Job Search Behavior among the Employed and Non-Employed*

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May 2021

Abstract

We develop a unique survey that focuses on the job search behavior of individuals regardless of their labor force status and field it annually starting in 2013. We use our survey to study the relationship between search effort and outcomes for the employed and non-employed. Three important facts stand out: (1) on-the-job search is pervasive, and is more intense at the lower rungs of the job ladder; (2) the employed are at least three times more effective than the unemployed in job search; and (3) the employed receive better job offers than the unemployed. We set up a general equilibrium model of on-the-job search with endogenous search effort, calibrate it to fit our new facts, and find that the search effort of the employed is highly elastic. We show that search effort substantially amplifies labor market responses to productivity shocks over the business cycle.

Keywords: job search, unemployment, on-the-job search, search effort, wage dispersion
JEL Classifications: E24, J29, J60

*We thank Christine Braun, Fatih Karahan, Rasmus Lentz, Ilse Lindenlaub, Giuseppe Moscarini, Chris Moser, Emi Nakamura, Richard Rogerson, Robert Valletta, and Thijs van Rens, in addition to participants from several conferences and seminars, for useful comments. We also thank Luis Armona, Sadhika Bagga, René Chalom, Rebecca Friedman, Thomas Haasl, Ali Haider Ismail, Elizabeth Klepper, Max Livingston, Sean Mihaljevich, and Rachel Schuh for their excellent research assistance. The views expressed here are our own and do not necessarily reflect those of the Federal Reserve Banks of New York or Chicago, or those of the Federal Reserve System.

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1 Introduction

Job-to-job transitions are an important feature of the U.S. labor market. They account for one-third to one-half of all hiring (Fallick and Fleischman, 2004) and are an important driver of reallocation, wage growth, and productivity growth (Faberman and Justiniano, 2015; Moscarini and Postel-Vinay, 2017; Karahan et al., 2017; Haltiwanger et al., 2018). Despite the critical importance of on-the-job search for understanding labor market dynamics and the central role it has in search theories of the labor market, evidence on its extent and nature remains scant, much in contrast with the abundance of evidence on the job search behavior of the unemployed.

In this paper, we help fill this void with new evidence on the job search behavior and job search outcomes of the employed and non-employed alike. To this end, we design and implement a unique new survey that focuses on job search behavior and outcomes for *all* individuals, regardless of their labor force status. Existing labor force surveys typically only collect information on the search behavior of the unemployed. We administer the survey as a supplement to the Survey of Consumer Expectations and have fielded it annually each October since 2013. The survey asks an expansive list of questions on the employment status and current job search, if any, of all respondents, including questions on an individual's search effort, search methods, search outcomes, and demographic information. Consequently, our survey represents an enormous expansion of available information on the job search process.

Our findings provide the most comprehensive evidence to date on the nature of on-the-job search for the U.S. While we uncover multiple new facts, three key findings stand out. First, the employed frequently engage in on-the-job search, with around 20 percent of the employed actively looking for work in the prior four weeks based on multiple measures of search activity. Their search intensity declines strongly with their current wage, consistent with a central prediction of models that include on-the-job search. Controlling for worker characteristics, we estimate an elasticity of search intensity with respect to the current wage of between -0.52 and -0.36.

Second, on-the-job search is more effective than search by the unemployed: employed job seekers receive a similar number of offers despite exerting a fraction of the search effort of the unemployed. We define the job *offer yield* as job offers received per unit of search effort and estimate that the employed receive over three times more offers per application sent. Moreover, the relative offer yield is well over two and often greater than three within demographic groups defined by age, gender and education, reinforcing the idea that on-the-job search is much more effective in generating job offers than search while unemployed.

Third, the employed appear to sample from a higher-quality job offer distribution than the unemployed. Unconditionally, the wages offered to the employed are 36 log points (44 percent) higher than the wages offered to the unemployed. Accounting for observable worker and job characteristics only reduces the wage offer differential to 19 log points (21 percent). An obvious concern, however, is that unobserved differences in productivity between employed and unemployed job seekers may be the reason for what appears to be a *wage offer premium.* Those with higher unobserved skills are more likely to be employed and earn higher wages, so a wage offer premium is a natural consequence of this selection effect. We have survey data on an individual's prior work history, which provides a useful proxy for unobserved heterogeneity that may be correlated with one's current labor force status. Controlling for these histories only reduces the wage offer premium to 13 log points (14 percent).

In the second part of our paper, we match our new facts to a general equilibrium random search model of the labor market with on-the-job search, wage bargaining and endogenous search effort and vacancy creation. We build on earlier models of on-the-job search with endogenous search effort such as Christensen et al. (2005) and Hornstein et al. (2011) and the wage bargaining protocol in Cahuc et al. (2006). In particular, we set up a version of the framework in Bagger and Lentz (2019) with match-specific productivity and augment it in three important dimensions to accommodate the salient features of our survey: (i) differences in search efficiency by employment status; (ii) differences in bargaining weights by employment status; and (iii) censoring and rejection of job offers. We parameterize the model by matching it to a number of key moments from our survey data, and obtain a good fit along multiple dimensions of the data. Two implications follow immediately from our quantitative analysis. First, the unemployed are willing to accept low-paying job offers despite a relatively high flow value of unemployment. Given the high relative search efficiency of the employed implied from the data, the unemployed are better off accepting a low-paying job so they can enjoy the efficiency of on-the-job search. This in turn generates *frictional* wage dispersion consistent with the data and provides an intuitive resolution of the *wage dispersion puzzle* posited by Hornstein et al. (2011). Second, the model suggests that over 60 percent of the residual wage offer premium enjoyed by the employed is due to differences in unobserved heterogeneity by labor force status, whereas censoring and bargaining account for about 20 percent each. The contribution of censoring suggests that the employed partially direct their search towards jobs with higher match-specific productivity, while the contribution of bargaining suggests that employed workers receive better wage offers than unemployed workers even when holding worker- and match-specific productivity constant.

Our calibration replicates the empirical elasticity between search effort and wages observed in the data, which uniquely identifies the curvature of search costs in the model. In particular, we find that job search effort is more elastic than suggested by a quadratic search cost function—the most common assumption in the literature (e.g., Christensen et al., 2005; Hornstein et al., 2011). The elasticity we identify using our data has direct implications for how search intensity responds to changes in labor market conditions. To quantify the macroeconomic implications of this higher elasticity, we consider the economy's response to a negative aggregate productivity shock, which then reverts back to its initial level over time following Shimer (2005). We find that the resulting decline in search effort in our experiment is over six time larger relative to a model with quadratic search costs, leading to substantial amplification of the declines in vacancies, labor market tightness and job-to-job transitions. Search effort also responds more strongly as labor market conditions improve, increasing the speed of reallocation to better jobs on the job ladder. Yet, despite the relatively fast reallocation, vacancy creation and unemployment in our model exhibit substantial persistence, unlike in the standard search and matching model as discussed in Cole and Rogerson (1999). Our quantitative exercise highlights the importance of modeling search effort endogenously and with the appropriate elasticity to characterize labor market dynamics.

In sum, our paper breaks new ground along several dimensions. We design and implement a unique new survey on job search behavior and job search outcomes regardless of employment status. We document several new stylized facts on the search process of the employed relative to the unemployed. Our findings speak to margins that are at the heart of on-the-job search models but have been mostly unobservable in data available thus far. Finally, we examine our findings through the lens of a general equilibrium job-ladder model and show that search effort is more elastic than typically assumed in the literature, which substantially amplifies the response of the labor market to aggregate shocks.

1.1 Related Literature

The literature on job search has typically focused on the unemployed, primarily because of limited availability of on-the-job search data. Some studies that focus on the unemployed use the number of job search methods as a measure of search effort (Shimer, 2004), while others use direct measures of time spent looking for work (Krueger and Mueller, 2010, 2011; Aguiar, Hurst, and Karabourbanis, 2013; and Mukoyama, Patterson, and Şahin, 2018). Notable exceptions that have examined on-the-job search include earlier work by Kahn (1982), Holzer (1987), and Blau and Robins (1990), all of which use older, discontinued surveys. Recent studies use the American Time Use Survey (ATUS) to document on-the-job search behavior (Mueller, 2010; Ahn and Shao, 2017), but the diary-based structure and the lack of data on job search outcomes limit the usefulness of the ATUS to describe the process of on-the-job search as we discuss in detail in the Online Appendix C. A growing literature studies job search behavior using job application data from online job search platforms (Kuhn and Shen, 2013; Kroft and Pope, 2014; Marinescu, 2017; Hershbein and Kahn, 2018; Faberman and Kudlyak, 2019; Banfi and Villena-Roldan, 2019, among others). While this literature has started to provide novel insights into the job search process, the data typically lack information on labor force status as well as job search outcomes, such as the incidence and characteristics of job offers.

Despite a lack of supporting data, the literature on labor search theory has recognized the importance of on-the-job search as far back as early work by Parsons (1973) and Burdett (1978). More recently, Christensen et al., (2005), Cahuc, Postel-Vinay, and Robin (2006), and Bagger and Lentz (2019), among others, have documented the importance of on-the-job search and its related job ladder dynamics. There is also a natural connection between our paper and a growing literature that emphasizes the importance of on-the-job search for macroeconomic outcomes, such as Elsby, Michaels and Ratner (2015), Eeckhout and Lindenlaub (2019), Moscarini and Postel-Vinay (2019), and Faccini and Melosi (2019). Job seeker's search effort, and how it affects one's success in moving up the job ladder, is prominent in all of these models. Given the growing interest in the relationship between business cycle fluctuations and job ladder dynamics, our finding of highly elastic on-the-job search effort is particularly relevant.

The next section describes our survey. Section 3 presents our evidence concerning search behavior and outcomes by labor force status. Section 4 presents a model of on-the-job search with endogenous search effort and discusses its quantitative implications. Section 5 concludes.

2 Survey Design and Data

We design and implement a new survey on job search behavior and outcomes. The survey is a supplement to the Survey of Consumer Expectations (SCE), administered by the Federal Reserve Bank of New York. The SCE is a monthly, nationally-representative survey of roughly 1,300 individuals that asks respondents their expectations about various aspects of the economy. Our survey draws its respondents from the monthly SCE. We first administered our survey, the Job Search supplement to the SCE, in October 2013 and have repeated the survey each October since then. In this paper, we present estimates for a sample that pools the 2013-17 data together.

Our supplement asks a broad range of questions on employment status, job search behavior, and job search outcomes. Demographic data are also available for respondents through the monthly SCE. Since we draw our respondents from the monthly SCE, our supplement, like that survey, is a nationally representative survey of heads of households. Armantier et al. (2017) present a detailed evaluation of the monthly SCE's design, implementation, and representativeness. They show that its demographic statistics match up to those of the American Community Survey very well. In Online Appendix A, we evaluate the representativeness of the Job Search supplement relative to the monthly SCE and the Current Population Survey (CPS). We show that, overall and for each survey year, our Job Search supplement matches the demographics of the monthly survey and CPS well. The notable exceptions are relatively higher shares of White, younger, and married individuals in both the Job Search supplement and the monthly SCE compared to the CPS.[1] Note also that our Job Search supplement sample is a set of annual repeated cross-sections. The main monthly SCE surveys its respondents for up to 12 months. Since the Job Search supplement draws from these respondents each October, individuals will be in the supplement, at most, once.[2]

[1] Consequently, we control for differences in demographics where appropriate in our analysis, and report a replication of all of our empirical results that control for observable characteristics in our additional Supplemental Appendix S-B.

[2] We are still able to match our Job Search supplement data to respondents' responses in the monthly SCE. We do this to evaluate the performance of some of our labor market measures in Online Appendix B.

Our Job Search supplement survey asks a variety of questions that are tailored to an individual's employment status and job search behavior.[3] For the employed, the supplement asks questions about their wages, hours, benefits, and the type of work that they do, including questions on the characteristics of their workplace. For the non-employed, regardless of whether they are unemployed or out of the labor force, the supplement asks a range of detailed questions on their most recent employment spell and their reasons for non-employment. The supplement also asks questions related to the type of non-employment, including those related to retirement, school enrollment status, and any temporary layoff. It also asks individuals about their prior work history. This includes detailed information about the previous job of the currently employed. Most importantly, the supplement asks all individuals, regardless of their employment status, if they have searched for work within the last four weeks, and if they have not searched, whether or not they would accept a job if one was offered to them. Among the employed, the survey distinguishes between those searching for new work and those searching for a job in addition to their current one. For individuals who have searched or would at least be willing to accept a new job if offered, the survey asks a series of questions relating to their job search (if any), including the reasons for their decision to (not) search. It then asks an exhaustive set of questions on the types of effort exerted when seeking new work (e.g., updating resumes, searching online, contacting employers directly). Many of our questions on labor force status and job search behavior follow the wording and response choices for analogous questions from the CPS.

Additionally, the Job Search supplement asks about the number of job applications completed within the last four weeks and the number of employer contacts and job offers received. It probes further to see how those contacts and offers came about, i.e., whether they were the result of traditional search methods or whether they came about through a referral or an unsolicited employer contact. For those who received an offer, the survey asks about a range of characteristics of the job offer, including the wage offered, the expected hours, its benefits, as well as the type of work to be done and the characteristics of the employer. It also asks what led, or may lead, the respondent to accept or reject the offer, and asks a range of questions about whether there was any bargaining with either the current or future employer. Since only a fraction of respondents

[3]We include the wording and descriptions of the key survey questions for our analysis in Online Appendix A. We also replicate the relevant survey questions directly from the Job Search supplement questionnaire in Supplemental Appendix S-A.

in our sample report a job offer in the months leading up to the survey, we ask those who are currently employed a range of additional, retrospective questions about the search process that led to their current job.

The supplement has survey questions that allow us to identify an individual's labor force status at several points in time. This allows us to deal with time aggregation and other timing issues that often plague studies of labor market dynamics. Specifically, we have survey data on one's labor force status at the time of the survey interview and at the time they received any job offer. We also derive a labor force status for the month prior to the survey interview using a series of survey questions on an individual's current labor force status, job tenure, nonemployment spell, and search activity. This allows us to study search outcomes based on an individual's labor force status prior to accepting a job offer or otherwise changing their employment status. We detail our methodology for identifying labor force status and evaluate our results under differing methodologies in Online Appendix B.[4]

In general, we identify whether an individual is actively searching for work in a similar manner to the methods the Bureau of Labor Statistics (BLS) uses to identify active search among the unemployed in the CPS. That is, we identify individuals as actively searching through a direct question asking whether they have looked for work in the last four weeks and follow up with a question on their search methods used to ensure that their search behavior fits the standard BLS definition of "active" search. Our survey allows us to identify search more broadly as well. Specifically, we can identify individuals who might not have reported employing an "active" search method but nevertheless reported sending a job application in the prior four weeks (which satisfies the active search criteria). The key feature of our survey is that we ask about job search regardless of labor force status (rather than ask just the unemployed, as is done in the CPS) and we ask individuals regardless of whether they state that they "want work," so we can derive a broader measure of job search than the CPS affords. We evaluate how our broader measure of job search compares to using the CPS definition of job search in Supplemental Appendix S-B.

Our analysis sample is the SCE Job Search supplement, pooled across its 2013-17 surveys and restricted to individuals aged 18 to 64 with non-missing demographic and labor force status

[4]Specifically, we discuss the survey questions on labor force status at the times of the survey interview or job offer and detail our methodology for deriving labor force status in the prior month in the Online Appendix.

data. This provides just under 4,700 observations. Our survey does not ask the self-employed about job search, so the self-employed are generally excluded by construction throughout the job search portions of our analysis. We also focus on a subsample of individuals who received a job offer within the last six months. By construction, some of these offers will reflect the respondent's current job, which we identify through a separate question in the survey. After removing offers with only partial data, this subsample has 1,054 observations. We use this sample to examine a range of job offer characteristics, including the offer wage distribution. Note that the Job Search supplement first asks respondents whether they received any offer in the last four weeks, and only if not, it follows up and asks about offers received in the last six months. Thus, the survey allows us to determine a monthly offer rate that we can match to other labor market and job search statistics that are measured at the same frequency.

3 Evidence on Job Search Behavior and Outcomes

In this section, we present our empirical analysis. Our main findings can be summarized as follows: (i) the employed frequently engage in on-the-job search and the intensity of on-the-job search declines with the current wage; (ii) employed job seekers search less than the unemployed but receive just as many offers, implying that their search is more effective per unit of effort; (iii) the employed receive better offers with higher wages and benefits, even after controlling for observable characteristics, but at the same time are less likely to accept them.

3.1 Extensive and Intensive Margins of Job Search

We begin with evidence on the basic characteristics of individual job search effort. It is useful to analyze the extensive and intensive margins of job search separately since the distribution of total search effort along both dimensions is informative to appropriately measure search inputs. Table 1 reports the incidence of job search by labor force status at the time of the survey interview, which we interpret as the *extensive margin* of job search. By definition, all unemployed, save for those on temporary layoff, search. We employ a search-based definition of unemployment that is somewhat broader than the CPS definition, so we find that only a minimal fraction of those

Table 1: Basic Job Search Statistics by Labor Force Status

	Employed	**Unemployed**	**Out of Labor Force**
Percent that actively searched for work	22.4	99.6	2.4
	(0.7)	(0.8)	(0.6)
Percent that actively searched and are available for work	13.2	99.6	0.0
	(0.6)	(0.5)	(0.0)
Percent reporting no active search or availability, but would take job if offered	5.9	0.2	6.1
	(0.4)	(0.3)	(0.9)
Percent applying to at least one vacancy in last four weeks	21.4	92.8	2.2
	(0.7)	(1.7)	(0.6)
Percent with positive time spent searching in last seven days	21.3	86.7	2.3
	(0.7)	(2.3)	(0.6)
Conditional on Active Search			
Percent only searching for an additional job	36.0	—	—
	(1.7)		
Percent only seeking part-time work	21.7	22.5	—
	(1.5)	(2.8)	
Percent only seeking similar work (to most recent job)	25.3	7.4	—
	(1.7)	(1.8)	
N	3,725	228	706

Notes: Estimates come from authors' tabulations from the October 2013-17 waves of the SCE Job Search Supplement, for all individuals aged 18-64, by labor force status. Standard errors are in parentheses.

out of the labor force engage in search.[5] Among the employed, over 21 percent can be classified as searchers regardless of the criteria we employ to define job search. Over 22 percent of the employed looked for work in the last four weeks, with 21 percent applying to at least one job and a similar amount searching at least once in the last seven days. Around 22 percent of those searching on the job report looking for only part-time jobs. Among the employed, 36 percent of those actively searching (representing 9 percent of all employed) report only looking for an additional job, with no intention of leaving their current job. This is a notably large fraction since this type of job search is absent from nearly all models of on-the-job search.

According to our survey responses, dissatisfaction with pay and benefits is the main reason for on-the-job search, with 55 percent of employed searchers indicating it as a reason for search.

[5] We discuss the differences between our broader definition and the CPS definition of unemployment in Online Appendix A and present results on their differences in Supplemental Appendix S-B. The key difference is that our definition does not restrict measuring active job search to those who report wanting work. Using the CPS definition implies that 12.4 percent of those out of the labor force actively search.

Table 2: Intensive Margin: Search Effort by Labor Force Status

	Employed			Unemployed	Out of Labor Force
	Looking for Work	Not Looking	All		
A. Labor Force Status at Time of Survey					
Hours spent searching, last 7 days	4.40	0.07	1.16	9.19	0.10
	(0.29)	(0.01)	(0.08)	(0.69)	(0.04)
Mean applications sent, last 4 weeks	4.17	0	1.06	8.50	0.09
	(0.31)	(—)	(0.08)	(1.01)	(0.04)
N	804	2,498	3,292	228	706
B. Labor Force Status in Prior Month					
Mean applications sent	4.08	0.00	1.03	10.39	0.47
	(0.30)	(0.00)	(0.08)	(1.37)	(0.09)
Mean applications sent, ignoring applications to additional jobs	3.06	0.00	0.77	10.39	0.47
	(0.29)	(0.00)	(0.08)	(1.37)	(0.09)
N	822	2,526	3,348	166	721

Notes: Estimates come from authors' tabulations from the October 2013-17 waves of the SCE Job Search Supplement for all individuals aged 18-64, excluding the self-employed, by detailed labor force status. The top panel reports estimates by labor force status at the time of the survey, while the bottom panel reports the results by labor force status in the prior month. See Online Appendix B for how prior month's labor force status is determined. Standard errors are in parentheses.

