***
	(0.012)	(0.043)	(0.033)	(0.026)	(0.045)	(0.030)
Nonwhite	0.059***	-0.188**	0.091**	-0.073	0.150**	0.065
	(0.020)	(0.081)	(0.046)	(0.045)	(0.061)	(0.041)
Age	-0.019***	0.029*	-0.008	-0.012	-0.018	-0.054***
	(0.004)	(0.015)	(0.008)	(0.008)	(0.014)	(0.008)
Age Squared	0.000***	-0.000**	0.000	0.000	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.100***	0.009	-0.058*	-0.122***	-0.210***	-0.093***
	(0.015)	(0.055)	(0.032)	(0.020)	(0.044)	(0.032)
Full time	-0.270***	-0.048	-0.207***	-0.206***	-0.444***	-0.372***
	(0.014)	(0.054)	(0.037)	(0.032)	(0.061)	(0.031)
0-2 years of tenure	0.055	0.757***	-0.110	0.332	-0.637*	-0.028
	(0.147)	(0.271)	(0.303)	(0.281)	(0.331)	(0.311)
2-10 years of tenure	-0.301**	0.333	-0.358	0.054	-0.802**	-0.357
	(0.149)	(0.273)	(0.303)	(0.283)	(0.339)	(0.307)
10+ years of tenure	-0.558***	0.154	-0.641**	-0.206	-0.896**	-0.687**
	(0.149)	(0.268)	(0.308)	(0.287)	(0.348)	(0.306)
Degree or higher ed.	0.225	-0.101	0.466***	0.086	-0.088	0.609***
	(0.136)	(0.115)	(0.124)	(0.154)	(0.229)	(0.150)
GCE, A-level or equiv.	0.081	-0.162	0.303**	-0.036	-0.170	0.350**
	(0.133)	(0.111)	(0.125)	(0.151)	(0.225)	(0.148)
GCSE, A*-C or equiv.	-0.003	-0.252**	0.215*	-0.084	-0.283	0.219
	(0.134)	(0.107)	(0.124)	(0.155)	(0.227)	(0.151)
No/Other qualification	-0.247*	-0.501***	-0.063	-0.356**	-0.444**	0.097
	(0.134)	(0.135)	(0.125)	(0.152)	(0.223)	(0.154)
Time	-0.006***	-0.006***	-0.006***	-0.007***	-0.004***	-0.007***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	4.041***	2.928***	3.961***	3.574***	4.578***	4.015***
	(0.193)	(0.446)	(0.414)	(0.346)	(0.424)	(0.431)
R-squared	0.052	0.055	0.042	0.052	0.050	0.075
No. Persons	53,783	4,867	8,933	13,477	4,162	10,169
No. Observations	134,804	11,392	21,809	32,364	9,776	23,868

Notes: Standard errors are clustered by quarter. Quarter fixed effects and linear time trend included. Industry dummies excluded from table. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

Table A.6: Intensive Margin: Fixed Effect Regression Results

		OJS by Reason				
Dependent variable: *No. of search methods*	All OJS	Fear of Job Loss	Better Pay	Better Amenities	Add'l Job	Other Reasons
UE Rate	0.134***	0.242***	0.099	0.136**	0.269***	0.075
	(0.027)	(0.092)	(0.069)	(0.054)	(0.097)	(0.067)
Age	0.137***	0.241	0.206*	0.244***	-0.053	0.113
	(0.043)	(0.158)	(0.110)	(0.093)	(0.166)	(0.095)
Age Squared	-0.002***	-0.003	-0.003*	-0.004***	-0.001	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Married	-0.065	0.091	-0.109	-0.064	0.053	0.096
	(0.069)	(0.255)	(0.157)	(0.145)	(0.299)	(0.161)
Full time	-0.398***	-0.578***	-0.215	-0.353***	-0.307*	-0.173**
	(0.037)	(0.132)	(0.134)	(0.090)	(0.169)	(0.087)
0-2 years of tenure	-0.084	0.070	-0.371	0.507**	-0.721*	0.256
	(0.124)	(0.401)	(0.345)	(0.257)	(0.404)	(0.311)
2-10 years of tenure	-0.018	-0.009	-0.413	0.463*	-0.482	0.404
	(0.125)	(0.401)	(0.345)	(0.257)	(0.411)	(0.316)
10+ years of tenure	-0.039	0.097	-0.579	0.499*	-0.490	0.625*
	(0.133)	(0.417)	(0.365)	(0.266)	(0.498)	(0.361)
Time	0.225***	0.275***	0.203***	0.230***	0.241***	0.210***
	(0.006)	(0.021)	(0.016)	(0.012)	(0.024)	(0.015)
Constant	-13.658***	-19.043***	-13.843***	-16.769***	-10.051***	-13.819***
	(0.908)	(3.116)	(2.382)	(1.868)	(3.634)	(1.996)
No. Persons	53,783	4,867	8,933	13,477	4,162	10,169
No. Observations	134,804	11,392	21,809	32,364	9,776	23,868
R-squared	0.693	0.739	0.728	0.726	0.734	0.750