Other important reasons include dissatisfaction with job duties (46 percent), poor utilization of one's skills or experience (36 percent), or simply "wanting a change" (34 percent). Only 3.4 percent of the employed reported that they searched because they had been given advance notice, while 10.7 percent cited job instability. Another 8.5 percent cited a need to relocate. Note that respondents can cite more than one reason, so these percentages do not need to add up to 100. Overall, these answers are consistent with the notion that workers seek to move to more productive, better paid jobs through job-to-job transitions.

Table 2 reports the amount of effort spent on the job search process, the *intensive margin* of job search. We categorize those employed at the time of the survey by whether or not they actively looked for work. This distinction highlights the stark differences in search activity among the employed. The unemployed send substantially more job applications and dedicate more hours to search than the other groups. They put in roughly twice as much effort as the employed that actively look for work. On average, unemployed workers spent around 9.2 hours *per week* on job search and sent 8.5 applications in the *last four weeks*.[6]

[6] In the Supplemental Appendix S-B.3, we show that the unemployed use more search methods than the employed, relying more on both direct employment contacts and employment agencies.

We can also use a range of current and retrospective questions on labor force history to generate a labor force status for respondents four weeks prior to the survey interview. This allows us to deal with a selection issue whereby some employed at the time of the interview may report search activity that they performed while unemployed prior to their current job.[7] Using this measure of prior labor force status, we find that the differences in search intensity between the employed and unemployed are more stark. The employed who actively looked for work sent 4.1 applications in the subsequent four weeks while the unemployed sent 10.4 applications in the subsequent four weeks. If we ignore applications sent by the employed only looking for additional work (i.e., work does not include leaving their current job), the difference between the employed and unemployed is even more stark. These findings are remarkably similar to the statistics reported by Barron and Gilley (1981), who use a special survey of the unemployed in the CPS from May 1976. They find that the typical unemployed individual contacted over three employers *per week* and spent approximately eight and two-thirds hours *per week* to make such contacts.

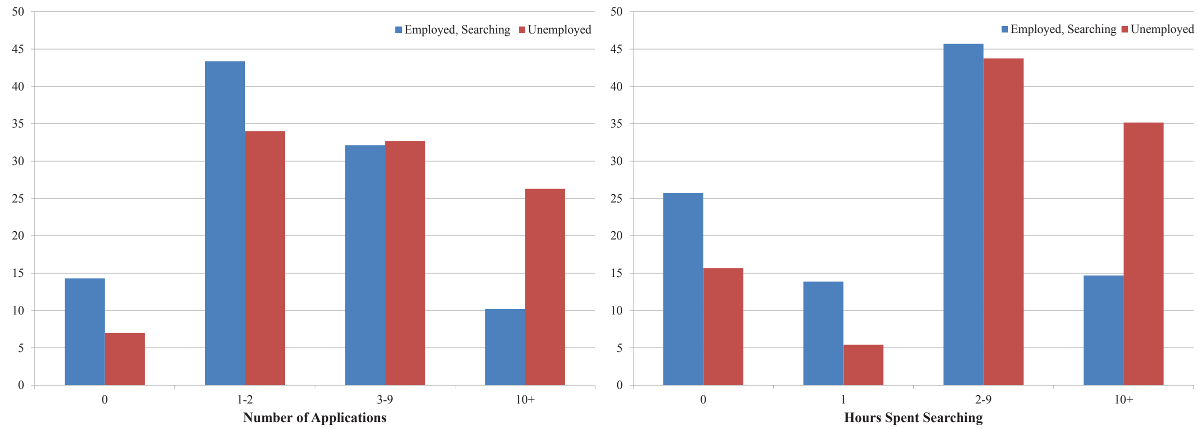
Figure 1 shows the distributions of search time in the last seven days and the number of applications sent in the last four weeks for job seekers employed and unemployed at the time of the survey interview, conditional on searching in the last four weeks.[8] The left panel of the figure shows that the majority of employed job seekers (58 percent) sent two or fewer applications in the previous four weeks, while just over 26 percent of the unemployed sent more than 10 applications. The right panel of the figure shows that over 42 percent of employed job seekers searched for one hour or less within the last seven days, while over 81 percent of the unemployed searched for two hours or more, with 37 percent searching 10 hours or more (compared to 13 percent of employed job seekers that searched for 10 hours or more). Despite both groups defined as actively looking for work, 25 percent of the employed and 13 percent of the unemployed performed no search within the last seven days, highlighting the intermittent nature of job search effort.

Comparison with other surveys. Empirical evidence on the incidence of on-the-job search is scarce and mostly comes from outdated surveys, making it hard to provide a good comparison for our estimates of search intensity. The American Time Use Survey (ATUS) is a recent survey

[7] This selection issue is similar to the time-aggregation issue that plagues calculations of the separation rate. We detail our methodology for identifying labor force status four weeks prior in Online Appendix B.

[8] Recall from Table 1 that around 22 percent of the employed report actively searching. The remainder is excluded from the analysis to provide a more relevant comparison of distributions. We report these distributions over a finer grid in the Supplemental Appendix S-B.

Figure 1: Distribution of Number of Applications Sent in the Last Four Weeks (left panel) and Search Time in Hours in the Last Seven Days (right panel) by Labor Force Status



Notes: Figure reports the histograms of the number of applications sent in the last four weeks (left panel) and the hours of time spent searching for work in the last seven days (right panel). Estimates are for all individuals, excluding the self-employed, who reported actively searching for work in the October 2013-17 waves of the SCE Job Search Supplement.

that provides estimates of time spent on job search in the *prior day*, but there are reasons to believe that the ATUS understates job search intensity, particularly for the employed. The first contributing factor is the time span of the job search question. The potentially intermittent nature of job search activity implies that one cannot simply multiply average daily search time by seven to come up with weekly search statistics. Second, the ATUS does not account for job search activity unless it is the respondent's primary activity, which may lead to understating search intensity especially for the employed. Finally, time use surveys do not prompt participants to report their search activity, but instead simply ask participants to report how they spent their previous day, which may lead respondents to underreport shorter episodes of job search.

In Online Appendix C, we provide a detailed comparison of the ATUS data pooled over the 2013-2017 period with the SCE. We find that, on average, only around 0.6 percent of the employed actively search for work according to the ATUS. The corresponding fraction is only 16.5 percent for the unemployed (who by definition had searched in the last four weeks), revealing the intermittent nature of search. The ATUS data also suggest that the employed only spend about 0.8 minutes per day looking for work, while the unemployed spend 26.7 minutes per day looking for work. These estimates contrast sharply with the evidence we report in Tables 1 and 2. In Online Appendix C, we examine data from the ATUS, combined with supplemental evidence from the United Kingdom Time Use Survey (UKTUS), which reports potential job search activity on two consecutive days and time spent on secondary activities. We use these data to derive *weekly* estimates of extensive-margin and intensive-margin job search for the ATUS that addresses its measurement differences. With these adjustments, the weekly extensive-margin incidence of job search for the unemployed is comparable in the ATUS and SCE, but the ATUS estimates are still well below what we observe in the SCE data for the employed. We conclude that the survey instrument combined with the prevalence of intermittent search and search as a secondary activity likely leads to a downward bias in estimates of search activity in time use surveys, particularly among the employed. This is consistent with studies of time use survey measurement, which highlight the difficulty of accurately capturing intermittent and secondary activities in the context of home production (e.g., Floro and Miles, 2003).

The SCE estimates are more in line with older studies of job search activity that do not rely on diary-based information. Black (1980) finds that around 14 percent of White workers and 10 percent of Black workers reported on-the-job search in the 1972 interview of the Panel Study of Income Dynamics (PSID). Blau and Robins (1990) report that employed search spells represent about 10 percent of all employment spells in the Employment Opportunity Pilot Project (EOPP) in 1980.[9] Given that we designed our survey to cast a wide net to identify any "search activity," we find our estimates of search intensity reasonable and broadly in line with the limited comparable evidence on on-the-job search.

3.2 Search Intensity and Wages

A key implication of job ladder models is that workers near the bottom of the job ladder search harder for a better job while those near the top of the job ladder do not search as hard since their chances of improving upon their current job are smaller (see, for example, Christensen et al., 2005; Bagger and Lentz, 2019; and Moscarini and Postel-Vinay, 2019). While this relationship is at the heart of job-ladder models, one could not measure it empirically with a direct, reliable measure

[9]The CPS does not ask questions about on-the-job search, but its recent Computer and Internet Use Supplements ask all respondents, regardless of their labor force status, whether they used the internet to search for a job in the past *six months*. Around 28 percent of the employed reported using the internet for job search in the 2015 survey. Our survey also asks a question about whether an individual searched in the last *twelve months*. Around 45 percent of the employed report searching in the last twelve months using any active search method, including online job search.

Table 3: The Relationship between Search Effort and the Current Wage

	Incidence of Search		**Search Effort**	
	Active Search	Applied	Applications	Search Time
log current real wage	-0.070^{***}	-0.063^{**}	-0.385^{**}	-0.599^{***}
	(0.020)	(0.019)	(0.118)	(0.163)
Dependent variable mean	0.252	0.213	1.059	1.163
R^2	0.077	0.086	0.031	0.065
N	3,278	3,278	3,278	3,278

Notes: The table reports the estimated relationship from an OLS regression between the dependent variables listed in each column and the (log) real current wage for all employed individuals in the October 2013-17 waves of the SCE Job Search Supplement. "Active Search" equals one if an individual actively looked for work in the last four weeks. "Applied" equals one if an individual applied to at least one job in the last four weeks. "Applications" refers to the number of applications sent in the last four weeks. "Search Time" refers to the number of hours spent looking for work in the last seven days. Regressions are sample weighted and control for gender, age, age squared, four education dummies, four race dummies, a homeownership dummy, marital status, marital status×male, the number of children aged 5 and younger, and fixed effects for state and year. Standard errors are in parentheses. *** represents significance at the 1 percent level. ** represents significance at the 5 percent level.

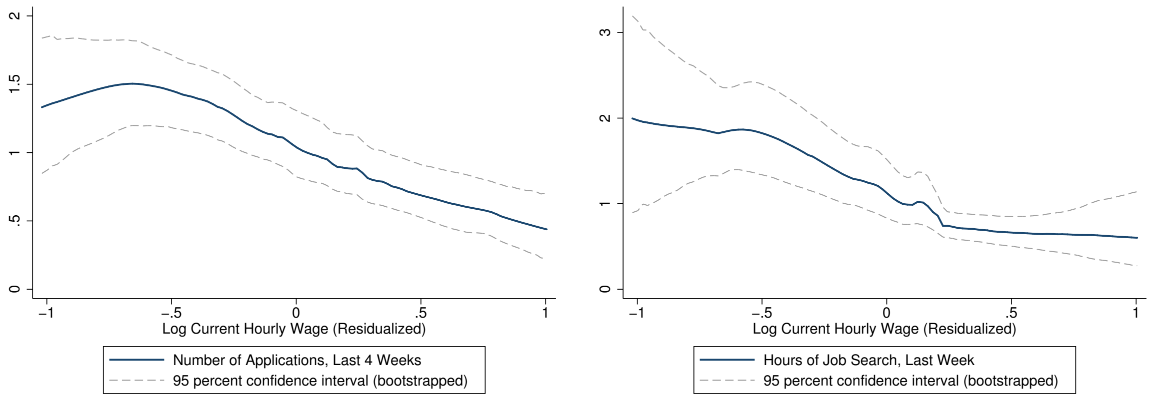
of search effort until the development of our survey.[10] Measurement error and unobserved worker heterogeneity in wages make it difficult to assess the exact position of a worker on the job ladder, but a worker's wage relative to her peers with similar observable characteristics should still provide a useful proxy. Therefore, we estimate a linear regression of the relationship between a worker's search behavior and her (log) current wage controlling for observable worker characteristics. Our estimates are in Table 3 and show that workers with lower wages in their current job are more likely to engage in search regardless of the measure of search activity that we use. In addition, the overall intensity of search activity, measured by the total number of applications in the last four weeks or the total hours spent searching the last seven days, is higher for workers with lower wages.[11] The estimates in the right columns of Table 3 imply a search effort-wage elasticity of -0.36 using applications sent and -0.52 using hours spent searching.

We also explore potential non-linearities in the search-wage relationship. Figure 2 shows the estimates from a locally weighted regression (LOWESS) between the different measures of search effort and the residualized current wage, i.e., the wage conditional on the controls from Table 3. The figure highlights the negative wage-search effort relationship in Table 3 for both the total number of applications and hours of search, and illustrates the quantitatively large decline in

[10]An exception is Mueller (2010), who documents a negative relationship in the ATUS data, though it is subject to the caveats for measuring on-the-job search with the ATUS that we noted earlier.

[11]In results available on request, we report the effect of various observables on the incidence and intensity of search. Females, more educated workers, and workers who identify as Black and Hispanic search harder.

Figure 2: Job Search Effort by the Current Wage



Notes: Figure reports the LOWESS estimates (with smoothing parameter 0.8) of the relationship between the measures of search effort listed on each vertical axis and the (log) real current wage of the employed, residualized after controlling for observable worker characteristics (see Table 3 for the list of specific variables). Dashed lines represent 95 percent confidence intervals. The confidence intervals are based on a bootstrap with 500 replications. The estimates use all employed individuals, excluding the self-employed, age 18-64 from the October 2013-17 waves of the SCE Job Search Supplement.

search effort from low to high residual wages.[12] There is some nonlinearity in the relationship for low wages, but otherwise the relationship is close to linear. These plots provide direct evidence of declining search intensity with respect to current wages, a key implication of the job ladder models with endogenous search mentioned earlier.[13]

3.3 Search Outcomes by Labor Force Status

Our survey puts us in a unique position to examine both job search effort and outcomes and assess the relative effectiveness of employed versus unemployed search. We next show that on-the-job search generates a substantial number of offers that are high-quality, on average, especially when compared to the job search outcomes of the unemployed.

Table 4 reports job offer estimates by labor force status measured at two points in time.[14] The first uses labor force status at the time of the survey interview. This definition suffers from the selection issues noted earlier but is consistent with how labor force status is captured in the

[12]In Supplemental Appendix S-B, we show that similar patterns hold for our measures of search intensity when we do not control for observable characteristics in the wage.

[13]One may worry that individuals with high search efficiency may search less but still climb the ladder faster, which could account for the patterns we report in Figure 2. This would imply an increasing return to search along the job ladder. In Supplemental Appendix Table S-B16, however, we show that the returns to search (in terms of offers per application sent) are similar across all quartiles of the wage distribution.

[14]We report results for additional search outcomes, including employer contacts and job interviews, by labor force status and search incidence in Supplemental Appendix S-B.

Table 4: Search Outcomes by Labor Force Status

	Employed			Unemployed	Out of Labor Force
	Looking for Work	Not Looking	All		
A. Labor Force Status at Time of Survey					
Mean offers	0.442	0.117	0.200	0.511	0.101
	(0.033)	(0.023)	(0.019)	(0.210)	(0.027)
Fraction with at least one formal offer,	0.291	0.058	0.117	0.223	0.049
including unsolicited offers	(0.016)	(0.005)	(0.006)	(0.028)	(0.008)
Fraction with at least one	0.044	0.027	0.031	0.052	0.023
unsolicited offer	(0.007)	(0.003)	(0.003)	(0.015)	(0.008)
Fraction with at least one formal	0.350	0.098	0.162	0.252	0.062
or unrealized offer	(0.017)	(0.006)	(0.006)	(0.029)	(0.009)
N	804	2,498	3,294	228	705
B. Labor Force Status in Prior Month					
Fraction with at least one formal offer,	0.261	0.053	0.106	0.342	0.079
including unsolicited offers	(0.015)	(0.004)	(0.005)	(0.037)	(0.010)
Fraction with at least one	0.044	0.025	0.030	0.042	0.033
unsolicited offer	(0.007)	(0.003)	(0.003)	(0.016)	(0.007)
Fraction with at least one formal	0.318	0.094	0.150	0.370	0.089
or unrealized offer	(0.016)	(0.006)	(0.006)	(0.038)	(0.011)
Fraction of best formal offers accepted	0.460	0.111	0.328	0.493	0.195
	(0.027)	(0.036)	(0.027)	(0.069)	(0.052)
C. Labor Force Status in Prior Month, Ignoring Search Outcomes for Additional Jobs					
Fraction with at least one formal offer,	0.173	0.051	0.081	0.342	0.079
including unsolicited offers	(0.013)	(0.004)	(0.005)	(0.037)	(0.010)
Fraction with at least one	0.030	0.024	0.026	0.042	0.033
unsolicited offer	(0.006)	(0.003)	(0.003)	(0.016)	(0.007)
Fraction with at least one formal	0.217	0.091	0.123	0.370	0.089
or unrealized offer	(0.014)	(0.006)	(0.006)	(0.038)	(0.011)
Fraction of best formal offers accepted	0.488	0.106	0.309	0.493	0.195
	(0.046)	(0.028)	(0.030)	(0.069)	(0.052)
N	822	2,526	3,348	166	721

Notes: Estimates come from authors' tabulations from the October 2013-17 waves of the SCE Job Search Supplement for all individuals aged 18-64, excluding the self-employed, by labor force status. The top panel reports estimates by labor force status at the time of the survey, while the middle and bottom panels report the results by labor force status in the prior month. See Online Appendix B for how prior month's labor force status is determined. Standard errors are in parentheses.

CPS. The second uses labor force status in the prior month, our preferred measures since it does not suffer from those selection issues. We also report estimates that exclude offers to those only looking for additional work. These estimates are most relevant for current models of labor market search since these models usually focus on job offers that lead to a job-to-job transition.

The top panel of Table 4 reports mean offers received in the last four weeks by labor force status at the time of the survey. The unemployed and the subset of employed actively looking for work receive a similar number of offers, on average. Keep in mind, though, that the unemployed search more than twice as much as those employed and actively looking. The employed not looking for work also receive a fair number of job offers, on average. In the data, the vast majority of respondents receive either zero or one offer, so outliers skewing the mean estimate is a concern.[15] Therefore, we also report the fraction of each labor force state that received any offer in the last four weeks. These estimates show that a somewhat higher fraction of the employed actively looking for work received a formal job offer in the last four weeks than the unemployed, 29 percent compared to 22 percent, respectively. About 6 percent of the employed who were not looking for work and 5 percent of those out of the labor force also received a formal job offer in the last four weeks.

Comparison of top two panels of Table 4 shows that the timing of the labor force status definition matters for measuring these offer arrival rates. Based on their labor force status four weeks prior, 26 percent of the employed looking for work received a formal offer and 34 percent of the unemployed received a formal offer. Based on this definition, the unemployed have a higher offer arrival rate. Just over 4 percent of both the employed looking for work and the unemployed in the prior month received an *unsolicited* job offer. These are job offers that did not result from a job seeker's search efforts. While these estimates are comparable in their arrival rates, they are quite different in terms of their share of formal offers—17 percent of offers received by the employed looking for work, and 28 percent of formal offers received all employed, are unsolicited but only 12 percent of formal offers received by the unemployed are unsolicited.

Some individuals may not pursue offers they are likely to reject. In this case, the job offers we observe in the data would be *censored*, and potentially disproportionately censored by labor force status. To address this issue, our survey asks respondents whether a potential employer was willing to make an offer but the respondent indicated that he or she was not interested. We label these offers as *unrealized* rejected offers as respondents rejected these offers even before a formal offer was made. We indeed find that these unrealized offers are more common for the employed. Among those without a formal offer over the last four weeks, 5.7 percent of the employed looking for work, and 4.4 percent of all employed, indicated that they did not pursue such an offer, compared to only 2.8 percent of the unemployed. Again, these make up a disproportionately

[15] See Table in the Supplemental Appendix for the distribution of number of offers by labor force status.

higher share of total offers (formal and unrealized) for the employed.