Notes: Standard errors are clustered by individual. Quarter fixed effects and linear time trend included. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

Table A.7: Heterogeneity Analysis: Extensive Margin Regression Results

Dependent variable: OJS Decision	(1)	(2)	(3)	(4)	(5)	(6)
UE Rate	0.00159***	0.00127***	0.00158***	0.00108**	0.00118***	0.00051
	(0.00023)	(0.00033)	(0.00037)	(0.00048)	(0.00028)	(0.00065)
UE Rate Interactions						
Male		0.00064				0.00073*
		(0.00042)				(0.00043)
Married		-0.00000				-0.00001
		(0.00001)				(0.00001)
Degree or higher ed.			0.00080*			0.00079*
			(0.00047)			(0.00047)
GCE, A level			0.00032			0.00031
			(0.00043)			(0.00043)
GCSE grades A-C*			0.00044			0.00044
			(0.00044)			(0.00044)
No/Other qualification			0.00022			0.00022
			(0.00043)			(0.00043)
18-34 yrs old				0.00075*		0.00040
				(0.00040)		(0.00041)
35-49 yrs old				0.00039		0.00026
				(0.00030)		(0.00030)
0-2 yrs of tenure					0.00057	0.00056
					(0.00035)	(0.00037)
2-10 yrs of tenure					0.00017	0.00016
					(0.00032)	(0.00032)
10+ yrs of tenure					-0.00085***	-0.00084***
					(0.00032)	(0.00032)
R-squared	0.45242	0.45242	0.45280	0.45242	0.45242	0.45281
No. Persons	1,208,080	1,208,080	1,208,080	1,208,080	1,208,080	1,208,080
No. Observations	4,559,914	4,559,914	4,559,914	4,559,914	4,559,914	4,559,914

Notes: Standard errors are clustered by individual. Quarter fixed effects and linear time trend included. Sample weights are used. The excluded category for education consists of individuals with missing education information. The excluded category for age consists of 50-64 year old respondents. The excluded category for tenure consists of individuals with missing tenure information. *, **, and *** show significance at the 1%, 5%, and 10% levels.

Appendix B

Chapter 2 Appendix

B.1 Figures

Figure B.1: Example Vignette

Employee wanted for a position:

- Involving 40 hours of work per week
- Requiring readiness to work over time during peak periods

The relevant employer is offering the following:

- A permanent employment relationship
- A monthly salary of [realistic gross monthly salary for full time job * 1.20] euros

The employer is a company:

- Which provides poor internal opportunities for promotion
- Which provides internal child care at customary local costs
- In which some working hours can be performed at home
- In which flexible working hours can be determined by employees
- Which usually receives very few job applications

How likely would you be to apply for this job?

Very unlikely										Very likely
0	1	2	3	4	5	6	7	8	9	10
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Let's assume you are offered the job (even without applying for it). How likely would you be to accept this job?