There are also notable differences in the rates at which the employed and unemployed *accept* these job offers.[16] The unemployed accept 49 percent of their best offers. In contrast, the employed accept 33 percent of their best offers. Table 4 shows that much of this difference is driven by low acceptance rates among the employed who did not look for work. Notably, however, the unemployed reject half of all offers received. This contrasts with most models of labor market search where, in equilibrium, the unemployed accept *all* job offers. Our evidence suggests that the unemployed actually receive a sizable number of unsuitable job offers.[17] The large fraction of rejections among the employed also suggests substantial randomness in the job search process. This is inconsistent with models of directed search, which imply an acceptance of all best offers.

The bottom panel of Table 4 reports offer outcomes excluding job offers for additional work. These estimates are relevant for calibrating existing models of on-the-job search, since these models almost exclusively focus on transitions that involve leaving one's current job. Excluding this type of job search reduces the offer arrival rate of the employed looking for work from 26 percent to 17 percent, and the offer arrival rate of all employed from just under 11 percent to 8 percent. Acceptance rates for the employed are comparable regardless of whether we abstract from search for additional work.

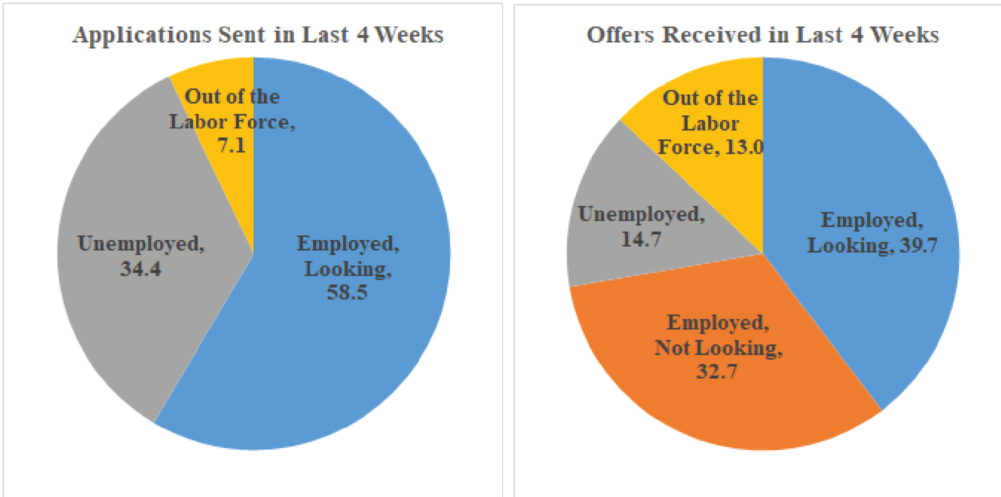
Finally, we present the distribution of job applications sent and formal job offers received by labor force status in the prior month and search incidence.[18] These distributions provide another way of characterizing the stark differences in search effort and search outcomes between the employed and unemployed. Figure 3 presents pie charts of the distributions. The unemployed make up just over 4 percent of our sample, but account for over 34 percent of all job applications sent. At the same time, they only receive 15 percent of all offers made. In stark contrast, the employed who report not looking for work send no applications by construction but receive around 33 percent of all job offers. In Supplemental Appendix S-B, we show that they receive an even higher share of *unsolicited* offers (59 percent). Those actively searching on the job account for 40

[16] We only report acceptance rates by labor force status in the prior month because we use labor force status at the time of a job offer in the construction of prior month's labor force status. Therefore, this labor force status definition is the one relevant for offer acceptance rates.

[17] In addition, rejections could result from heterogeneity in leisure values as in Albrecht and Axell (1984).

[18] We report the distribution of additional search outcomes by labor force status in the prior month and search incidence in Supplemental Appendix S-B.

Figure 3: Distribution of Search Activity by Labor Force Status



Notes: Estimates come from authors' tabulations from the October 2013-17 waves of the SCE Job Search Supplement, for all individuals aged 18-64, excluding the self-employed, by labor force status in the prior month.

percent of all job offers. Thus, the job search behavior of the unemployed can be characterized by high effort but relatively low returns in terms of job offers. The employed, on the other hand, do fairly well regardless of whether they actually look for work. While the unemployed are seemingly less effective in their job search efforts, they are more likely to accept the offers they receive.

3.4 The Offer Yield by Labor Force Status

The differences in search effort and the returns to search between the employed and unemployed are stark. To quantify these differences, we introduce the concept of the *offer yield*, which we define as the incidence of an offer received per unit of search effort. We illustrate how important it is to have detailed data on search effort and search outcomes to properly compute the offer yield by computing the offer yield step by step. We then present differences in offer yields for different groups of workers.

A simple approach to compute the average offer yield is to use data on transition rates to a new job, which are available in various sources including the CPS. Let EE denote the job-to-job transition rate and UE denote the unemployment-to-employment transition rate, then the relative offer yield of the employed to unemployed in the SCE data is:

$$\frac{EE}{UE} = \frac{0.025}{0.168} = 0.148.$$

The calculation implies that the employed are only 15 percent as effective as the unemployed in job search, or inversely, that the unemployed have a 6.8 times higher yield to their search effort.[19] This calculation assumes that the employed and unemployed exert the same level of search effort and have identical job acceptance rates—neither of which are supported by our data. Our data allow us to directly observe the incidence of offer arrivals that we can use instead of realized transition rates. In this case, let λ_e be the offer arrival rate of the employed and λ_u be the offer arrival rate of the unemployed. The calculation of the relative offer yield is then:

$$\frac{\lambda_e}{\lambda_u} = \frac{0.081}{0.342} = 0.237.$$

The calculation implies that the employed are now 24 percent as effective as the unemployed at job search, or that the unemployed's offer yield is 4.2 times that of the employed.[20]

However, these calculations do not use any information on search effort and abstract from differences in search inputs by labor force status. Since we can measure search effort, we can compute offer yields of the employed and unemployed directly from our survey evidence. Letting s_e and s_u denote the search effort of the employed and unemployed, respectively (measured here as job applications), our calculation for the relative offer yield is now:

$$\frac{\lambda_e/s_e}{\lambda_u/s_u} = \frac{(0.081/0.77)}{(0.342/10.39)} = 3.22.$$

This calculation shows that taking into account differences in search effort paints a very different picture of the effectiveness of on-the-job search. The employed have an offer yield that is more than three times as high as that of the unemployed. Relying on realized transition rates alone would imply the opposite.

Differences in average offer yields by employment status might reflect differences in other characteristics of workers. While we find some variations in the relative offer yield across different groups, our main finding holds for all demographic groups regardless of which search measures from Tables 2 and 4 we use—on-the-job search is much more effective in generating job offers than search while unemployed. Table 5 reports search effort (measured as job applications sent), offer arrival rates, offer yields, and the relative offer yield of the employed to the unemployed

[19] Note that transition rates from the CPS would suggest an even higher level of search efficiency for the unemployed over this period. In the CPS, the job-finding rate of the unemployed is 24.0 percent while the job-to-job transition rate is 1.9 to 2.3 percent (depending on the estimation method used, see Fujita et al., 2019), implying that the unemployed are 10.4 to 12.6 times more effective at search than the employed.

[20] Note that the relative offer arrival rates we measure directly in our data are similar to the ones estimated indirectly from transition data using job ladder models (e.g., see Hornstein et al., 2011).

for several groups.[21] If we take into account the differences in unrealized offers between the two groups reported in Table 4, the relative offer yield of the employed to the unemployed increases from 3.2 to 4.5. Excluding search for an additional job only slightly changes these ratios. Part-time workers have offer yields between 2.9 and 4.6 times higher than the unemployed, depending on how we account for search for additional work and unrealized offers. These ratios are very similar to the ratios for all employed despite the fact that part-time work is typically at the lower end of the job ladder.

We find that there are differences in search effort and offer arrival rates by age, gender, race, education, and the labor force situation of the job seeker. In particular, younger workers, women, and non-White workers search more. Yet, older workers, men, and White workers have higher offer yields. We also find some notable variations in the relative offer yield of the employed to the unemployed. The relative offer yield rises with age—i.e., one is relatively worse off as an older worker searching while unemployed than a younger worker searching while unemployed. The relative offer yield is about the same for men and women, and exhibits little variation between those with or without a college degree, but we do find differences by race. Non-Whites have a lower relative offer yield than Whites. Notably, the relative offer yield is well over two and often greater than three within every demographic group, reinforcing the idea that on-the-job search is much more effective in generating job offers than search while unemployed.

The relatively higher offer yield may be intrinsically related to employment status (e.g., through the networking or signaling effects of employment), or it may be due to declining *marginal* returns to search. To distinguish between the two, we run individual-level regressions of offer arrival on a quadratic polynomial in search effort (applications sent) and find a substantially higher marginal return to search effort for the *employed* (see Supplemental Appendix Table S-B15). Moreover, the marginal return to search is nearly constant for both the employed and unemployed over the empirically relevant range of search effort. These results support the view that the higher offer yield of the employed is not driven by differences in average search effort,

[21] In the Supplemental Appendix Tables S-B13 and S-B14, we report estimates by demographics and selected job search characteristics by labor force status (i.e., those searching because of skill fit and those searching for similar work to their current/most recent job). We also report demographic estimates including search for additional jobs. While there are some differences in search effort and offer arrival rates, the relative offer yields of the employed to the unemployed remain large and very similar to what we report in Table 5.

Table 5: Search Effort, Outcomes, and Offer Yields by Selected Characteristics

	Number of Applications Sent, s	Fraction with an Offer, λ	Offer Yield, λ/s	Relative Offer Yield, $\frac{\lambda_e/s_e}{\lambda_u/s_u}$
Panel A. Employment Status				
All Employed				
All formal offers	1.03	0.106	0.103	3.13
...excluding search for addl. work	0.77	0.081	0.106	3.22
All formal and unrealized offers	1.03	0.150	0.146	4.48
...excluding search for addl. work	0.77	0.123	0.160	4.12
Part-Time Employed				
All formal offers	1.91	0.181	0.094	2.87
...excluding search for addl. work	1.00	0.130	0.130	3.96
All formal and unrealized offers	1.91	0.217	0.113	3.19
...excluding search for addl. work	1.00	0.165	0.165	4.62
Unemployed				
All formal offers	10.4	0.342	0.033	—
All formal and unrealized offers	10.4	0.370	0.036	—
Panel B. Demographics				
Age 18 to 39	1.26	0.102	0.080	2.94
Age 40 to 54	1.29	0.101	0.083	3.33
Age 55 to 64	0.76	0.070	0.093	3.84
Male	1.05	0.088	0.084	3.06
Female	1.20	0.096	0.080	3.33
White	0.93	0.082	0.090	3.82
Non-White	1.67	0.121	0.072	2.52
Less than college	1.08	0.098	0.091	3.30
College or more	1.13	0.077	0.068	3.52

Notes: Estimates come from authors' tabulations from the October 2013-17 waves of the SCE Job Search Supplement for all individuals aged 18-64, except for results by education, which are for those aged 25-64. Labor force status is from the prior month. Search behavior by demographic group excludes search for additional work and unrealized job offers.

but rather by a higher marginal return to job search effort for the employed at *all* levels of search effort.[22]

3.5 Characteristics of Job Offers and Accepted Jobs

The employed are more effective at generating job offers, but our evidence thus far is silent on whether the employed receive *better* offers than the unemployed. We analyze this issue next. Our survey asks individuals about any offers they received in the last four weeks, and for those who received none, it probes further to elicit information on any offers received within the last six

[22] In the Supplemental Appendix, we provide evidence on the use and returns to search *methods*. See Tables S-B17 and S-B18.

months. It asks a variety of questions about the characteristics of the best job offer, including information about the search and bargaining process and whether the offer was accepted.

Table 6 presents the characteristics of best job offers received within the last six months by labor force status (employed vs. non-employed) at the time of the job offer.[23] Note that 72 percent of job offers in our sample go to those who were employed at the time of the offer. The results consistently show that the employed also receive much *better* job offers than the non-employed. Unconditionally, the wage offers of the employed are about 36 log points (44 percent) higher than the wage offers of the non-employed.[24] Even after conditioning on the observable characteristics of the worker and the job offer, the wage offers of the employed remain 19 log points (21 percent) higher than the wage offers of the non-employed.[25]

The middle panel of Table 6 shows that job offers received by the employed are superior on other margins as well. Their hours are 13 log points higher, and they are 21 percentage points more likely to include at least some benefits such as retirement pay or health insurance. The nature of how these offers came about and the experiences of job seekers following the receipt of the offer differ by employment status as well. The employed are nearly 60 percent (9 percentage points) more likely to have received their offer through an unsolicited contact. The employed are also significantly more likely to bargain over their offers, with 38 percent of their offers involving some bargaining, compared to 26 percent for the non-employed. These findings are consistent with Hall and Krueger (2012), who find that around a third of all workers engaged in some bargaining over their pay with their current employer. Counter-offers by the current employer, defined in the survey as anything from matching the outside offer to offering a promotion, pay raise, or some added job benefit, occurred for about 12 percent of the employed who received an

[23] Starting in 2014, we added a question to the survey that identifies those who searched prior to the receipt of the job offer. Most of the non-employed report actively searching, and in unreported results, we find that the residual wage offer differential that we document is even larger if we restrict the non-employed to those who were searching prior to the job offer.

[24] The offer wage, as well as all other wages in our analysis, refers to the real hourly wage. Respondents report their nominal earnings as an hourly wage, or as a measure of weekly or annual earnings. In the latter cases, we measure the wage as earnings per hour, based on the reported usual hours worked. We convert all wages used into real terms using the Consumer Price Index (CPI).

[25] Our conditional estimates of the offered wage and the prior wage control for worker and job characteristics, as well as state and year fixed effects. Our worker controls include sex, age, age squared, marital status, marital status×sex, education, race, homeowner status, and number of household children. Our firm and job controls are the two-digit occupation of the job and the size of the offering firm. We report estimates of the other job offer characteristics that control for observable characteristics in Supplemental Appendix Table S-B3.

Table 6: Characteristics of Best Job Offer by Labor Force Status at Time of Offer

	Employed at Offer	**Non-Employed at Offer**	**Difference, E - NE**
Percent of job offers	72.1	27.9	
Offer Wage Estimates			
log real offer wage,	2.935	2.573	0.362
unconditional	(0.031)	(0.047)	(0.101)
Controlling for observable	2.891	2.697	0.194
characteristics	(0.026)	(0.031)	(0.048)
Additional Job Offer Characteristics			
log offer usual hours	3.396	3.269	0.126
	(0.025)	(0.038)	(0.059)
Pct. of offers with no benefits	40.5	62.0	-21.5
	(1.7)	(3.0)	(4.8)
Pct. of offers through an unsolicited	25.0	15.9	9.1
contact	(1.5)	(2.3)	(3.5)
Pct. of offers with some counter-offer	12.3	—	—
given	(1.2)		
Pct. of offers that involved bargaining	38.0	25.8	12.2
	(1.7)	(2.7)	(4.3)
Pct. of offers accepted as only option,	7.7	26.5	-18.8
conditional on acceptance	(1.6)	(3.9)	(7.8)
Accepted Wage Estimates			
log real accepted wage,	3.000	2.542	0.458
unconditional	(0.041)	(0.042)	(0.170)
Controlling for observable	2.931	2.545	0.189
characteristics	(0.032)	(0.039)	(0.065)
Prior-Job Wage Estimates			
log real prior wage,	2.839	2.717	0.122
unconditional	(0.041)	(0.053)	(0.088)
Controlling for observable	2.798	2.790	0.008
characteristics	(0.036)	(0.044)	(0.071)
N	797	257	

Notes: Estimates come from authors' tabulations from the October 2013-17 waves of the SCE Job Search Supplement, for individuals aged 18-64, excluding the self-employed, with at least one job offer in the last six months. Observable characteristics controlled for in the conditional wage estimates include fixed effects for survey year and state as well as a vector of demographic controls: sex, age, age squared, four education categories, four race categories, a dummy for homeownership, the number of children under age 6 in the household, marital status, and marital status×sex. They also include the two-digit SOC occupation of the job and six categories of the firm size of the potential employer. Standard errors are in parentheses.

offer from an outside firm.

As we showed in Table 4, the unemployed are about one-and-a-half times more likely than the employed to accept a job offer. Table 6 shows that a primary reason the unemployed are more likely to accept what turn out to be relatively poor job offers is a perceived lack of alternative options—nearly 27 percent of those non-employed when they receive an offer cite a lack of other alternatives as the main reason for their acceptance; only 8 percent of the employed cite this as their primary reason. If we focus on accepted wages instead of offered wages, we find that the accepted wages of the employed are 46 log points (58 percent) higher than the accepted wages of the non-employed, somewhat higher than the offered wage gap, though the difference is not statistically significant. After controlling for observed worker and job characteristics, the accepted wages of the employed are 19 log points (21 percent) higher than the accepted wages of the non-employed, nearly identical to the residual offered wage gap.

The bottom panel of Table 6 reports prior-job wages, with and without controls for observable characteristics. The prior-job wage is a rough proxy for unobserved heterogeneity. For the employed, it is the wage earned *prior to* their current job, while for the non-employed, it is the wage earned in their most recent job. Unconditionally, the prior wages of the employed are 12 log points (13 percent) higher than the prior wages of the non-employed, but conditional on observables the difference is essentially zero. That is, despite our finding of a large differential in offered wages, we find almost no difference in residual prior wages. In our model's calibration, we use the residual prior-wage differential to discipline its degree of unobserved heterogeneity.

3.6 Accounting for Differences in Offered Wages

We can dig deeper into the wage offer differential between the employed and non-employed using a rich set of additional survey questions. Our estimates in Table 6 imply that observable worker and job characteristics account for 46 percent of the unconditional wage offer differential. Differences in education, occupation, and age are the most important observables in accounting for this difference. The remaining differential may arise simply because we cannot control for differences that are observed by employers but unobserved in our data. For example, workers may differ in unobserved characteristics such as communication or time-management skills that make them more likely to be employed and earn a higher wage. This creates a selection effect that would naturally generate a wage offer gap. An individual's prior work history can provide a useful proxy for such unobserved heterogeneity because it reflects repeated labor market outcomes determined at least partly by their unobserved skills. Our survey asks about an individual's labor force history over the previous five years. As Table 7 shows, controlling for the fraction of the last five years

Table 7: Offer Wage Gap Estimates, Additional Controls.

Offer Wage Gap Estimates	**E-NE**
log real offer wage, unconditional	0.362
	(0.101)
log real offer wage, controlling for observables	0.194
	(0.048)
log real offer wage, controlling for observable characteristics	0.132
and employment history	(0.047)
Controlling for observable characteristics	0.127
and labor force history	(0.047)
Controlling for observable characteristics, labor force history,	0.193
and prior wage	(0.058)
Controlling for observable characteristics, labor force history, prior wage,	0.186
hours, benefits, and how offer came about	(0.058)

Notes: Estimates come from authors' tabulations from the October 2013-17 waves of the SCE Job Search Supplement, for individuals aged 18-64, excluding the self-employed, with at least one job offer in the last six months. See note to Table 6 for the included observable characteristics. Employment history controls for the fraction of the prior five years spent employed. Labor force history additionally controls for the fraction of the last five years spent unemployed or in school. The (log) real prior wage is the wage of the previous job for the employed and the most recent job for the non-employed. Additional job controls include (log) hours and dummies for the incidence of health, retirement, or other benefits. Controls for how the job offer came about include dummies for whether it was through a direct employer contact, an intermediary, a referral, or an unsolicited contact. Standard errors are in parentheses.

that an individual was employed reduces the residual wage offer gap from 0.194 to 0.132. When we additionally control for the share of the last five years spent unemployed and the share spent as a student, the difference falls somewhat more to 0.127, implying that labor force history can account for an additional 19 percent of the (unconditional) wage offer gap. As we noted, prior wages of workers can also reflect workers' unobserved skills. Additionally controlling for the *prior* wage of workers in Table 7 actually widens the wage offer gap. In our model calibration, we show that this occurs because most of the employed who receive a job offer are near the bottom of the job ladder. Therefore, the model implies that controlling for the prior wage does not fully account for unobserved differences in productivity since the prior wage also captures the position on the job ladder.