Very unlikely										Very likely
0	1	2	3	4	5	6	7	8	9	10
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

B.2 Tables

Table B.1: Vignette Job Attribute Randomization

	F-test P-value	
Vignette Job Attribute	Employed Sample	Full Sample
20 hour work week	0.23	0.12
30 hour work week	0.60	0.84
40 hour work week	0.37	0.70
Overtime required	0.48	0.84
1 yr employment contract	0.21	0.41
3 yr employment contract	0.43	0.66
Permanent employment contract	0.63	0.19
Poor promotion opportunities	0.13	0.33
Good promotion opportunities	0.16	0.40
Very good promotion opportunities	0.43	0.87
Child care available	0.60	0.93
Work location flexible	0.13	0.29
Work location inflexible	0.58	0.67
Work schedule flexible	0.91	0.51
Firm receives few applications	0.40	0.33
Firm receives many applications	0.08	0.01
Salary -10%	0.51	0.08
Salary +0%	0.40	0.55
Salary +10%	0.82	0.70
Salary +20%	0.22	0.67
Salary +30%	0.91	0.80
Salary +40%	0.13	0.02

Notes: Job attribute dummies are regressed on gender, marital status, education group, age, region, and realistic gross monthly salary responses. P-values of the F-tests for joint significance of coefficients are reported. Standard errors are clustered by individual. Regressions are completed without sample weights.

Table B.2: Job Attributes in Germany: Overall and by Subgroup

		Gender		Education		
	Overall	Women	Men	Lower	Int./Upper	Univ.
Means hours per week	34.8	30.7	38.2	35.1	34.5	35.2
	(0.3)	(0.4)	(0.2)	(0.6)	(0.3)	(0.6)
Mean wage	18.7	17.1	20.0	15.7	17.6	24.3
	(0.3)	(0.4)	(0.4)	(0.5)	(0.3)	(0.7)
Log wage differential						
<u>Percent with each attribute</u>						
Work overtime	70.6	66.4	74.1	63.2	69.5	81.4
	(1.9)	(2.5)	(2.8)	(4.6)	(2.4)	(3.1)
Temporary employment contract	2.2	1.8	2.5	4.7	1.8	0.4
	(0.6)	(1.0)	(0.7)	(2.0)	(0.6)	(0.3)
Fixed-term employment contract	9.6	10.6	8.8	8.1	8.1	14.5
	(1.2)	(1.7)	(1.5)	(2.2)	(1.4)	(2.8)
Permanent employment contract	88.2	87.6	88.7	87.1	90.1	85.1
	(1.3)	(1.9)	(1.6)	(2.8)	(1.5)	(2.9)
Good promotion opportunities	40.6	37.6	43.0	39.5	39.2	44.8
	(1.9)	(2.8)	(2.3)	(3.7)	(2.5)	(3.8)
Flexible working hours	36.4	29.9	41.7	16.9	31.6	68.7
	(2.0)	(2.7)	(2.7)	(3.3)	(2.4)	(3.5)
No. observations	2,732	1,385	1,347	662	1,482	588

Notes: Summary statistics are reported for the sample of workers aged 18 to 60 who completed the 2018 PASS vignette module and had non-missing wage and job attribute information. Standard errors are in parentheses. Sample weights are used.

Table B.2: Job Attributes in Germany: Overall and by Subgroup, Continued

	Age Group			Wage Quintile		
	18-29	30-44	45-60	Bottom	Middle	Top
Means hours per week	36.3	35.1	33.9	32.2	35.8	36.5
	(0.6)	(0.4)	(0.4)	(0.8)	(0.5)	(0.6)
Mean wage	15.0	18.4	20.5	9.8	17.8	33.2
	(0.4)	(0.4)	(0.5)	(0.1)	(0.1)	(0.7)
Log wage differential						
Percent with each attribute						
Work overtime	72.6	72.7	68.0	64.9	71.8	81.2
	(4.0)	(3.3)	(2.6)	(4.0)	(4.2)	(3.7)
Temporary employment contract	2.5	1.8	2.5	3.0	1.4	3.1
	(1.0)	(0.7)	(1.2)	(0.8)	(0.9)	(2.7)
Fixed-term employment contract	20.2	10.4	4.2	22.3	7.8	2.6
	(3.8)	(1.7)	(1.1)	(4.3)	(2.4)	(1.5)
Permanent employment contract	77.2	87.9	93.3	74.7	90.8	94.3
	(3.8)	(1.8)	(1.6)	(4.2)	(2.5)	(2.8)
Good promotion opportunities	49.4	40.3	36.9	28.8	38.9	55.5
	(4.8)	(3.2)	(2.6)	(3.7)	(3.5)	(4.9)
Flexible working hours	34.6	38.2	35.8	15.0	30.5	72.7
	(5.2)	(2.8)	(2.7)	(3.9)	(3.5)	(4.2)
No. observations	468	1,112	1,152	899	462	279

Notes: Summary statistics are reported for the sample of workers aged 18 to 60 who completed the 2018 PASS vignette module and had non-missing wage and job attribute information. Standard errors are in parentheses. Sample weights are used.

Table B.3: Estimates of Willingness to Pay for Job Attributes Using Log Earnings

Job Attribute	Employed	Nonemployed	Full Sample
Overtime work	-0.079**	-0.019	-0.059**
[Blank]	(0.033)	(0.059)	(0.026)
20 hour work week	0.261***	0.437***	0.297***
[40 hour work week]	(0.044)	(0.044)	(0.031)
30 hour work week	0.203***	0.178***	0.190***
[40 hour work week]	(0.034)	(0.062)	(0.027)
3 year employment contract	0.213***	0.083	0.175***
[1 year employment contract]	(0.040)	(0.062)	(0.031)
Permanent employment contract	0.308***	0.199***	0.268***
[1 year employment contract]	(0.038)	(0.058)	(0.030)
Good promotion opportunities	0.130***	0.199***	0.133***
[Poor promotion opportunities]	(0.033)	(0.067)	(0.027)
Very good promotion opportunities	0.145***	0.093	0.131***
[Poor promotion opportunities]	(0.034)	(0.068)	(0.028)
Child care	0.016	0.127**	0.033
[Blank]	(0.031)	(0.052)	(0.024)
Work from home possible	0.038	0.038	0.031
[Blank]	(0.041)	(0.058)	(0.031)
Work from home not possible	-0.029	0.028	-0.013
[Blank]	(0.039)	(0.049)	(0.029)
Schedule flexibility	0.081**	0.128**	0.094***
[Fixed schedule]	(0.033)	(0.059)	(0.027)
Firm receives few applications	-0.028	-0.060	-0.021
[Blank]	(0.041)	(0.068)	(0.033)
Firm receives many applications	0.022	0.048	0.024
[Blank]	(0.035)	(0.057)	(0.028)
Observations	8,196	2,751	15,321

Notes: Omitted job attribute dimensions are italicized and expressed in brackets. Regressions include individual fixed effects. Standard errors are clustered by individual. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

Table B.4: Job Attribute Valuations from Hedonic Wage Regressions

Job Attribute	OLS	Fixed Effects
Overtime work	-0.049**	-0.012
	(0.025)	(0.022)
Permanent employment contract	-0.153***	-0.063
	(0.042)	(0.044)
Good promotion opportunities	-0.087***	-0.020
	(0.023)	(0.023)
Schedule flexibility	-0.175***	-0.055*
	(0.026)	(0.031)
Observations	2,732	6,598

Notes: The sample for column 1 is the employed sample described in the text. The sample for column 2 restricts the sample of column 1 to workers with non-missing information on wages and job attributes in 2019 and 2020. While the OLS specification uses data from a single year (2018), the fixed effect specification uses data from 2018, 2019, and 2020. Robust standard errors are reported in the OLS specification and standard errors clustered at the individual level are reported in the fixed effect specification. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