Differences in the job search process between the employed and non-employed may account for the remaining gap. Employed workers may have better access to more rewarding job search channels (see, for example, Arbex, O'Dey, and Wiczer, 2016). Our empirical analysis shows that the employed are more likely to receive an offer through an unsolicited contact than the non-employed. If these informal offers represent higher-quality jobs, then the higher incidence of unsolicited offers should also contribute to the wage offer gap. Alternatively, non-employed workers may be more likely to pursue jobs with lower wages but more preferred hours or non-wage job amenities. In the last row of Table 7, we control for how a job offer came about using dummies for whether the offer was the result of a direct contact by the worker, whether an intermediary (such as an employment agency) was involved, whether it was the result of a referral, or whether the offer was unsolicited. We also control for the (log) hours of the job offer and the incidence of any benefits (categorized into health, retirement, or other benefits). These controls result in little change in our estimate of the wage offer differential.[26] Thus, while controlling for observable worker and job offer characteristics, prior labor force history, and the source of the job offer reduces the offered wage gap by about two-thirds, a substantial gap between the wages offered to the employed and non-employed remains.

Another concern is that human capital may depreciate during periods of non-employment. In this case, the employed and non-employed may have a similar wage (and potentially similar skill levels) when they separate from their previous job, but the skills of the non-employed depreciate, leading them to have lower-quality job offers, on average. Our controls for work history should account for such depreciation, however, and these controls only reduce the wage offer gap from 0.19 to 0.13. Keep in mind, too, that five-year work histories also capture fixed unobserved differences in worker productivity even in the absence of human capital depreciation.

Finally, bargaining and counter-offers are additional ways the search process can affect the wage offer gap. We find that the employed are more likely to bargain with the potential employer and 12 percent of them received some form of counter-offer from their current employer. While the latter estimate falls short of the rate of counter-offers in models such as Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay, and Robin (2006), it is possible that the threat of such counter-offers could affect the wage offer gap. We quantify how much bargaining and other aspects of the job offer process affect this gap in our quantitative framework in the next section.

[26] If we reestimate the last row of Table 7 excluding the prior wage, we obtain a wage offer gap of 0.119.

4 An Equilibrium Search Model with On-the-Job Search

In this section, we set up a general equilibrium job ladder model with endogenous vacancy creation and endogenous search effort, and analyze the responsiveness of aggregate search effort to changes in the value of employment, a key elasticity that arises in the presence of search and matching frictions in the labor market. When we calibrate our model to match the new evidence from our survey, we find a more prominent role for workers' job search effort than is typically assumed in the literature (e.g., see Eeckhout and Lindenlaub, 2019; Moscarini and Postel-Vinay, 2019; and Faccini and Melosi, 2019). Moreover, our model does remarkably well in generating a plausible amount of frictional wage dispersion, and provides insights on the implications for high search efficiency and the sources of the wage offer premium among the employed.

Our model builds on earlier models of on-the-job search with endogenous search effort such as Christensen et al. (2005) and Hornstein et al. (2011) and the wage bargaining protocol in Cahuc et al. (2006). In particular, we set up a version of the framework in Bagger and Lentz (2019) with match-specific productivity and augment it in three important dimensions to accommodate the salient features of our survey: (i) differences in search efficiency by employment status; (ii) differences in bargaining weights by employment status; and (iii) censoring and rejection of job offers. In what follows, we describe the model setup, calibration and results, and refer to Online Appendix D for details.

4.1 Model Setup

Time is discrete and its discount rate is r. Firms are ex ante homogeneous and post vacancies, v, to recruit workers. Workers are either employed (e) or unemployed (u), with their labor force status denoted by i. Workers are *ex ante* heterogeneous in their productivity, x, with population share, $\pi(x)$.[27]

Job Search and Production. Matching between firms and workers is random across both labor force status i and productivity x of the worker and is governed by a matching function $M(S; v)$ which satisfies the standard properties.[28] Labor market tightness, $\theta = v/S$, is defined

[27]We introduce ex ante heterogeneity in worker productivity to capture the unobserved heterogeneity that remains in our data after controlling for observable characteristics.

[28]While the assumption of random search is natural in light of the high rejection rate of offers in the data, we allow for censoring of job offers which can be interpreted as partially directed search.

as the vacancy, v, per effective number of searchers, S, which weighs job seekers as defined further below (where we characterize firms' vacancy posting decision). Workers receive offers at a rate $\lambda_i(s)\lambda(\theta)$ which depends on their labor force status, search effort, and the equilibrium arrival rate of offers per unit of search, $\lambda(\theta) = M(1;\theta)$. Search effort has an increasing, convex cost, $c(\cdot)$, that may vary by labor force status, with $c_i', c_i'' > 0$ and $c_i(0) = c_i'(0) = 0$. When a worker and a firm meet, a match-specific productivity y is drawn from a distribution $F(\cdot)$, which is assumed to be fixed over the duration of the match. The output of the match is pyx, where p is aggregate productivity and is assumed to be constant.[29] Job matches are subject to exogenous separation shocks, $\delta(x)$, which depend on a worker's productivity and an exogenous job reallocation shock, δ_0. Workers who are subject to a reallocation shock sample an outside offer from the offer distribution $F(\cdot)$ and flow into unemployment if they reject the offer.

Joint Match Value. We assume that firms' and workers' search and separations decisions are jointly optimal, which makes the problem tractable in general equilibrium as in Bagger and Lentz (2019).[30] Let $W(n, y, x)$ be the value of the worker in a match with productivity n when the outside option is a match with productivity y, with $y = 0$ if the worker's outside option is unemployment. The joint value of a match, $K(y, x)$, then satisfies:

$$\begin{aligned}K(y,x) = &\max_{\bar{s}_e \geq s \geq 0, R_\delta, R_e} \Bigg\{ pyx - c_e(s)x + \frac{1}{1+r}\Bigg[K(y,x) - \delta(x)[K(y,x) - U(x) - V] \\ &+ \tilde{\delta}_0(x,\theta)\int_{R_\delta} [W(n,0,x) + V - K(y,x)]dF(n) - \tilde{\delta}_0(x,\theta)F(R_\delta)[K(y,x) - U(x) - V] \\ &+ \tilde{\lambda}_e(s,x,\theta)\int_{R_e} [W(n,y,x) + V - K(y,x)]dF(n)\Bigg]\Bigg\}, \end{aligned} \tag{1}$$

where $\tilde{\delta}_0(x,\theta) = (1-\delta(x))\delta_0\lambda(\theta)$ and $\tilde{\lambda}_e(s,x,\theta) = (1-\delta(x))(1-\delta_0)\lambda_e(s)\lambda(\theta)$.[31] A worker who receives an exogenous separation shock flows into unemployment. If a worker receives a reallocation shock δ_0, she samples an outside offer and accepts it if the offered wage is above the optimal reservation productivity $R_\delta(x)$. In the absence of separation or reallocation shocks, the worker samples an outside offer with probability $\tilde{\lambda}_e(s,x,\theta)$ from the distribution $F(\cdot)$ and accepts the offer if its match-specific productivity is above the optimal reservation productivity, $R_e(y,x)$.

[29] In Supplementary Appendix S-C, we describe the non-stationary model where p follows a deterministic path.

[30] We consider a partial equilibrium model where the worker unilaterally chooses search effort in an earlier version of our paper in Faberman et al. (2017).

[31] Search effort is bounded above at $\bar{s}_i$ such that the probability of an offer does not exceed one.

Value of Unemployment. The value of unemployment, $U(x)$, satisfies:

$$U(x) \quad = \quad \max_{\bar{s}_u \geq s \geq 0, R_u} \left\{ bx - c_u(s)x + \frac{1}{1+r}\Big[U(x) + \lambda_u(s,\theta) \int_{R_u} [W(n,0,x) - U(x)]dF(n)\Big]\right\} \quad (2)$$

where bx is the flow value of unemployment, $\lambda_u(s,\theta) = \lambda_u(s)\lambda(\theta)$ is the probability of matching with a firm, and $R_u(x)$ is the type-x unemployed worker's optimal reservation productivity.[32]

Vacancy Posting. Firms pay a per-period vacancy posting cost, c, and vacancies are filled with probability $q(\theta)$. Let $J(n, y, x)$ be the value of the firm in a match with productivity n when the outside option of the worker is a match with productivity y, and with $y = 0$ if the worker's outside option is unemployment. The value of a vacancy, V, satisfies:

$$\begin{aligned} V \quad &= \quad -c + \frac{1}{1+r}\Bigg[V + q(\theta)\sum_x \pi(x)\Bigg(\frac{u(x)}{S}\lambda_u(s_u(x)) \int_{R_u(x)} (J(n,0,x) - V)dF(n) \\ &+ \quad \frac{1-u(x)}{S}\tilde{\delta}_0(x)\int_{R_\delta(x)} (J(n,0,x) - V)dF(n) \\ &+ \quad \frac{1-u(x)}{S}\int \tilde{\lambda}_e(s_e(\hat{y},x),x)\int_{R_e(\hat{y},x)} (J(n,\hat{y},x) - V)dF(n)dG(\hat{y}|x)\Bigg)\Bigg], \end{aligned} \quad (3)$$

where $\tilde{\delta}_0(x) = (1 - \delta(x))\delta_0$ and $\tilde{\lambda}_e(s, x) = (1 - \delta(x))(1 - \delta_0)\lambda_e(s)$. Aggregate effective search effort is $S = \sum \pi(x)S(x)$, where the effective number of searchers with productivity x is $S(x) = u(x)\lambda(s_u(x)) + (1 - u(x))[\tilde{\delta}_0(x) + \int \tilde{\lambda}_e(s_e(\hat{y}, x), x)dG(\hat{y}|x)]$ and where $G(y|x)$ is the cumulative distribution function of match productivities y for worker type x. As is evident from the equation, the value of a vacancy is calculated taking into account matching with different types of workers.

Wage contracts. Wage contracts are negotiated at the beginning of the match and renegotiated in the presence of an outside offer as in Cahuc et al. (2006). The value of a job offer with productivity n for workers in a match with productivity y satisfies the Nash-Bargaining solution:

$$W(n, y, x) = \tau_e(K(n, x) - V) + (1 - \tau_e)K(y, x). \quad (4)$$

Similarly, the value of a job offer with productivity n for unemployed workers satisfies:

$$W(n, 0, x) = \tau_u(K(n, x) - V) + (1 - \tau_u)U(x), \quad (5)$$

[32] We posit that the flow value of unemployment net of search costs is proportional to unobserved productivity, i.e. $b(x) - c_u(x, s) = (b - c_u(s))x$. This is consistent with the observations that job-finding rates differ little by skill group (Mincer, 1991; Elsby, Hobijn and Şahin, 2010) or by prior wages (Mueller, 2017) and also consistent with our evidence in Supplementary Appendix S-B, which shows that controlling for observable characteristics does little to affect the likelihood of receiving a job offer.

where the workers' bargaining shares, τ_e and τ_u, vary by labor force status. The value of the match for firms, $J(n, y, x)$, is the remainder of the joint value $K(n, x)$.

Rejected and Censored Offers. Given our empirical findings, an important consideration is how to incorporate rejected and censored offers into our framework. First, we assume that firms commit to making an offer even when the match-specific productivity is below the reservation threshold, otherwise all formal offers would be accepted. We assume that the value of a rejected offer equals the joint value, $W(n, y, x) = K(n, x)$. Second, we assume that the productivity of the match is revealed prior to the firm extending a formal offer with probability χ_i. This feature is consistent with our finding in the SCE data that the employed appear to reject and therefore *censor* many offers before they are made.[33] These assumptions imply that the probability of receiving a formal offer is:

$$Pr(\text{Formal Offer}) = Pr(\text{Offer})(\chi_i(1 - F(R)) + 1 - \chi_i), \tag{6}$$

where $1 - F(R)$ is the probability that a match is above the worker's reservation threshold.

The Stationary Equilibrium. We only briefly characterize the equilibrium and relegate the formal definition of the stationary equilibrium and its solution to Online Appendix D. It is important to note that we can solve the model without explicitly solving for the bargained wage, $w(y, ., x)$, by plugging the equations for the value of offers into the expressions for $K(y, x)$, $U(x)$ and V. We close the model by deriving the steady-state conditions for the unemployment rate, $u(x)$, and the steady-state distribution of workers, $G(y|x)$, and imposing zero profits from vacancy creation. The joint value, $K(y, x)$, and the bargained wage, $w(y, ., x)$, are increasing in the match-specific productivity, y. Since the cost of search effort is increasing and convex, search effort declines with y—i.e., effort falls as workers move up the job ladder. The reservation productivity for employed workers who receive a reallocation shock is the same as the reservation productivity for the unemployed, $R_\delta(x) = R_u(x)$. Finally, the reservation productivity of employed workers with an outside offer is $R_e(y, x) = y$, implying that workers transition to a new match whenever its productivity is greater than the productivity of their current match.

[33] Hall and Mueller (2018) introduce censoring in a similar way to capture partially directed search.

Table 8: Targeted Moments in the Data and in the Model

Moment	Data	Model	Moment	Data	Model
Search effort (U, E)	10.39, 0.769	10.39, 0.769	Search-wage elasticity	-0.36	-0.36
Unsolicited offer rate (U, E)	0.042, 0.026	0.042, 0.026	Stdev. of wage offers	0.678	0.678
Formal offer rate (U, E)	0.342, 0.081	0.342, 0.081	Offer wage diff. (E-U)	0.194	0.193
Censored offer rate (U, E)	0.028, 0.041	0.028, 0.041	Prior wage diff. (E-U)	0.008	0.008
Acceptance Rate (U, E)	0.494, 0.309	0.494, 0.309	Unemployment rate	0.068	0.068

Notes: All moments referring to wages are based on residualized wage data.

4.2 Parameterization and Targeted Moments

We calibrate the model to our 2013-2017 data and set its frequency to be monthly. The discount rate is set to match an annual interest rate of 4 percent.

Search Technology. We match parameters that govern search technology to key moments computed using our survey, as shown in Table 8.[34] We use the total formal and unsolicited offer rates of the employed and unemployed from Table 4 to match the intercept and slope of a linear job offer arrival function, $\lambda_i(s) = \alpha_i + \beta_i s$. The aggregate matching function is Cobb-Douglas, $M(S; v) = \mu S^{(1-\eta)} v^{\eta}$. We set the censoring parameter χ_i to match the average rate of censored/unrealized offers by employment status in the data.

We assume that the search cost function take the form $c_i(s) = \kappa_i s^{1+(1/\gamma)}$, as in Christensen et al. (2005) and Hornstein et al. (2011) but allowing for a shifter by labor force status. We calibrate κ_i to match the average search effort by labor force status in Table 2. The high level of search efficiency and low level of search effort among the employed imply a high cost of search for the employed in our calibration. We set γ to match a search effort-wage elasticity of -0.36 implied from the estimates based on job applications sent in Table 3, which yields $\gamma = 3.6$. This is substantially higher than the typical assumption of quadratic search costs, i.e., $\gamma = 1$. The search effort-wage elasticity implied from job search hours is -0.52, which would imply an even higher estimate of γ. We set γ to 3.6 and present robustness results in Online Appendix D for model specifications with a higher value of γ.

Productivity and Wages. Match-specific productivity, y, is assumed to follow a log-normal distribution with a standard deviation of 0.27, which—conditional on individual-specific productivity x—yields a standard deviation of log wage offers of 0.24 as in Hall and Mueller (2018).[35]

[34] Where relevant, we use the moments based on labor force status in the prior month and search behavior and outcomes that exclude search for an additional job only.

[35] This estimate is close to other estimates of frictional wage dispersion, see, e.g., Low, Meghir, and Pistaferri

We also assume that observed wages are subject to i.i.d. measurement error $\varepsilon_w \sim N(0, \sigma_{\varepsilon_w})$. Consistent with Bound and Krueger (1991), we assume a moderate degree of measurement error and set $\sigma^2_{\varepsilon_w}$ to 13 percent of the unconditional variance in offered wages. We set the elasticities of the matching function and the bargaining share to 0.5 following Petrongolo and Pissarides (2001) and consider deviations of the unemployed's bargaining share from this value.

We parameterize the extent of heterogeneity in our model by assuming that there are 10 types of workers who differ by a productivity-shifting parameter x. The distribution of types approximates a log-normal distribution with standard deviation σ_x over the interval $[-2\sigma_x, 2\sigma_x]$. We parameterize σ_x to match the standard deviation of our residual wage offer estimates since our goal is to quantify the role of *unobserved* heterogeneity. We set the unemployed worker's bargaining share, τ_u, to match the gap in residualized wages between the employed and non-employed. Note that even with $\tau_u = \tau_e = 0.5$, the model predicts a wage offer premium for the employed due to their better outside options. Our estimate of $\tau_u = 0.4$ implies that the differences in outside options alone are insufficient to match the observed wage offer differential. This estimate is in line with our evidence in Table 6 that shows that unemployed workers engage less frequently in bargaining compared to the employed. Not surprisingly, our calibration of the χ_i parameters imply a much larger fraction of censored offers among the employed, as their unrealized offer rate in the data is much higher relative to their formal offer rate (see Table 4).

Separation and Reallocation Shocks. We target the average separation rate to match an unemployment rate of 6.8%, which is the sample average for 2013-2017 in the SCE. We allow separation rates to vary by worker type x, which is consistent with the well-known fact that differences in unemployment rates across skill groups are driven by separations and not job finding. We assume $\delta(x) = \delta - \delta_x \ln(x)$, which results in a value of 0.0123 for the average separation rate, δ. We parameterize δ_x by matching the difference in residual prior wages of 0.008 between the employed and unemployed in Table 6. Intuitively, as δ_x increases, there is greater negative selection among the unemployed and thus a lower average prior wage of the unemployed.[36]

(2010) and Tjaden and Wellschmied (2014). We choose this estimate of wage dispersion over one derived from the SCE data because of the relatively small sample of wage offers that we observe in the SCE data.

[36]If we were to ignore negative selection and set $\delta_x = 0$, the simulation of our model would predict that prior wages are higher for the unemployed by about 11 log points. This is because the employed tend to transition up the wage ladder, so their prior wages tend to be from jobs further down on the wage ladder, while the prior wages

Table 9: Calibrated Parameter Values in Model

Symbol	Parameter Description	Value	Source/Target
A. Externally calibrated parameters and normalizations			
Symbol	Parameter Description	Value	Source/Target
r	Monthly interest rate	0.34%	Annual interest rate of 4%
c	Vacancy posting cost	0.80	$\theta = 1$
μ	Matching efficiency	1.00	Normalization
η	Elasticity of matching function	0.50	Petrongolo and Pissarides (2001)
τ_e	Employed workers' bargaining share	0.50	Hosios condition
p	Aggregate productivity	1.00	Normalization
μ_y	Mean (of log) of match-specific prod.	0.00	Normalization
σ_y	Dispersion in match-specific prod.	0.27	Hall and Mueller (2018)
σ_ε	Dispersion in measurement error	0.31	Bound and Krueger (1991)
B. Internally calibrated parameters			
Symbol	Parameter Description	Value	Main Target
γ	Elasticity of search cost	3.60	Search-wage elasticity
τ_u	Unemployed workers' bargaining share	0.40	Offer wage differential (E-U)
κ_u, κ_e	Search cost parameter	0.014, 0.062	Search effort by LFS
α_u, α_e	Offer rate, intercept	0.042, 0.026	Unsolicited offer rate by LFS
β_u, β_e	Offer rate, slope coefficient	0.032, 0.115	Formal offer rate by LFS
χ_u, χ_e	Censoring parameter	0.139, 0.459	Censored offer rate by LFS
σ_x	Dispersion in unobserved ex-ante het.	0.570	Std. dev. of offer wages
δ	Separation rate for median x	0.007	Unemployment rate
δ_x	Separation rate gradient	0.0021	Prior wage differential (E-U)
δ_0	Reallocation rate	0.010	Acceptance rate of E
z	Flow value of unemployment	0.662	Acceptance rate of U

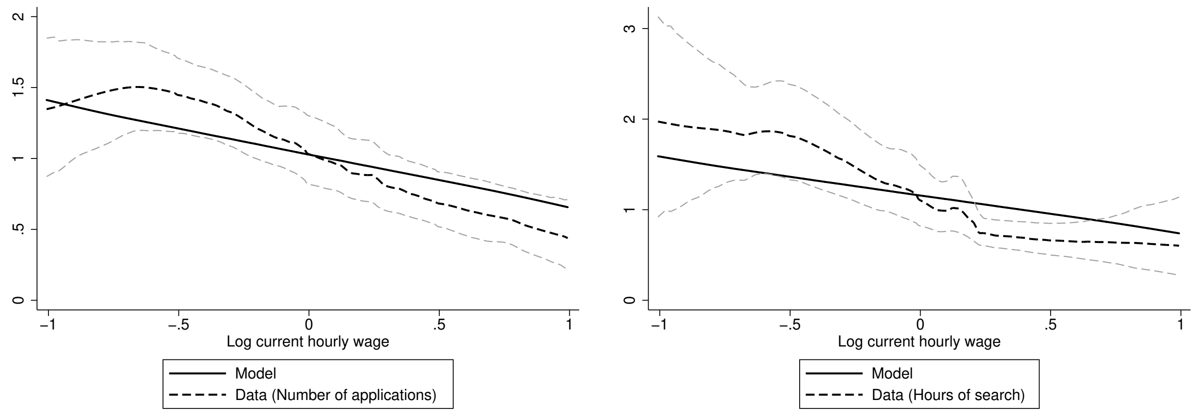
We calibrate the reallocation shock, δ_0, to match the acceptance rate of employed workers in the data, which is 0.309. For a given formal offer rate, this strategy implicitly targets the job-to-job transition rate of 0.025 in the data and implies a relatively modest rate of reallocation of 1% per month, corresponding to about 8 percent of all employed offers.[37] This number is in line with our data, where 11 percent of employed searchers indicate that their main reason for on-the-job search was either a relocation or advance notice of a layoff. We believe our approach to identifying the reallocation rate is more plausible than in the literature, which typically relies on matching the fraction of job-to-job transitions associated with a wage decline which could also be due to measurement error, differences in wage-tenure profiles (e.g., Cahuc et al., 2006) or non-wage amenities (e.g., Sorkin, 2018).

Flow Value of Unemployment. We define the flow value of unemployment as the fraction of

of the unemployed are from jobs prior to a separation and thus further up on the wage ladder.

[37] Without reallocation shocks, our model underpredicts the acceptance rate of the employed. With reallocation shocks, the acceptance rate is higher since the outside option of workers subject to these shocks is unemployment.

Figure 4: On-the-Job Search Effort by Current Wages (Model vs. Data)



Note: The dashed lines show the 95 percent confidence interval (bootstrapped with 500 replications).

average productivity net of average search costs, $z = E(b - c_u(s_u(x)))/E(py - c_e(s_e(y,x))$, and set it to match the acceptance rate of the unemployed, implicitly pinning down a value for the parameter b. By construction, this strategy matches the job-finding rate of 0.169 in the data.[38]

Normalizations. We solve for the stationary model where the labor market tightness is normalized to 1, and then solve for the vacancy cost that is consistent with this normalization. Other normalizations include the matching efficiency parameter, $\mu = 1$, aggregate productivity, $p = 1$, and the mean of the (log) match-specific productivity distribution $\mu_y = 0$.

4.3 Model Fit and Micro Implications

While the main goal of our quantitative analysis is to analyze the responsiveness of aggregate search effort to changes in labor market conditions, we first highlight the success of our model in fitting the data and several of its micro implications.

Fit of the Search Effort-Wage Relationship. A key implication of on-the-job search models with endogenous search effort is that employed workers will reduce their search effort as they climb the job ladder. We explicitly target the search-wage elasticity, which identifies the elasticity of search costs with respect to search effort through γ. The evidence in Figure 2 shows that the fit of the relationship is clearly negative between different measures of search effort and the worker's current wage. In Figure 4, we compare the relationship implied by a simulation of our model to its counterpart from our survey data. The model produces a good fit to the data with the model-

[38]We could assume a value for z, as in Shimer (2005) or Hall and Milgrom (2008), but we prefer to infer it from our data because there is little consensus on its appropriate value. In fact, our findings on search efficiency have direct implications for the value of z, and our approach allows the model to speak to these implications.

Table 10: Wage Offer Differentials in the Data and the Model

	Wage Offer Differential	Decomposition: Worker Heterogeneity	Censoring	Bargaining	Controlling for 5-year Employment History
Data	0.194	—	—	—	0.132
Model	0.193	0.118	0.036	0.039	0.132

Notes: The first column shows the wage offer differential controlling for the same set of observables as in Table 7. The next columns decompose the differential in the model into its three sources. The last column reports the wage offer differential with the fraction of time non-employed over the last five years as additional control.

implied relationship generally lying within the 95 percent confidence interval. Note that the fit is particularly good for applications, which is our target measure of search effort. Adjusting γ to further improve the fit in Figure 4 would imply an even higher value for γ and thus make search effort even more responsive to labor market conditions.[39] Overall, we view this as clear evidence in support of models with endogenous search effort.

Wage Offer Premium of the Employed. In Section 3.6, we examined how much of the wage offer differential between the employed and unemployed could be accounted for by a rich set of controls. We match this differential in our calibrated model, which allows us to decompose the differential into three parts: the part due to unobserved heterogeneity, the part due to censoring of the wage offer distribution, and a residual that we attribute to bargaining. Table 10 shows that the model attributes 11.8 log points (61 percent) of the 19.3 log point residual wage offer differential to unobserved heterogeneity. This represents 33 percent of the 36.2 log point unconditional wage offer differential. The contribution of censoring is smaller because job offers are concentrated among employed workers who are at the bottom of the job ladder. The contribution of bargaining accounts for the remaining 3.9 log points, which is due both to better outside options of employed workers and the lower bargaining weight of unemployed workers. This represents 20 percent of the residual wage offer gap and 11 percent of the unconditional wage offer gap. The main takeaway is that negative selection into unemployment accounts for over 60 percent of the wage offer differential observed in the data but leaves a non-trivial fraction accounted for by censoring and bargaining.

Additionally, our model predicts a correlation between *ex ante* unobserved heterogeneity and labor force histories, which can provide guidance for addressing unobserved heterogeneity in

[39]See Online Appendix D for results with higher levels of γ.

empirical work. The model implies that low-x workers are not only more likely to be *currently* unemployed, but also less likely to have worked *in the past*. This suggests that an individual's *work history* is a useful proxy for unobserved heterogeneity. As we showed in Table 7, controlling for the fraction of the last five years that someone was employed reduces the residual wage offer gap from 0.194 to 0.132. We implement the same regression analysis on model-simulated data and find that the wage offer gap falls from 0.193 to 0.132, which is essentially identical to what we observe empirically. Controlling for work history in our simulation-based regression accounts for about half of the contribution of differences in x and shows the usefulness of labor force history as a control for unobserved heterogeneity.[40]

The Flow Value of Unemployment and Frictional Wage Dispersion. Our model also performs demonstrably well in matching the amount of wage dispersion observed in the data. Hornstein et al. (2011) argue that a standard model of frictional search and matching in the labor market can only account for a tiny fraction of the wage dispersion observed in the data. They show that extending the model to include on-the-job search can generate a higher degree of wage dispersion but the success of the model depends on the *efficiency of on-the-job search* relative to unemployed search—for which we did not have data until our survey. Consistent with their intuition, our model generates a mean-min ratio of 1.56, within the range of empirical values for the mean-min ratio (see Hornstein et al., 2006, who estimate a range between 1.48 and 1.83). Moreover, our model generates empirically consistent wage dispersion while yielding a reasonable value for the flow utility of unemployment (net of search costs) of 0.66, in line with Hall and Milgrom (2008) and Mas and Pallais (2019). Attempts to match the observed wage dispersion typically require very low or even negative values for this parameter (see Hornstein et al., 2011).[41] Intuitively, our model does well in this respect because the *higher search efficiency of the employed* implied by our findings limits the option value of unemployment. The unemployed perceive little value in waiting for a better offer if they can sample better offers and search more efficiently while employed. Consequently, they are willing to accept lower-wage offers despite a

[40]The congruence of the regression results in the data and the model is particularly noteworthy because the calibration of our model targets variation in prior wages rather than employment histories.

[41]We evaluate the performance of alternative models for the wage dispersion puzzle in Online Appendix D and show that the resolution of the wage dispersion puzzle in our baseline model is due to our model's key ingredients. To underscore our point, shutting down endogenous search effort ($\beta_e = \beta_u = \kappa_e = \kappa_u = 0$), censoring ($\chi_e = \chi_u = 0$) and bargaining ($\tau_e = \tau_u = 1$) yields a mean-min ratio of 1.35 and a flow value of unemployment of 0.15.

high value of unemployment, increasing the dispersion of realized wages from below.

4.4 Search Effort as an Amplification Mechanism

Finally, we use our model to quantify the responsiveness of labor market tightness, search effort, and job-to-job transitions to business cycle shocks. To this purpose, we consider an economy that is in stationary equilibrium and subject it to a one-time, unexpected decline in aggregate productivity which reverts back to its initial level over time. We calibrate the productivity shock as a 4 percent drop with an auto-correlation of 0.95, as seen in Panel (a) in Figure 5. This shock corresponds to a two-standard deviation shock to productivity, as reported by Shimer (2005), and matches the quarterly auto-correlation in the same paper. In Supplemental Appendix S-C, we define the equilibrium of this economy with perfect foresight of the future path of p.[42]

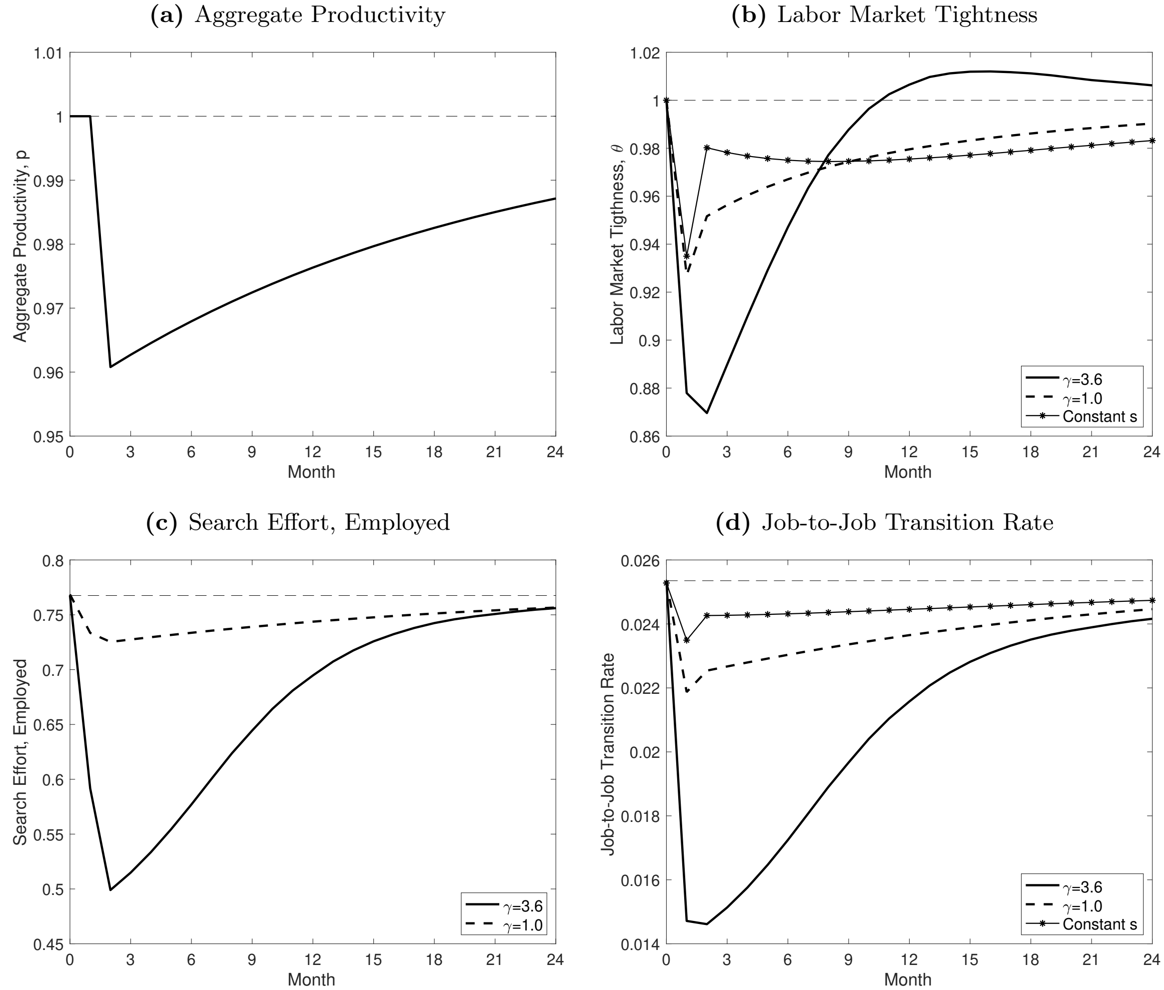
We consider the effects of an unexpected aggregate productivity shock for three different specifications: (1) our baseline model with $\gamma = 3.6$, (2) a model with quadratic search costs (i.e., $\gamma = 1$), and (3) a model with exogenous job search. We recalibrate the parameters in the alternative specifications to match the same moments from Table 8 with the exception of the elasticity of search effort to wages. Quadratic search costs imply an elasticity of -0.21, which is below its empirical counterpart of -0.36.[43]

Figure 5 shows that the response of the job-to-job transition rate varies considerably across specifications. While the job-to-job transition rate goes down in all specifications, endogenous search effort amplifies the decline in job-to-job transitions when the negative productivity shock hits the economy. The strength of amplification depends on the value of γ because the decline in productivity reduces the returns to search. The value of γ implied by our empirical results (3.6) produces a decline in the job-to-job transition rate that is about 3 times larger than the decline implied by quadratic search costs ($\gamma = 1$). In line with Eeckhout and Lindenlaub (2019), we find that equilibrium vacancy-posting behavior amplifies the response of job-to-job transitions further by reducing firms' incentives to post vacancies. As we show in the Online Appendix Figure D1, vacancies in the model drop sharply by 40% in response to the 4% drop in aggregate productivity.

[42]We solve the model for two x-types, as it becomes computationally challenging with more types. Note, however, that the cross-sectional implications of the 2-type model and the 10-type model are nearly identical, suggesting that little is lost by focusing on two types only, see Online Appendix D for details.

[43]Note that model (3) sets $\kappa_i = \beta_i = 0$ for both the employed and unemployed and calibrates the remaining parameters to match the same transition rates (E-to-U, U-to-E and job-to-job) as in the other two models.

Figure 5: Labor Market Tightness and Transitions in Response to Aggregate Productivity Shock



Note: The figures show the response of the economy to an unexpected 4% decline in aggregate labor productivity with a monthly auto-correlation of 0.95 and with the economy starting out in steady state in month 0.

The model's implication for relative volatility of vacancies lines up perfectly with Shimer (2005), who shows that the standard deviation of the cyclical variation in vacancies is 10 times that of aggregate productivity. Labor market tightness decreases sharply on impact by 13% in the economy with $\gamma = 3.6$, which is substantial and much larger than in the other two economies. Note that labor market tightness is defined as vacancies per number of effective job seekers and does not have a direct empirical counterpart.

As aggregate productivity gradually returns to its pre-recession value, the job-to-job transition rate and employed search effort gradually return to their previous levels. Interestingly, labor market tightness overshoots its pre-recession level, which is due to shifts in the unemployment rate and in the distribution of workers across the job ladder. As the economy recovers, more unemployed workers find jobs, but predominantly at the bottom of the ladder. This shifts the distribution of job seekers towards low-productivity jobs where workers exert high search effort. From the perspective of the firm, workers who are unemployed or at the bottom of the productivity distribution yield the highest expected profits. The key takeaway is that a job ladder model with highly elastic search effort—as implied by our empirical evidence—considerably amplifies the business cycle swings in aggregate search effort and job-to-job transitions. Highly elastic search effort also suggests that workers reallocate to better jobs more quickly than what quadratic search costs or models that abstract from endogenous search effort imply. In Online Appendix D, we also show the effects of the productivity shock on the search effort, reservation productivity and job-finding rate of the unemployed, and the separation rate and the unemployment rate. All measures exhibit an amplified response to the shock when we use the search cost elasticity implied by our empirical findings.

We show that our model's implications for amplification are not driven by a high elasticity of job search when unemployed. We still find substantial amplification even when we set $\gamma = 1$ for the unemployed, but leave $\gamma = 3.6$ for the employed as we show in Online Appendix D. The reason is that search effort among the employed drops sharply, particularly for those at the bottom of the ladder, which reduces firms' incentives to post vacancies.

5 Concluding Remarks

In this paper, we design and implement an expansive new survey on job search behavior and job search outcomes for all individuals and document a wide range of new empirical facts. Though job search is the centerpiece of search and matching models of the labor market, the literature has lacked comprehensive evidence of the nature and extent of on-the-job search and its relation to labor market outcomes until our study. We view our contribution as an important step in deciphering the black box of job search, especially among the employed. Since our survey has an established history and is ongoing, we also expect it to be an important tool for labor market analysis going forward.

Among our empirical findings, three main results stand out. First, on-the-job search is pervasive—over 20 percent of the employed look for work each month—and it declines sharply with one's current wage. We estimate an elasticity of search effort with respect to wages between -0.52 and -0.36. Second, we find that job search while employed is over three times as effective in generating job offers compared to job search while unemployed. Third, the employed receive better offers per unit of search effort, and a significant wage offer premium exists for the employed even after applying a variety of controls. Overall, our results suggest that on-the-job search is pervasive, elastic and dominates job search while unemployed along several margins.

We then develop a general equilibrium model of on-the-job search that incorporates key features related to our empirical findings. The model provides a good fit of the data and has several notable micro implications. Namely, the model suggests that much of the observed wage offer premium enjoyed by the employed reflects a negative selection of those with low unobservable skills into unemployment. Still, a nontrivial fraction of the gap is explained by censoring and bargaining. The latter is particularly relevant as it implies that workers who are employed receive better wage offers for the same level of match productivity. Along with the high relative search efficiency of the employed, this leads the unemployed to accept relatively low wage offers despite a relatively high flow utility of unemployment. This finding itself provides a simple and intuitive resolution of the *wage dispersion puzzle* introduced to the literature by Hornstein et al. (2011).

Finally, our model highlights important macroeconomic implications of a relatively high elasticity of search effort with respect to wages. Most models of labor market search ignore the responsiveness of job search effort to aggregate shocks because of a lack of data, or they use stylized assumptions, such as quadratic search costs, to examine the issue. In our model, our estimate of the search effort-wage elasticity identifies this responsiveness directly. Our evidence suggests that aggregate search effort is more elastic than implied by a quadratic cost function. Consequently, we obtain greater amplification of vacancies, labor market tightness, on-the-job search effort, and job-to-job transition rates in response to an aggregate productivity shock. Clearly, the responsiveness of search effort affects labor reallocation in the economy through its impact on transition rates. Given the growing interest in the job ladder implications of business cycle fluctuations such as Eeckhout and Lindenlaub (2019), Faccini and Melosi (2019), and Moscarini and Postel-Vinay (2019), and the focus on their implication for the Beveridge curve (Elsby, Michaels, Ratner, 2015), these findings are particularly important.

References

[1] Aguiar, Mark A., Erik Hurst, and Loukas Karabarbounis, 2013. "The Life-Cycle Profile of Time Spent on Job Search," American Economic Review 103(3): 111-116.

[2] Albrecht, James W., and Bo Axell, 1984. "An Equilibrium Model of Search Unemployment." Journal of Political Economy 92(5): 824–840.