Table B.5: Sorting and Estimates of Willingness to Pay for Job Attributes

Job Attribute	Has Job Attribute	Lacks Job Attribute	WTP Difference
Overtime work	-0.076**	-0.082	0.007
[Blank]	(0.039)	(0.072)	(0.083)
3 year employment contract	0.215***	0.144	0.071
[1 year employment contract]	(0.042)	(0.111)	(0.116)
Permanent employment contract	0.325***	0.207**	0.119
[1 year employment contract]	(0.043)	(0.098)	(0.107)
Good promotion opportunities	0.124***	0.129***	-0.004
[Poor promotion opportunities]	(0.048)	(0.048)	(0.066)
Very good promotion opportunities	0.206***	0.089*	0.118*
[Poor promotion opportunities]	(0.051)	(0.046)	(0.065)
Childcare	0.011	0.011	–
[Blank]	(0.032)	(0.032)	–
Work from home possible	0.041	0.041	–
[Blank]	(0.040)	(0.040)	–
Work from home not possible	-0.019	-0.019	–
[Blank]	(0.039)	(0.039)	–
Schedule flexibility	0.148***	0.071*	0.077
[Fixed schedule]	(0.048)	(0.042)	(0.061)
Firm receives few applications	-0.024	-0.024	–
[Blank]	(0.044)	(0.044)	–
Firm receives many applications	0.038	0.038	–
[Blank]	(0.038)	(0.038)	–
Observations	8,196	8,196	8,196

Notes: Omitted job attribute dimensions are italicized and expressed in brackets. Column 1 gives willingness to pay (WTP) estimates for individuals who have the listed job attributes, while column 2 gives WTP estimates for individuals who do not have the listed job attributes. Column 3 gives estimates of WTP differences between workers *with* and *without* the job attributes. Coefficients in columns 1 and 2 are obtained through interactions of job attribute dimensions and dummy variables indicating possession of the attributes. Regressions include individual fixed effects. Standard errors are clustered by individual. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

Table B.6: Estimates of Willingness to Pay for Job Attributes by Gender

Job Attribute	Women	Men	WTP Difference
Overtime work	-0.061	-0.093**	-0.032
[Blank]	(0.052)	(0.045)	(0.069)
3 year employment contract	0.234***	0.190***	-0.044
[1 year employment contract]	(0.073)	(0.047)	(0.087)
Permanent employment contract	0.349***	0.295***	-0.054
[1 year employment contract]	(0.062)	(0.051)	(0.081)
Good promotion opportunities	0.113**	0.135***	0.022
[Poor promotion opportunities]	(0.052)	(0.046)	(0.070)
Very good promotion opportunities	0.154***	0.125***	-0.029
[Poor promotion opportunities]	(0.057)	(0.047)	(0.073)
Childcare	-0.005	0.011	0.016
[Blank]	(0.061)	(0.038)	(0.072)
Work from home possible	0.068	0.034	-0.033
[Blank]	(0.078)	(0.046)	(0.090)
Work from home not possible	0.006	-0.037	-0.044
[Blank]	(0.062)	(0.048)	(0.079)
Schedule flexibility	0.155**	0.058	-0.097
[Fixed schedule]	(0.060)	(0.039)	(0.072)
Firm receives few applications	0.009	-0.043	-0.052
[Blank]	(0.074)	(0.056)	(0.092)
Firm receives many applications	0.043	0.037	-0.006
[Blank]	(0.062)	(0.048)	(0.079)
Observations	8,196	8,196	8,196

Notes: Omitted job attribute dimensions are italicized and expressed in brackets. Column 1 gives willingness to pay (WTP) estimates for women, while column 2 gives WTP estimates for men. Column 3 gives estimates of WTP differences between men and women. Coefficients in columns 1 and 2 are obtained through interactions of job attribute dimensions and a dummy variable for men. Regressions include individual fixed effects. Standard errors are clustered by individual. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