[3] Arbex, Marcelo, Dennis O'Dea, and David Wiczer, 2016. "Network Search: Climbing the Job Ladder Faster," Federal Reserve Bank of St. Louis Working Paper No. 2016-009A.

[4] Armantier, Olivier, Giorgio Topa, Wilbert van der Klaauw, and Basit Zafar, 2017. "An Overview of the Survey of Consumer Expectations", Economic Policy Review, December 2017, Vol. 23(2): 51-72.

[5] Bagger, Jesper and Rasmus Lentz, 2019. "An Empirical Model of Wage Dispersion with Sorting," The Review of Economic Studies, 86(1): 153-190.

[6] Barron, John M. and Otis W. Gilley, 1981. "Job Search and Vacancy Contacts: Note," American Economic Review 71(4), 747-752.

[7] Bound, John and Alan B. Krueger, 1991. "The Extent of Measurement Error in Longitudinal Earnings Data: Do Two Wrongs Make a Right?," Journal of Labor Economics 9(1): 1-24.

[8] Black, Matthew, 1980. "Pecuniary Implications of On-The-Job Search and Quit Activity," Review of Economics and Statistics 62(2): 222-229.

[9] Blau, David M. and Philip K. Robins, 1990. "Job Search Outcomes for the Employed and Unemployed," Journal of Political Economy 98(3): 637-655.

[10] Burdett, Kenneth, 1978. "A Theory of Employee Job Search and Quit Rates." The American Economic Review 68(1): 212-220.

[11] Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin, 2006. "Wage Bargaining with On-the-job Search: Theory and Evidence," Econometrica 74(2): 323-364.

[12] Carrillo-Tudela, Carlos, 2009. "An Equilibrium Search Model When Firms Observe Workers' Employment Status," International Economic Review 50(2): 485-506.

[13] Christensen, Bent Jesper, Rasmus Lentz, Dale T. Mortensen, George R. Neumann, and Axel Werwatz, 2005. "On-the-Job Search and the Wage Distribution," Journal of Labor Economics 23(1): 31-58.

[14] Cole, Harold L. and Rogerson, Richard, 1999. "Can the Mortensen-Pissarides Matching Model Match the Business-Cycle Facts?," International Economic Review, 40(4), 933-959.

[15] Eeckhout, Jan, and Ilse Lindenlaub. 2019. "Unemployment Cycles," American Economic Journal: Macroeconomics, 11(4): 175-234.

[16] Elsby, Michael W.L., Bart Hobijn, and Ayşegül Şahin, 2010. "The Labor Market in the Great Recession," Brookings Papers on Economic Activity 41(1): 1-48.

[17] Elsby, Michael W.L., Ryan Michaels, and David Ratner, 2015. "The Beveridge Curve: A survey." Journal of Economic Literature 53(3): 571-630.

[18] Faberman, R. Jason and Alejandro Justiniano, 2015. "Job Switching and Wage Growth," Chicago Fed Letter No. 337.

[19] Faberman, R. Jason and Marianna Kudlyak, 2019. "The Intensity of Job Search and Search Duration," American Economic Journal: Macroeconomics 11(3): 327-57.

[20] Faberman, R. Jason, Andreas I. Mueller, Ayşegül Şahin and Giorgio Topa, 2017. "Job Search Behavior Among the Employed and Non-Employed," NBER Working Paper No. 23731.

[21] Faccini, Renato and Leonardo Melosi, 2019. "Bad Jobs and Low Inflation," CEPR Discussion Paper No. DP13628.

[22] Fallick, B., and C. A. Fleischman, 2004. "Employer-to-Employer Flows in the U.S. Labor Market: The Complete Picture of Gross Worker Flows," Finance and Economics Discussion Series 2004-34. Board of Governors of the Federal Reserve System.

[23] Floro, Maria Sagrario, and Marjorie Miles, 2003. "Time Use, Work and Overlapping Activities: Evidence from Australia", Cambridge Journal of Economics, Vol. 27(6): 881-904.

[24] Fujita, Shigeru, Giuseppe Moscarini, and Fabien Postel-Vinay, 2019. "Labor Markets and Job Search Measuring Employer-to-Employer Reallocation," mimeo.

[25] Hall, Robert E. and Paul R. Milgrom, 2008. "The Limited Influence of Unemployment on the Wage Bargain," American Economic Review 98(4): 1653-74.

[26] Hall, Robert E. and Alan B. Krueger, 2012. "Evidence on the Incidence of Wage Posting, Wage Bargaining, and On-the-Job Search," American Economic Journal 4(4): 56-67.

[27] Hall, Robert E. and Andreas I. Mueller, 2018. "Wage Dispersion and Search Behavior: The Importance of Non-Wage Job Values," Journal of Political Economy 126(4): 1594-1637.

[28] Haltiwanger, John. C., Henry. R. Hyatt, Lisa. B. Kahn, and Erica Mcentarfer, 2018. "Cyclical Job Ladders by Firm Size and Firm Wage," American Economic Journal: Macroeconomics, 10(2), 52–85.

[29] Hershbein, Brad, and Lisa B. Kahn, 2018. "Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings," American Economic Review 108(7): 1737-72.

[30] Holzer, Harry J., 1987. "Informal Job Search and Black Youth Unemployment," American Economic Review 77(3): 446-452.

[31] Hornstein, Andreas, Per Krusell, and Giovanni L. Violante, 2006. "Frictional Wage Dispersion in Search Models: A Quantitative Assessment," Federal Reserve Bank of Richmond Working Paper WP-06-07.

[32] Hornstein, Andreas, Per Krusell, and Giovanni L. Violante, 2011. "Frictional Wage Dispersion in Search Models: A Quantitative Assessment," American Economic Review 101(7): 2873-98.

[33] Kahn, Lawrence M., 2012. "Temporary Jobs and Job Search Effort in Europe," Labour Economics 19(1): 113-128.

[34] Karahan, Fatih, Ryan Michaels, Benjamin Pugsley, Ayşegül Şahin, and Rachel Schuh, 2017. "Do Job-to-Job Transitions Drive Wage Fluctuations over the Business Cycle?" American Economic Review 107(5): 353-57.

[35] Kroft, Kory, Fabian Lange, and Matthew J. Notowidigdo, 2013. "Duration Dependence and Labor Market Conditions: Theory and Evidence from a Field Experiment," Quarterly Journal of Economics 128(3): 1123-1167.

[36] Kroft, Kory, and Devin Pope, 2014. "Does Online Search Crowd Out Traditional Search and Improve Matching Efficiency? Evidence from Craigslist," Journal of Labor Economics 32(2): 259-303.

[37] Krueger, Alan B. and Andreas I. Mueller, 2010. "Job Search and Unemployment Insurance: New Evidence from Time Use Data," Journal of Public Economics 94(3-4): 298-307.

[38] Krueger, Alan B. and Andreas I. Mueller, 2011. "Job search, Emotional Well-Being, and Job Finding in a Period of Mass Unemployment: Evidence from High Frequency Longitudinal Data," Brookings Papers on Economic Activity: 1-81.

[39] Kuhn, Peter, and Kailing Shen, 2013. "Gender Discrimination in Job Ads: Evidence from China," The Quarterly Journal of Economics 128(1): 287-336.

[40] Low, Hamish, Costas Meghir and Luigi Pistaferri, 2010. "Wage Risk and Employment Risk over the Life Cycle," American Economic Review 100(4): 1432-1467.

[41] Marinescu, Iona E., 2017. "The General Equilibrium Impacts of Unemployment Insurance: Evidence from a Large Online Job Board," Journal of Public Economics, 150(1): 14-29.

[42] Mas, Alexandre, and Amanda Pallais. 2019. "Labor Supply and the Value of Non-work Time: Experimental Estimates from the Field," American Economic Review: Insights, 1 (1): 111-26.

[43] McCall, John Joseph, 1970. "Economics of Information and Job Search," Quarterly Journal of Economics 84(1): 113-126.

[44] Mincer, Jacob, 1991. "Education and Unemployment," NBER Working Paper No. 3838, National Bureau of Economic Research.

[45] Mortensen, Dale T., 1977. "Unemployment Insurance and Job Search Decisions," Industrial and Labor Relations Review 30(4): 505-517.

[46] Moscarini, Giuseppe, and Fabien Postel-Vinay, 2017. "The Relative Power of Employment-to-Employment Reallocation and Unemployment Exits in Predicting Wage Growth," American Economic Review 107(5): 364-68.

[47] Moscarini, Giuseppe, and Fabien Postel-Vinay, 2019. "The Job Ladder: Inflation vs. Reallcation," mimeo.

[48] Mueller, Andreas I., 2010. "On-the-Job Search and Wage Dispersion: New Evidence from Time Use Data," Economics Letters 109(2): 124-127.

[49] Mueller, Andreas I., 2017. "Separations, Sorting and Cyclical Unemployment," American Economic Review 107(7): 2081-2107.

[50] Mukoyama, Toshihiko, Christina Patterson and Ayşegül Şahin, 2018. "Job Search Behavior over the Business Cycle," the American Economic Journal: Macroeconomics 10(1) 190-215.

[51] Parsons, Donald O, 1973. "Quit Rates over Time: A Search and Information Approach," The American Economic Review 63(3): 390-401.

[52] Pissarides, Christopher A., 1985. "Short-run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages," American Economic Review 75(4): 676-690.

[53] Postel-Vinay, Fabien and Jean-Marc Robin, 2002. "Equilibrium Wage Dispersion with Worker and Employer Heterogeneity," Econometrica 70(6): 2295-2350.

[54] Shimer, Robert J., 2004. "Search Intensity," mimeo.

[55] Shimer, Robert J., 2005. "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," American Economic Review 95(1): 25-49.

[56] Sorkin, Isaac, 2018. "Ranking Firms Using Revealed Preference," Quarterly Journal of Economics 133(3): 1331-1393.

[57] Tjaden, Volker and Felix Wellschmied, 2014. "Quantifying the Contribution of Search to Wage Inequality," American Economic Journal: Macroeconomics 6(1): 134-161.

ONLINE APPENDIX

A SCE Job Search Supplement Design and Additional Details

A.1 Job Search Supplement Design, Administration, and Representativeness

This appendix describes the Job Search supplement of the Survey of Consumer Expectations (SCE), administered by the Federal Reserve Bank of New York. This section details the design and implementation of the supplement, while the next section details the survey questions most relevant to our analysis. We developed the Job Search supplement ourselves and first fielded the survey in October 2013. We have fielded the survey every October since then and use a sample that pools the 2013-17 responses together in our main analysis.

Our Job Search supplement draws its respondents and its sample weights from the main monthly survey of the SCE. Consequently, understanding the survey design of the monthly SCE is integral to understanding the design of the Job Search supplement. The main SCE is a monthly, nationally representative survey of roughly 1,300 *heads of households* that asks respondents their expectations about various aspects of the economy. Armantier et al. (2017) describe the development, design, and implementation of the monthly SCE. Perhaps the most important thing to note about the monthly SCE is that respondents remain in the survey sample for up to 12 months, giving the monthly SCE a rotating panel dimension. Since we administer the Job Search supplement once per year, however, our survey is a series of repeated cross sections.

Both the monthly SCE and Job Search supplement are online surveys. Individuals are paid a modest amount to take each survey. Armantier et al. (2017) report a survey response rate in the monthly SCE of 54 percent for individuals initially contacted to participate. The response rate of incumbent respondents in subsequent months ranges between 59 and 72 percent. They also show that the weighted monthly SCE sample matches the demographic statistics of the American Community Survey (ACS) well. In fact, the monthly SCE sample is stratified and weighted to match the ACS, so this is essentially by construction.

Table A1 presents basic labor force and demographic statistics for the monthly SCE, our Job Search supplement, and the Current Population Survey (CPS). All three surveys use a sample of respondents for each October between 2013 and 2017 that are restricted to heads of households (in the CPS) age 18 to 64. The CPS serves as a nationally representative benchmark for comparison to the two SCE surveys. We additionally report summary statistics for each year of our survey separately. The table shows that both the Job Search supplement and the

Table A1: Summary Statistics, Selected Surveys

	SCE Job Search Supplement						Monthly	
	2013	*2014*	*2015*	*2016*	*2017*	*Pooled*	**SCE**	**CPS**
Number of Sample Observations								
Total in survey	1,378	1,217	1,065	1,172	1,119	5,951	6,804	—
Total in restricted sample	1,109	969	835	901	863	4,677	5,337	198,228
Labor Force Statistics (weighted population shares)								
Employment-population ratio	77.1	73.3	78.2	78.8	75.7	76.6	74.9	74.9
Unemployment Rate (CPS definition)	7.1	4.9	3.1	3.6	2.9	4.5	4.9	4.5
Unemployment Rate (job search def.)	8.9	8.4	6.2	5.1	4.6	6.8	—	—
Labor force part. rate (CPS def.)	79.7	77.1	80.7	81.7	78.0	80.2	78.7	78.4
Demographics (weighted population shares)								
Percent male	48.7	48.9	49.2	43.4	49.1	48.3	47.6	48.7
Pct. White, non-Hispanic	76.6	71.4	68.6	69.9	74.0	72,3	72.4	63.0
Percent married	65.5	64.6	66.8	62.1	63.7	64.6	65.3	51.0
Pct. with college degree	32.1	32.2	34.3	34.3	35.9	33.6	33.5	34.7
Percent aged 18-39	35.6	33.4	36.6	36.5	34.4	35.3	35.4	39.2
Percent aged 40-54	36.2	33.6	36.8	38.5	36.4	36.3	37.4	35.9
Percent aged 55-64	28.2	33.0	26.6	25.1	29.2	28.5	27.3	24.9

Notes: Estimates come from authors' tabulations from the October 2013-17 waves of each listed survey: the SCE Job Search Supplement, the SCE Monthly Survey, and the Current Population Survey (CPS). The table reports the number of total observations in each survey (and survey year for the SCE Job Search Supplement) and the total number of observations and summary statistics for the sample restricted to heads of households aged 18-64, with nonmissing demographic and labor force data.

main SCE sample have labor force statistics that are comparable to the CPS.[2] Relative to the CPS, the Job Search supplement has a slightly higher employment-to-population ratio and the monthly SCE has a slightly higher share of unemployed, but the estimates are otherwise very similar. In terms of demographics, the SCE Job Search supplement and monthly SCE are nearly identical to each other. Compared to the CPS, both surveys have a notably higher share of White respondents, older respondents, and married respondents. Consequently, we control for observable demographic characteristics throughout much of our analysis, including replicating many of our estimates conditional on these characteristics in the Supplemental Appendix S-B.1.

A.2 Survey Format

We structured the Job Search supplement's questionnaire into several sections, generally grouped by topic. The full supplement questionnaire is available through the Federal Reserve Bank of

[2]For the Job Search supplement, Table A1 reports the "CPS" definition of unemployment, which is with its measurement in the other two surveys, and the "Job Search" definition of unemployment, which is a broader measure that counts active search effort regardless of whether they report wanting work. See the next section for more details.

New York at `https://www.newyorkfed.org/microeconomics/databank.html`, and we list the specific survey questions relevant to our analysis in the Supplemental Appendix S-A.1. The questionnaire starts with a section that asks basic questions on the respondent's current labor force situation, including whether or not they have looked for work in the last four weeks, and the type of work they are looking for. Many of these questions are nearly identical to labor force questions asked in the CPS. If an individual is employed, the survey follows up with a series of questions on the characteristics of their current job, including its hours, earnings, benefits, start date, industry, occupation, firm (and establishment) size, union status, and temporary/seasonal work status.[3] If an individual reports that they are self-employed, the survey has a set of questions on job characteristics that are tailored to self-employment. If an individual is not employed, the survey follows up with a variety of questions about the nature and duration of their non-employment spell (e.g., schooling, characteristics of any temporary layoff, etc.). It also asks about the characteristics of their most recent job (if they had one) in a similar manner to its questions about the job characteristics of the currently employed. Finally, it asks respondents to report the fraction of months over the prior five years they spent in various labor force states (employed, unemployed, in school, etc.) In our analysis, we use these variables to identify an individual's labor force status at the time of the survey interview and for various controls for job and worker characteristics, including their employment history.

For individuals who stated that they either looked for work or might take a (new or additional) job, "depending on the circumstances," the survey asks a series of questions about job search and any potential outcomes of that search. One of the main innovations of our survey relative to government-administered household surveys, like the CPS, is that we ask all individuals who meet this criteria about their job search, regardless of their current labor force status.[4] For the employed, the survey identifies whether their job search was for a new job or only for an additional job without leaving their current job. This section of the questionnaire begins with questions on reasons for job search and search methods used that are similar to those asked of the unemployed in the CPS. It then asks about specific metrics of search effort, namely the number of applications sent in the previous four weeks and the hours spent searching in the seven days

[3]Several of these questions are only available from 2014 forward.

[4]Notably, we do not ask self-employed about job search since it is not clear whether job search for this group reflects the desire for a new employment transition (e.g., to formal employment), or for new business or work for their current self-employed profession.

prior to the survey interview. From there, the survey asks a series of questions on any outcomes of this job search, including employer contacts, job interviews, and job offers. It asks several of these questions regardless of whether the respondent looked for work. When asking about job offers, the survey first asks whether the respondent received any offer in the previous four weeks. This allows us to generate a monthly offer rate to compare to other monthly labor market statistics. If there are none, they survey follows up and asks if they received any offers in the last six months. This provides us with a sufficient amount of job offers to examine since the survey is relatively small and job offers are infrequent.

For individuals who report at least one job offer, the survey asks a series of questions on the characteristics of the offer (or "best" job offer, if there was more than one). These ask about the same characteristics as those asked about the current job of the employed. The survey also asks how the job offer came about (e.g., directly contacting the employer, a referral, an unsolicited contact, etc.) It then asks respondents their labor force status at the time of the job offer. The survey then asks whether the job offer has been (or will be) accepted or rejected, and the reasons for acceptance or rejection. It also asks whether the job offer was for their current job (if currently employed). The survey follows this up with a series of questions on the job offer process (i.e., whether the respondent received a counter-offer from their current employer, whether there was any bargaining involved, and whether they had a good idea of what the potential new job paid), and also asks whether any potential offers were rejected before they could be made (i.e., whether they had any *unrealized* job offers).

The next section of the survey asks a series of questions on the respondent's reservation job values. These include eliciting a reservation wage, the respondent's desired hours worked (at their preferred wage), and how much the respondent's reservation wage would have to change to accept adverse job characteristics (relocation, longer commute, longer hours, or a lack of benefits), with an option that the respondent would "not accept such a job" with the adverse job characteristic at any wage. It asks these questions to all respondents who stated that they looked for work or might want a (new or additional) job.

For those who are employed at the time of the survey, the survey asks a series of retrospective questions about how they were hired to their current job. These include questions about the job search process similar to those asked about their recent job search (i.e., applications sent, contacts received, offers received, etc.) It also includes questions about their starting wage, their employment status at the time of hire, and a set of questions on the wages, hours, and other characteristics of their previous job (if any).

Finally, the survey asks about a variety of miscellaneous labor market and household questions. These include questions about any transfer payments received (e.g., disability or unemployment benefits), household composition, and spousal employment and income.

A.3 Relevant Survey Questions

LFS at time of survey. We highlight several specific survey questions that are relevant for our identification of labor force status and "active" search effort. We also highlight the specific questions regarding several aspects of the job offer process. First, we define labor force status in a similar manner to the CPS. That is, an individual is employed if they worked for pay at the time of the survey. They are unemployed if they were not employed and actively looked for work in the last four weeks and respond that they are available to start work, or if they were on temporary layoff. The CPS only asks about actively looking for work if an individual states that they "want work," while our survey asks about active search regardless. Consequently, we can capture a wider definition of job search and thus unemployment than in the CPS. We evaluate how using the alternate definitions of unemployment affect our results in the Supplemental Appendix S-B.

We define *active search* identically to the official BLS definition. That is, we base it on the respondent's answers to their job search methods used in the previous four weeks. If a respondent only "looked at job postings," online or elsewhere, or updated their resume, without taking any additional action to look for work, they are counted as *passively* looking for work and are therefore not counted as unemployed. Our survey has additional information on whether an individual sent a job application in the previous four weeks, which satisfies the "active search" criteria. We therefore count all individuals who sent at least one job application as actively searching regardless of what they report for their job search methods used.