Table B.7: Estimates of Willingness to Pay for Job Attributes by Education

Job Attribute	(1) Lower Sec. Degree	(2) Int./Upper Sec. Degree	(3) Univ. Degree	(3)-(1) WTP Difference	(3)-(2) WTP Difference
Overtime work	-0.152**	-0.021	-0.148**	0.004	-0.126
[Blank]	(0.071)	(0.045)	(0.072)	(0.102)	(0.085)
3 year employment contract	0.212**	0.164***	0.331***	0.118	0.167
[1 year employment contract]	(0.083)	(0.054)	(0.087)	(0.120)	(0.102)
Permanent employment contract	0.337***	0.283***	0.375***	0.038	0.092
[1 year employment contract]	(0.102)	(0.049)	(0.079)	(0.129)	(0.093)
Good promotion opportunities	0.184**	0.095**	0.131**	-0.053	0.036
[Poor promotion opportunities]	(0.087)	(0.048)	(0.066)	(0.109)	(0.082)
Very good promotion opportunities	0.127	0.140***	0.156*	0.029	0.016
[Poor promotion opportunities]	(0.080)	(0.044)	(0.088)	(0.119)	(0.098)
Childcare	0.019	0.007	-0.007	-0.026	-0.014
[Blank]	(0.070)	(0.043)	(0.071)	(0.100)	(0.083)
Work from home possible	0.041	0.025	0.109	0.068	0.084
[Blank]	(0.082)	(0.057)	(0.081)	(0.115)	(0.099)
Work from home not possible	-0.056	-0.024	0.039	0.094	0.062
[Blank]	(0.083)	(0.053)	(0.083)	(0.118)	(0.099)
Schedule flexibility	0.012	0.131***	0.137**	0.124	0.005
[Fixed schedule]	(0.071)	(0.042)	(0.067)	(0.097)	(0.079)
Firm receives few applications	-0.076	-0.001	-0.004	0.071	-0.004
[Blank]	(0.103)	(0.054)	(0.086)	(0.135)	(0.102)
Firm receives many applications	0.033	0.031	0.085	0.052	0.054
[Blank]	(0.084)	(0.050)	(0.069)	(0.109)	(0.085)
Observations	8,196	8,196	8,196	8,196	8,196

Notes: Omitted job attribute dimensions are italicized and expressed in brackets. Column 1 gives willingness to pay (WTP) estimates for workers with lower secondary school degrees and less education. Column 2 gives WTP estimates for workers with intermediate and upper secondary school degrees. Column 3 gives WTP estimates for workers with university degrees. Columns 4 and 5 give estimates of WTP differences between education groups. Coefficients in columns 1-3 are obtained through interactions of job attribute dimensions and dummy variables for education. Regressions include individual fixed effects. Standard errors are clustered by individual. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

Table B.8: Estimates of Willingness to Pay for Job Attributes by Age Group

Job Attribute	(1) Ages 18-29	(2) Ages 30-44	(3) Ages 45-60	(3)-(1) WTP Difference	(3)-(2) WTP Difference
Overtime work	-0.096**	0.029	-0.162**	-0.066	-0.191**
[Blank]	(0.048)	(0.056)	(0.064)	(0.080)	(0.085)
3 year employment contract	0.147**	0.211***	0.239***	0.092	0.034
[1 year employment contract]	(0.064)	(0.070)	(0.065)	(0.091)	(0.096)
Permanent employment contract	0.165***	0.336***	0.369***	0.204**	0.034
[1 year employment contract]	(0.064)	(0.062)	(0.065)	(0.091)	(0.090)
Good promotion opportunities	0.070	0.109*	0.200***	0.129	0.091
[Poor promotion opportunities]	(0.056)	(0.057)	(0.065)	(0.086)	(0.086)
Very good promotion opportunities	0.122***	0.173***	0.138**	0.016	-0.036
[Poor promotion opportunities]	(0.046)	(0.065)	(0.061)	(0.076)	(0.089)
Childcare	-0.013	0.039	-0.012	0.001	-0.051
[Blank]	(0.047)	(0.055)	(0.056)	(0.073)	(0.078)
Work from home possible	0.076	0.048	0.027	-0.049	-0.021
[Blank]	(0.060)	(0.073)	(0.066)	(0.089)	(0.099)
Work from home not possible	0.079	-0.001	-0.111	-0.190**	-0.110
[Blank]	(0.060)	(0.065)	(0.071)	(0.093)	(0.096)
Schedule flexibility	0.136**	0.068	0.107**	-0.029	0.039
[Fixed schedule]	(0.058)	(0.050)	(0.052)	(0.078)	(0.072)
Firm receives few applications	-0.019	0.007	-0.032	-0.013	-0.039
[Blank]	(0.066)	(0.067)	(0.074)	(0.099)	(0.099)
Firm receives many applications	0.003	0.097	0.012	0.009	-0.085
[Blank]	(0.064)	(0.059)	(0.065)	(0.091)	(0.088)
Observations	8,196	8,196	8,196	8,196	8,196