LFS at time of offer. The survey allows us to identify respondents' labor force status at the time they received their job offer. The survey question only asks if they were employed full-time, employed part-time, or not employed at the time of the offer. From 2014 forward, the survey follows up and asks if they were looking for work at the time of the offer. As it turns out, nearly all of the non-employed report looking for work at the time of the offer. Given this, along with the fact that we do not have additional information on "active search" and availability for these respondents, we consider them as unemployed at the time of the offer for most of our analysis.

Search Effort. The survey's questions on search effort are straightforward and directly ask about what we consider an *intensive* margin of search intensity. With regard to job applications, the survey asks all individuals excluding the self-employed, *"How many potential employers, if any, did you apply to for employment within the LAST 4 WEEKS?"* The survey makes clear that the respondent should include all formal applications, including those made online or in person. With regard to time spent on job search, the survey asks all individuals that report engaging in some job search within the last four weeks, *"And within the LAST 7 DAYS, about how many TOTAL hours did you spend on job search activities?"* We use the answers to these questions as the direct measures of search effort in our analysis.

Job Offers. The survey asks a variety of questions on the characteristics of any job offer received. The questions are the same regardless of whether the offer was received in the previous four weeks or the last six months. Since surveys that ask about job offers are rare, we describe our questions regarding job offers in detail. First, the survey asks about the number and timing of any job offers received, as well as the respondent's labor force status at the time of the offer. Then it asks a series of questions on basic job offer characteristics. These are essentially identical to the job characteristics questions asked of the currently employed. It also asks whether the respondent has accepted or rejected (or will accept or reject) the job offer; it asks the respondent to identify the reasons for acceptance or rejection; and it asks about the search methods related to how the offer came about. For the latter, the survey offers an option for an unsolicited job offer (i.e., the offer came through an *"unsolicited contact by potential employer, recruiter, or headhunter"*). Finally, the survey asks a series of questions on the bargaining process. These questions are tailored to address facets of job offer acceptance characterized in many models of labor market search, such as wage bargaining and counter offers by a job seeker's current employer, that have previously had little guidance from the data (e.g., Cahuc, Postel-Vinay, and Robin, 2006, among others). Specifically, the survey asks respondents if they had a "good idea" of what the job paid prior to receiving the offer, with possible answers ranging from "knew exactly" what the job would pay to having "no idea" what it would pay. The survey also asks if there was any *bargaining* over the job offer's pay, or if the potential employer instead made the respondent a "take-it-or-leave it offer." For those who were employed at the time of the offer, they survey asks about any actual or potential counter-offers. Specifically, it asks if their current employer either did or would have matched the wage offered by the potential employer, with a follow up to ask if the respondent was able to secure any *"promotion, pay increase, or increase in benefits"* as a result of the outside job offer. Finally, the survey asks about what we refer to in the main text as *unrealized* job offers potentially made to the respondent. Specifically, the survey asks if *"In the LAST 4 WEEKS, have any employers indicated that they would be willing to make you a job offer, but you indicated that you were not interested?"* We consider any individuals who respond "Yes" to this question as receiving an unrealized job offer.

B Measuring Labor Force Status in the Prior Month

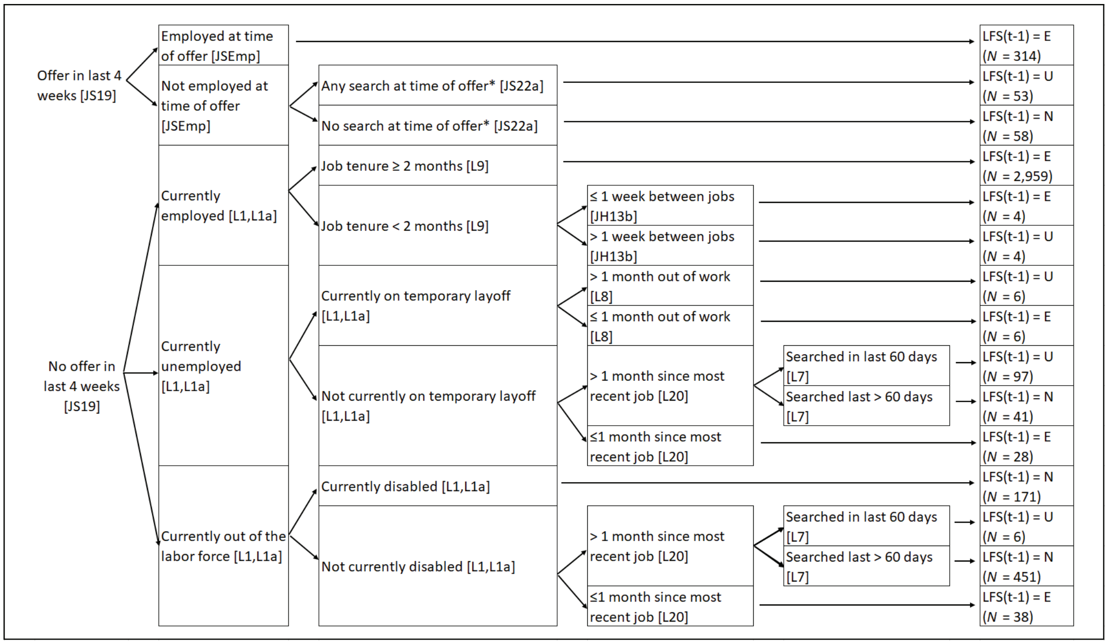
B.1 Prior Month's Labor Force Status Based on the SCE Labor Supplement

This appendix details our methodology for determining labor force status in the prior month and evaluates our measure along several comparable dimensions. We derive a labor force status for individuals four weeks prior to their survey interview using a range of survey responses from the SCE Job Search supplement. We use this measure in our model calibration because it treats the search effort and offer arrivals reported in the survey as subsequent outcomes based on this initial labor force status. This timing is consistent with most models of labor market search and addresses time aggregation and related selection issues.

Figure B1 details how we assign individuals to one of three states–employed (E), unemployed (U), or out of the labor force (N)—for their labor force status four weeks prior. As the figure shows, we draw from multiple survey questions to identify their labor force status. For reference, the figure notes the specific survey questions, as labelled in the Job Search supplement's online questionnaire, used at each stage of the identification process.[5] We first check to see if an individual received an offer in the four weeks prior to the survey. If so, we assign the labor force status at the time they received their job offer (employed or non-employed). This approach assumes that labor force status did not change between the time they received their job offer and four weeks prior to the labor supplement survey. We believe this is a reasonable assumption given the relatively short time interval. From 2014 forward, we have additional information on whether the respondent was actively searching at the time they received their offer. If so, we count them as unemployed, and if not, we count them as out of the labor force. For those in the 2013 wave,

[5]The complete survey questionnaire for the SCE Job Search supplement is available online through the Federal Reserve Bank of New York at `https://www.newyorkfed.org/microeconomics/databank.html`. Online Appendix A has additional detail on selected questions, and we list all questions used in Supplemental Appendix S-A.

Figure B1: Measuring Labor Force Status in the Prior Month



Notes: The figure details our methodology for identifying labor force status four weeks prior to the SCE Job Search supplement survey. Individuals are identified as either employed (E), unemployed (U), or out of the labor force (N), as noted in the rightmost boxes of the figure. The number of observations identified by each branch of the methodology are shown in parentheses. Codes in brackets refer to the question identifier in the SCE Job Search supplement questionnaire (available at: `https://www.newyorkfed.org/microeconomics/databank.html`). *For the 2013 survey wave, question JS22a was not asked, so we use a slightly different identification approach. See the text for details.

we make some modest assumptions to determine whether the respondent was unemployed or out of the labor force. If the respondent was employed at the time of the survey, we assume that they were actively searching and count them as unemployed. If they were unemployed at the time of the survey and have been searching for over four weeks, we also count them as unemployed. Otherwise, we count them as out of the labor force in the previous month. We identify 9 percent of the prior month's labor force status through their labor force status at the time of a job offer.

For the remaining individuals, we determine their prior month's labor force status starting with their labor force status at the time of the survey. The vast majority of respondents are currently employed with a job tenure greater than two months, and we identify these individuals as employed in the same job in the prior month. We identify the remaining handful of those employed at the time of the survey as either employed (via a job-to-job transition) or unemployed based on the time spent between their current and previous job.

If the respondent was unemployed at the time of the survey and did not receive an offer in the last four weeks, we first separate them based on whether or not they are on temporary layoff.

We only have 12 respondents on temporary layoff in our sample. We assign them a labor force status based on their reported time out of work, with those out for less than a month counted as employed in the prior month (i.e., recent layoff) and those out for more than a month counted as unemployed in the prior month. We assign the prior month's labor force status for the remaining unemployed based on their time out of work and reported amount of time looking for work. For those out of work for less than a month, we assign them as employed in the prior month (recent job loser). For the remaining, if they have looked for work for at least 60 days, we assign them as unemployed, and if they report looking for less than that (including not at all) we assign them as out of the labor force. Just over half of all those unemployed at the time of the survey have looked for at least 60 days. We identify just under a quarter as out of the labor force in the prior month, and just over 15 percent as recent (permanent) job losers.

Finally, if the respondent was out of the labor force at the time of the survey and did not receive an offer in the last four weeks, we separate them based on whether they reported that they were disabled at the time of the survey (in which case we assume they were disabled last month), and if not, we identify them based on the length of their non-employment spell and whether they looked for work in the last 60 days. These account for about one-quarter of all those currently out of the labor force. If an individual was not disabled but only out of work for one month or less, we identify them as employed four weeks prior. For the remainder, we count them as employed if their current non-employment spell is one month or less. We count them as unemployed if their current non-employment spell is greater than a month but they reported looking for work for at least 60 days—this represents only a handful of observations, however. The remainder are those whose non-employment spell is greater than a month and did not look for work in the last 60 days (if at all), and therefore counted as out of the labor force in the prior month. These represent the bulk of those who were out of the labor force at the time of the survey (68 percent) and a large portion of the full sample (just under 10 percent).

B.2 Evaluation of Imputation of Prior Month's Labor Force Status

Evaluation of this approach suggests that our methodology produces a sensible measure of the prior month's labor force status along several dimensions. First, our estimates imply an employment-to-population ratio of 0.779, an unemployment rate of 4.2 percent, and a labor force participation rate of 81.8 percent. All are very close to the current-month estimates for the

Table B1: Monthly Labor Market Transition Rates by Labor Force Status

(a) SCE Labor Supplement

	Transition Probability to		
Labor Force Status in Prior Month	**Employment**	**Unemployment**	**OLF**
Employed	0.969	0.009	0.022
Unemployed	0.196	0.526	0.277
Out of the Labor Force	0.016	0.045	0.939

(b) Current Population Survey

	Transition Probability to		
Labor Force Status in September	**Employment**	**Unemployment**	**OLF**
Employed	0.961	0.011	0.028
Unemployed	0.243	0.521	0.237
Out of the Labor Force	0.044	0.023	0.933

Notes: The top panel reports the labor force transition rates using the October 2013-17 waves of the SCE Job Search Supplement. It uses the methodology described in the appendix to determine the previous months' labor force status and uses the CPS definition of unemployment for labor force status at the time of the survey. The bottom panel reports the labor force transition rates from the CPS using data matched across September and October of 2013-17.

pooled SCE Job Search supplement, and are roughly comparable to the monthly SCE and CPS estimates in Table A1 of Online Appendix A.

Second, Table B1 shows that the monthly transition rates we obtain using our imputed prior-month labor force status and the labor force status at the time of the survey are comparable to those estimated from the CPS over the same period (i.e., between September and October in 2013 through 2017). The job-separation rates into unemployment and out of the labor force are nearly identical. Our sample has a slightly lower job-finding rate for the unemployed and a notably lower job-finding rate for those out of the labor force.[6] Transitions between unemployment and being out of the labor force are roughly comparable between the two surveys.

Third, we can compare the results we obtain on search outcomes using our imputed labor force status in the prior month with the prior month's labor force status implied by the monthly SCE data we have for the respondents in our sample. There is a timing issue with this approach because individuals may respond to the SCE Job Search supplement anywhere from a few days to nearly two months after their most recent monthly SCE interview. To deal with this, we assign a prior month's labor force status to individuals in the labor supplement based on the

[6]Note that these rates differ somewhat from the transition rates used in the main analysis. These rates are based on whether the respondent reports being employed at the time of the survey, while the rates we use in our analysis are the product of job offer rates and acceptance rates. Timing differences and respondent inconsistencies account for the small differences.

Table B2: Search Outcomes by Prior Month's Labor Force Status, based on Monthly SCE

	Employed	**Unemployed**	**OLF**
Labor Force Status in August/September, Monthly SCE			
Search Outcomes			
Fraction with at least one offer	0.112	0.277	0.091
	(0.006)	(0.036)	(0.011)
Fraction with at least one unsolicited offer	0.032	0.025	0.032
	(0.003)	(0.013)	(0.007)
Fraction with at least one offer, including unrealized offers	0.155	0.295	0.105
	(0.007)	(0.037)	(0.012)
Search Outcomes, Ignoring Offers for Additional Jobs			
Fraction with at least one offer	0.089	0.277	0.091
	(0.005)	(0.036)	(0.011)
Fraction with at least one unsolicited offer	0.028	0.025	0.032
	(0.003)	(0.013)	(0.007)
Fraction with at least one offer, including unrealized offers	0.129	0.295	0.105
	(0.006)	(0.037)	(0.012)
N	3,034	152	701

Notes: Estimates come from authors' tabulations from the October 2013-17 waves of the SCE Job Search Supplement, using respondents' labor force status reported in either the August or September waves of the monthly SCE survey, for all individuals aged 18-64, excluding the self-employed. Standard errors are in parentheses.

timing between the Job Search supplement and their September monthly SCE interview. If the gap between interviews is 22 days or more, we use their September labor force status from the monthly survey. If the gap is 21 days or less, or if the September data are missing, we use their August labor force status. We adjust all estimates of search outcomes so that they can be interpreted as monthly rates.

Table B2 replicates the bottom panels of Table 4 of the main text using prior month's labor force status based on the monthly SCE data. The table shows that the estimates are very similar to those estimated using our imputed prior month's labor force status. Offer rates are somewhat lower for the unemployed using the monthly SCE measure, but otherwise, the two measures produce nearly identical estimates for search outcomes.

C Search Effort Estimates in the SCE and ATUS

In this appendix, we compare our estimates of the time spent searching for work to estimates from the time diaries of the American Time Use Survey (ATUS). The ATUS is a *time use survey* which was designed to measure how people divide their time among various activities. ATUS statistics are based on interviews of individuals who are randomly selected from a subset of households that have completed their eighth month of interviews for the Current Population Survey (CPS). ATUS respondents are interviewed only one time about how they spent their time on the *previous day* while the SCE respondents report their search activity for the *prior week*. In this section, we generate comparable weekly job search estimates from the ATUS.

We first report the extensive and intensive margins of search activity by labor force status in the ATUS and the SCE in Table C1 without adjusting ATUS's daily estimates into weekly statistics. Specifically, the first panel reports the ATUS statistics that are based on time use during the *prior day* and the second panel reports the SCE-based statistics for job search activity that respondents report for the *prior week*. We find that only 0.6 percent of the employed report any time spent searching on a given day in the ATUS, but 21.3 percent of the employed report searching within the last *seven* days in the SCE. While these statistics are not comparable due to the different time frame of the two surveys, comparison of the unemployed in the two surveys reveals an important feature of job search. By definition, unemployed respondents in the ATUS reported having searched for work in the last four weeks. However, only 16.5% of them report searching for work in the previous day in their time use diary. This observation suggests that even unemployed individuals search for work intermittently. This contrasts with activities done with regularity, such as sleeping or eating.

Table C1 also reports the intensive margin of job search for each survey. The daily ATUS estimates are substantially lower than the daily average of the SCE estimates. For example, the ATUS daily estimates imply that the employed on average spend 6.7 minutes per week searching for work, while the SCE weekly estimates imply that on average the employed spend 70 minutes per week searching for work. If we restrict our attention to those with positive search time, in the ATUS the employed spend 156 minutes (2.6 hours) per day on job search and in the SCE that the employed spend 311 minutes (5.2 hours) per week on job search. It is difficult, however, to directly compare these numbers as they are expressed at different frequencies.

Imputing weekly job search estimates from the ATUS depends on whether the same group of job seekers look for work every day or if they do so less frequently. In light of these observations, we provide an interval for the implied weekly extensive and intensive margins for the ATUS in the third panel of Table C1. There are two extremes that define the interval. In one extreme, we assume that all who report looking for work are *steady searchers*. That is, the same group of individuals look for work every day of the week. In this case, 0.6% of the employed search every

Table C1: Time Spent Searching for Work, ATUS and SCE Labor Survey Data

	Employed	**Unemployed**	**OLF**
I. ATUS, prior-day estimates			
% reporting time spent searching for work, prior day	0.61	16.45	0.73
Average mins spent searching, prior day, all	0.95	26.92	1.29
Average mins spent searching, prior day, only searchers	155.7	163.6	176.7
Relative search intensity	0.035	1	0.048
II. SCE, search in last 7 days			
% reporting time spent searching for work, last 7 days	21.3	97.4	8.9
Average mins spent searching, last 7 days, all	69.6	687.9	36.1
Average mins spent searching, last 7 days, only searchers	310.8	692.4	294.6
Relative search intensity	0.101	1	0.052
III. ATUS, range of weekly estimates (no adjustment for secondary activities)			
% reporting time spent searching for work	0.6 to 4.3	16.5 to 100	0.7 to 5.1
Average mins spent searching, all	6.7	188.4	9.0
Average mins spent searching, only searchers	155.7-1090.2	188.4-1145.5	167.7-1237.0
Relative search intensity	0.035	1	0.052
IV. ATUS, imputed weekly estimates based on UK data (no adjustment for secondary activities)			
% reporting time spent searching for work	3.7	86.1	NA
Average mins spent searching, all	6.7	188.4	NA
Average mins spent searching, only searchers	181.8	218.8	NA
Relative search intensity	0.035	1	NA
V. ATUS, imputed weekly estimates based on UK data (with adjustment for secondary activities)			
% reporting time spent searching for work	4.4	100.0	NA
Average mins spent searching, all	8.0	218.8	NA
Average mins spent searching, only searchers	181.8	218.8	NA
Relative search intensity	0.037	1	NA

Notes: Estimates come from authors' tabulations from the 2013-17 waves of the American Time Use Survey (top panel) and the October 2013-17 waves of the SCE Job Search Supplement (bottom panel), for all individuals aged 18-64, by labor force status. The SCE estimates use the BLS definition of unemployment for determining labor force status. The estimates for the UK are based on the United Kingdom Time Use Survey, 2014-2015 (UKTUS).

day, with an average weekly search time of 1090 minutes, while 16.5% of the unemployed search every day, with an average weekly search time of 1146 minutes. In the other extreme, we assume that those who report looking for work are *intermittent searchers*. That is, they search only once per week, so that daily search estimates represent a different group of individuals each day. In this case, 4.3% of the employed search each week with a weekly search time of 156 minutes and 100% of the unemployed search each week with a weekly search time of 188 minutes.

The actual weekly amount of time spent searching for work implied by the ATUS time diary responses likely lies somewhere between these extremes, with some job seekers *steadily* looking for work and other job seekers search *intermittently*. There is no survey that interviews respondents in seven consecutive days for us to elicit information about their frequency of their job search for the US. However, the United Kingdom Time Use Survey (UKTUS) repeats its time-use interview over two consecutive days, providing some information on respondents' job search behavior that helps identify the prevalence of steady and intermittent job seekers.[7]

Evidence from the UKTUS. According to the UKTUS, only 16.7 percent of the employed who looked for work on the first day of the interview subsequently reported looking for work on the second day in 2014-15. Among the unemployed, 29.4 percent of respondents who searched on the first day also searched on the second day. These observations further support that job search is intermittent, even more so for the employed. Moreover, the ATUS only records a respondent's time spent on their *primary activity.* Thus, if an individual is literally searching while on the job or searching while engaging in some other primary activity, it will likely not show up as search time. The UKTUS asks respondents about primary and secondary activities: around 0.5% of the employed report searching for a job as a primary activity and adding individuals who search as their secondary activity increases this by 20 percent to 0.6%. For the unemployed, job search as a secondary activity increases the fraction of searchers from 17.7% to 20.7% in the UKTUS.