Notes: Omitted job attribute dimensions are italicized and expressed in brackets. Column 1 gives willingness to pay (WTP) estimates for workers 18-29 years of age. Column 2 gives WTP estimates for workers 30-44 years of age. Column 3 gives WTP estimates for workers 45-60 years of age. Columns 4 and 5 give estimates of WTP differences between age groups. Coefficients in columns 1-3 are obtained through interactions of job attribute dimensions and dummy variables for age group. Regressions include individual fixed effects. Standard errors are clustered by individual. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

Table B.9: Estimates of Willingness to Pay for Job Attributes by Wage Quintile

Job Attribute	(1) Bottom Quintile	(2) Middle Quintile	(3) Top Quintile	(3)-(1) WTP Difference	(3)-(2) WTP Difference
Overtime work	-0.093	-0.071	-0.101	-0.008	-0.030
[Blank]	(0.099)	(0.080)	(0.067)	(0.120)	(0.104)
3 year employment contract	0.275*	0.183**	0.243***	-0.031	0.060
[1 year employment contract]	(0.144)	(0.085)	(0.074)	(0.162)	(0.113)
Permanent employment contract	0.384***	0.358***	0.311***	-0.073	-0.047
[1 year employment contract]	(0.130)	(0.090)	(0.068)	(0.147)	(0.113)
Good promotion opportunities	0.116	0.226***	0.095	-0.021	-0.131
[Poor promotion opportunities]	(0.099)	(0.091)	(0.071)	(0.122)	(0.115)
Very good promotion opportunities	0.125	0.189**	0.144*	0.019	-0.045
[Poor promotion opportunities]	(0.101)	(0.081)	(0.075)	(0.126)	(0.110)
Childcare	-0.029	-0.014	0.082	0.111	0.096
[Blank]	(0.113)	(0.073)	(0.058)	(0.127)	(0.094)
Work from home possible	0.080	0.103	-0.069	-0.149	-0.172
[Blank]	(0.155)	(0.071)	(0.087)	(0.177)	(0.112)
Work from home not possible	0.007	0.101	-0.154*	-0.161	-0.256**
[Blank]	(0.135)	(0.074)	(0.085)	(0.160)	(0.113)
Schedule flexibility	0.025	0.113*	0.138**	0.113	0.025
[Fixed schedule]	(0.114)	(0.062)	(0.057)	(0.128)	(0.084)
Firm receives few applications	-0.070	-0.069	-0.009	0.061	0.060
[Blank]	(0.138)	(0.103)	(0.064)	(0.152)	(0.121)
Firm receives many applications	0.174	-0.118	0.071	-0.103	0.189
[Blank]	(0.135)	(0.112)	(0.057)	(0.147)	(0.126)
Observations	4,920	4,920	4,920	4,920	4,920

Notes: Omitted job attribute dimensions are italicized and expressed in brackets. Column 1 gives willingness to pay (WTP) estimates for workers in the bottom wage quintile. Column 2 gives WTP estimates for workers in the middle wage quintile. Column 3 gives WTP estimates for workers in the top wage quintile. Columns 4 and 5 give estimates of WTP differences between wage quintiles. Coefficients in columns 1-3 are obtained through interactions of job attribute dimensions and dummy variables for wage quintile. Regressions include individual fixed effects. Standard errors are clustered by individual. Sample weights are used. ***, **, and * show significance at the 1%, 5%, and 10% levels.

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