A model of daily and weekly participation in job search. We use the additional moments from the UKTUS along with the ATUS data to derive estimates of weekly job search activity assuming that job search behavior is similar in the two surveys.[8] The underlying assumptions are: (i) there are two types of searchers: *steady* or *intermittent* job seekers; (ii) individuals observed searching two days in a row are *steady* job seekers who search every day; (iii) individuals who do not search two days in a row are *intermittent* job seekers who search only once per week and could therefore be randomly observed looking for work on any day of the week.

Let π_j^{day} be the fraction of people in labor force status j who search on a given day (and similarly for π_j^{week}); s_j^{day} be the average daily search time for labor force status j, conditional on active search (and similarly for s_j^{week}); and μ_j^{uk} be the fraction of steady searchers in state j. Our assumptions on the distribution of steady and intermittent searchers imply that the fraction of individuals who look for work over a weekly interval is

$$\pi_j^{week} = \mu_j^{uk}\pi_j^{day} + 7(1-\mu_j^{uk})\pi_j^{day}. \tag{C1}$$

[7] The UKTUS is a large-scale household survey that provides data on how people aged 8 years and over in the UK spend their time. Similar to the ATUS, it is based on a time diary instrument in which respondents record their daily activities. This document uses the Multinational Time Use Study, Centre for Time Use Research, University College London 2019 at `http://www.timeuse.org/mtus/reference.html`.

[8] Note that UKTUS statistics that are based on primary day only are very close to the ATUS statistics.

Using this formulation with the daily ATUS statistics implies that 3.7% of the employed and 86.1% of the unemployed looked for work each week. Given the average weekly search time, $\bar{s}_j^{week} = 7\bar{s}_j^{daily}$, we compute the average weekly search time conditional on active search as $s_j^{week} = \frac{\bar{s}_j^{week}}{\pi_j^{week}}$, which amounts to 182 minutes for the employed and 219 minutes for the unemployed.

The fifth panel of Table C1 also adjusts the extensive-margin of individuals actively looking for work to account for (unreported) job search as a secondary activity. Using the statistics on secondary activities from the UKTUS increases the daily fraction of those actively looking from 0.61% to 0.73% for the employed and from 16.5% to 19.4% for the unemployed. Using equation C1 with these estimates implies that 4.4% of the employed and 100% of the unemployed look for work each week.[9] The average search time per week for all searchers also increases to 8 minutes for the employed and 219 minutes for the employed.

We conclude that while the aggregation from daily to weekly statistics closes part of the gap between the two surveys, the ATUS still fails to match the extensive margin of on-the-job search we observe in the SCE. It is, however, consistent with all unemployed looking for work over a weekly interval. On the intensive margin, the ATUS underestimates search activity relative to the SCE for both the employed and unemployed.

Relative search intensity. The ATUS also gives biased estimates of the relative search intensity of the employed to the unemployed. Indeed, we find that the ATUS estimates of job search imply that the employed search only around 3.7 percent as intensely as the unemployed, while the SCE estimates of job search imply that they search 10.1 percent as intensely as the unemployed. This difference matters for the composition of aggregate search effort in the economy. Let us define S^T as the total aggregate efficiency units of job search, which is computed by weighting individuals in each labor force state E, U, and N by their search intensity relative to the unemployed, s^e and s^n (with $s^u = 1$ by definition). Aggregate efficiency units of job search in this case are $S^T = s^e E + U + s^n N$. If we consider the time period we analyze, there were 148.7 million employed, 8.8 million unemployed, and 93.0 million out of the labor force, on average over the 2013-17 period. If we combine these numbers with the relative search intensities from the ATUS, they imply that on-the-job search makes up only 29 percent of aggregate search effort, while search among the unemployed makes up 47 percent of aggregate search effort. If we instead use

[9] Our results are also consistent with Braun (2021) who assumes that all searchers are intermittent and finds that about 16.7 percent of the employed engage in job search over a *month*.

the relative search intensities from the SCE data, it implies that on-the-job search makes up 52 percent, and search by the unemployed makes up 31 percent, of aggregate search effort. Thus, our broader and more direct measure of search intensity not only suggests an overall greater level of on-the-job search, but also a greater degree of *relative* search effort for the employed. If one wants to calculate effective labor market tightness taking into account the number and search intensity of employed and nonparticipant workers—such as in Eeckhout and Lindenlaub (2018) and Abraham et al. (2020), our estimates provide a direct estimate.

To summarize, there are three important measurement differences between the ATUS and the SCE with regard to job search. First is the time span of the job search question. The intermittent nature of job search activity implies that one cannot simply multiply average daily search time by seven to come up with weekly search statistics. Second, the ATUS does not account for job search activity unless it is the respondent's primary activity, which again is somewhat more relevant for the employed. Finally, time use surveys do not prompt participants to report their search activity, but instead simply ask participants to report how they spent their previous day, which may lead respondents to under-report smaller episodes of job search. This seems particularly relevant for the employed and thus may account for the large discrepancy in the extensive margin for the employed between the ATUS and the SCE. Overall, the survey mode combined by the prevalence of intermittent search and secondary activities is likely to lead to a downward bias in estimates of average search activity in time use surveys and this particularly so for the employed. This is also consistent with the literature on time use surveys, which emphasizes the difficulty of accurately assessing the prevalence and intensity of intermittent and secondary activities in the context of home production.[10] Given these issues, we believe that our estimates of search effort provide a more comprehensive and reliable measure than the ATUS.

D Model Appendix

In this section, we provide additional details regarding the model: First, we simplify the value functions and provide the first-order conditions. Second, we define the stationary equilibrium. Third, we show the details of how we solve for the equilibrium and compute the model moments for the calibration exercise. Finally, we provide a robustness analysis and additional results.

[10]See for example, Floro and Miles (2003) who argue that the time spent on activities such as childcare and housework, which are also performed secondary activities, are seriously underestimated in the time use surveys.

D.1 Value Functions and First-Order Conditions

Using the Nash-bargaining solutions in the paper (equations 4 and 5), one can simplify the value functions as follows. The joint value of a match can be rewritten as:

$$\begin{aligned} K(y,x) \quad &= \max_{\bar{s}_e \geq s \geq 0, R_\delta, R_e} \Bigg\{ pyx - c_e(s)x + \frac{1}{1+r}\Bigg[K(y,x) - [\delta(x) + \tilde{\delta}_0(x,\theta)](K(y,x) - U(x) - V) \\ &+ \tilde{\delta}_0(x,\theta) \int_{R_\delta} \tau_u (K(n,x) - V - U(x)) dF(n) \\ &+ \tilde{\lambda}_e(s,x,\theta) \int_{R_e} [\tau_e(K(n,x) - K(y,x)) + (1-\tau_e)V] dF(n) \Bigg] \Bigg\}. \end{aligned} \tag{D1}$$

The value of unemployment can be rewritten as:

$$\begin{aligned} U(x) \quad &= \max_{\bar{s}_u \geq s \geq 0, R_u} \Bigg\{ bx - c_u(s)x + \\ & \frac{1}{1+r}\Bigg[U(x) + \lambda_u(s,\theta) \int_{R_u} (\tau_u(K(n,x) - U(x) - V)) dF(n) \Bigg] \Bigg\}. \end{aligned} \tag{D2}$$

The value of a vacancy can be rewritten as:

$$\begin{aligned} V \quad &= \quad -c + \frac{1}{1+r}\Bigg[V + q(\theta) \sum_x \pi(x) \Bigg(\frac{u(x)}{S} \lambda_u(s_u(x)) \int_{R_u(x)} (1-\tau_u)(K(n,x) - U(x) - V) dF(n) \\ &+ \quad \frac{1-u(x)}{S} \tilde{\delta}_0(x) \int_{R_\delta(x)} (1-\tau_u)(K(n,x) - U(x) - V) dF(n) \\ &+ \quad \frac{1-u(x)}{S} \int \tilde{\lambda}_e(s_e(\hat{y},x),x) \int_{R_e(\hat{y},x)} (1-\tau_e)(K(n,x) - K(\hat{y},x) - V) dF(n) dG(\hat{y}|x) \Bigg) \Bigg]. \end{aligned} \tag{D3}$$

Given these simplified value functions, the first order condition w.r.t. s for employed and unemployed individuals, respectively, are:

$$(1+r)c_e'(s_e(y,x))x = \tilde{\lambda}_e^s(s_e(y,x),x,\theta) \int_{R_e(y,x)} [\tau_e(K(n,x) - K(y,x)) + (1-\tau_e)V] dF(n) \tag{D4}$$

$$(1+r)c_u'(s_u(x))x = \lambda_u^s(s_u(x),\theta) \int_{R_u(x)} \tau_u [K(n,x) - U(x) - V] dF(n), \tag{D5}$$

and the first order conditions for the reservation productivities are:

$$K(R_\delta(x),x) = U(x) + V \tag{D6}$$

$$K(R_u(x),x) = U(x) + V \tag{D7}$$

$$K(R_e(y,x),x) = K(y,x) - \frac{1-\tau_e}{\tau_e} V. \tag{D8}$$

Together with the zero-profit condition, this implies that $R_e(y,x) = y$ and $R_\delta(x) = R_u(x)$.

D.2 Stationary Distribution and Equilibrium

For a given type x, the steady-state unemployment rate, $u(x)$, is pinned down by equalizing the inflow and outflows as follows:

$$u(x)\lambda_u(s_u(x),\theta)[1-F(R_u(x))] = (1-u(x))[\delta(x)+\tilde{\delta}_0(\theta)F(R_\delta(x))]. \tag{D9}$$

For a given type x, the steady-state distribution of workers across y, $G(y|x)$, is pinned down by equating employment inflows and outflows as follows:

$$\begin{aligned} &u(x)\lambda_u(s_u(x),\theta)[F(y)-F(R_u(x))] + (1-u(x))\tilde{\delta}_0(x,\theta)[F(y)-F(R_\delta(x))] = \\ &(1-u(x))[\delta(x)+\tilde{\delta}_0(x,\theta)]G(y|x) + (1-u(x))\int^y [1-F(\max\{R_e(\hat{y},x),y\})]\tilde{\lambda}_e(s_e(\hat{y},x),x,\theta)dG(\hat{y}|x), \end{aligned} \tag{D10}$$

which shows the mass of workers who get an acceptable job offer equal to y or lower on the left-hand side and the mass of workers who either lose the job due to a separation shock or leave the job because they accept a better offer that is above y.

Definition 1 *A stationary equilibrium is defined as the search efforts $s_u(x)$ and $s_e(y,x)$, the reservation productivities $R_u(x)$, $R_\delta(x)$, and $R_e(y,x)$, the unemployment rates $u(x)$, the distributions $G(y|x)$, the labor market tightness θ, and the value functions $K(y,x)$, $U(x)$, and V, that for all x and y satisfy equations (D1)-(D3), the first-order conditions (D4)-(D8), the steady-state conditions (D9) and (D10), and the zero-profit condition $V=0$.*

The stationary equilibrium is independent of the offered values $W(y',.,x)$ and $J(y',.,x)$ and thus does not require us to solve for the wage contracts. This considerably simplifies the equilibrium solution. Given the Nash-Bargaining solution, it is easy to solve for the offered values. In Supplemental Appendix S-C, we derive the wage functions, $w(y',.,x)$, implied by these offered values.

D.3 Solving for the Equilibrium

Solving for the Value Functions. One can solve for the stationary equilibrium as follows. Taking the derivative of $K(y,x)$ w.r.t. y, imposing $V=0$, and re-arranging, gives:

$$K^y(y,x) = \frac{(1+r)px}{D(x,\theta)+\tau_e\tilde{\lambda}_e(s(y,x),x,\theta)(1-F(y))},$$

where $D(x,\theta) = r + \delta(x) + \tilde{\delta}_0(x,\theta)$. Using integration by parts, one gets:

$$\int_y (K(n,x) - K(y,x))dF(n) \quad = \quad \int_y K^y(n,x)(1-F(n))dn$$

Plugging this into the FOCs for search effort of the employed and unemployed, we get:

$$\frac{c_e'(s_e(y,x))}{\lambda_e^s(s_e(y,x),\theta)} = \tau_e \int_y \frac{p(1-F(n))}{D(x,\theta) + \tau_e\tilde{\lambda}_e(s_e(n,x),x,\theta)(1-F(n))}dn \tag{D11}$$

$$\frac{c_u'(s_u(x))}{\lambda_u^s(s_u(x),\theta)} = \tau_u \int_{R_u(x)} \frac{p(1-F(n))}{D(x,\theta) + \tau_e\tilde{\lambda}_e(s_e(n,x),x,\theta)(1-F(n))}dn. \tag{D12}$$

Taking the difference between equations D1 and D2, imposing $U(x) = K(R_u(x),x)$, and evaluating at $y = R_u(x)$, gives:

$$\begin{aligned} R_u(x) - \frac{c_e(s_e(R_u(x),x))}{p} &= \frac{b - c_u(s_u(x))}{p} + [\tilde{\delta}_0(\theta)\tau_u + \tilde{\lambda}_e(s_e(y,x),x,\theta)\tau_e - \lambda_u(s_u(x),\theta)\tau_u] \\ &\times \int_{R_u(x)} \frac{1-F(n)}{D(x,\theta) + \tau_e\tilde{\lambda}_e(s_e(n,x),x,\theta)(1-F(n))}dn, \end{aligned} \tag{D13}$$

which implicitly defines the reservation productivity level $R_u(x)$. Similarly, re-arranging equation D3, simplifying, and imposing zero profits, we get:

$$\begin{aligned} \frac{c}{q(\theta)} &= p\sum_x \pi(x)x\Bigg[(1-\tau_u)\frac{u(x)\lambda_u(s_u(x)) + (1-u(x))\tilde{\delta}_0(x)}{S} \\ &\times \int_{R_u(x)} \frac{1-F(n)}{D(x,\theta) + \tau_e\tilde{\lambda}_e(s_e(n,x),x,\theta)(1-F(n))}dn + (1-\tau_e)\frac{1-u(x)}{S} \\ &\times \int_{R_u(x)} \tilde{\lambda}_e(s_e(j,x),x)\Big(\int_j \frac{1-F(n)}{D(x,\theta) + \tau_e\tilde{\lambda}_e(s_e(n,x),x,\theta)(1-F(n))}dn\Big)dG(j|x)\Bigg] \end{aligned} \tag{D14}$$

Taken as given $R_\delta(x) = R_u(x)$ and $R_e(y,x) = y$, one can define the stationary equilibrium as:

Definition 2 *A stationary equilibrium is defined as the search efforts $s_u(x)$ and $s_e(y,x)$, the reservation productivities $R_u(x)$, the unemployment rates $u(x)$, the distributions $G(y|x)$, and the labor market tightness θ that for all x and y satisfy equations (D11)-(D14) and the steady-state conditions (D9) and (D10).*

This definition of the equilibrium is useful because it is not only independent of the wage functions but also does not rely on solving for the value functions.

Solution Algorithm. To solve for the equilibrium, we proceed as follows:

1. For each type x, we choose 68 grid points for y on an interval $[0, \bar{y}]$ and linearly interpolate $s_e(y, x)$ for points in between grid points. We start by imposing $s_e(\bar{y}, x) = 0$, which approximately holds true for $\bar{y}$ large enough. We then solve equation D11 for the grid point below $\bar{y}$ and so on, until we have solved for $s_e(y, x)$ for all 68 grid points.

2. For each type x, we define a function $s_u(R, x)$, which defines unemployed workers' search effort for a given reservation productivity R. We choose 68 grid points for R on an interval $[0, \bar{R}]$ and linearly interpolate $s_u(R, x)$ for points in between grid points. Given the solution for $s_e(y, x)$, we solve equation D12 for $s_u(R, x)$ for all 68 grid points.

3. For each type x, we replace $s_u(R_u(x), x)$ for $s_u(x)$ in equation D13 and solve for $R_u(x)$. Given $R_u(x)$, we get $s_u(x) = s_u(R_u(x), x)$.

4. For each type x, we use equation D9 to solve for the steady-state unemployment rate $u(x)$ and equation D10 to solve for the steady-state distribution of workers across match types y, $dG(y|x)$. For the latter, we choose 100 grid points for y on an interval $[R_u(x), \bar{y}]$ and linearly interpolate for points in between grid points. We first solve equation D10 for $dG(R_u(x)|x)$ and then solve equation D10 for the grid point above $R_u(x)$ and so on.

5. For each type x, we solve the offer values $W(y', ., x)$ and wage functions $w(y', ., x)$ as described in Supplemental Appendix S-C.

Note that throughout we normalize $\theta = 1$ and in a final step use the zero-profit condition to find the value of the vacancy posting cost c that rationalizes this value of θ.

Calibration. In our baseline model, the following 15 parameters are calibrated internally: γ, τ_u, κ_u, κ_e, α_u, α_e, β_u, β_e, χ_u, χ_e, σ_x, b (or z), δ_0, δ and δ_x (where $\delta(x) = \delta - \delta_x \ln(x)$). We target a total of 15 parameters as listed in Table 8 in the paper and, while most moments depend on the values of several parameters, it is straightforward to see which parameter is identified by which moment (see Table 9). Hence, our model is exactly identified.

Given the large number of parameters, it is difficult to use an equation solver to solve for all 15 parameters simultaneously. Moreover, we can solve for the set of moments that do not depend on wages (see the Supplemental Appendix for more details), whereas for wage moments we rely on simulated moments (based on 100,000 individuals simulated for 1,000 months). To match all targeted moments, we start by guessing values for γ, κ_u, σ_x and δ_x and then proceed as follows:

1. (Inner loop) We solve for the 11 parameters κ_u, κ_e, α_u, α_e, β_u, β_e, χ_u, χ_e, b (or z), δ_0, δ as a function of the 11 non-wage moments listed in Table 9. Using an equation solver in Matlab that minimizes the squared difference of the deviation of the model moments from the targeted moments, this inner loop converges relatively quickly.

2. (Outer loop) We simulate the remaining 4 wage moments and update the guesses for γ, τ_u, σ_x and δ_x. We go back to [1.] and iterate until all moments in the model match their empirical counterparts. We use the bisection method to find δ_x and choose γ, τ_u, and σ_x to match the targeted moments.

D.4 Additional Results and Robustness

In this section, we report additional results for our baseline quantitative analysis and provide alternative specifications to examine the robustness of our quantitative findings.

Additional results. Figure D1 shows the dynamic response to a productivity shock for additional variables not shown in the main paper. The economy with $\gamma = 3.6$ features larger responses for all of these variables including vacancies and the unemployment rate. Interestingly, the model also features a spike in separations at the time of the negative productivity shock, consistent with the observed dynamics of separations during recessions. The reason for the spike is a sharp increase in the reservation productivity, leading to a large wave of endogenous separations of all matches with productivity below the new reservation threshold.

Robustness. Table D1 provides a robustness analysis for alternative model specifications. Note that unless otherwise noted, in Table D1, we do not re-calibrate the parameters γ, τ_u and σ_x and thus these calibrations do not necessarily match the search-wage elasticity, the wage offer differential and the standard deviation of log wages in the data. All other parameters are re-calibrated to match the targeted data moments. We emphasize the following four sets of results:

<u>Heterogeneous γ by labor force status:</u> Our results are robust to allowing γ to depend on employment status ($\gamma_u = 1$ and $\gamma_e = 3.6$): the results in column (3) show that this model is nearly identical in terms of its parameters (except for those relating to the search cost function) and Figure D3 shows that this model still features substantial amplification on vacancy posting and search effort relative to an economy where $\gamma_u = \gamma_e = 1$.

<u>Number of x types:</u> We show that the results for the model with two x-types instead of ten are nearly identical in column (1) of Table D1. This suggests that there are no issues with restricting

the model to two types for the dynamic simulations shown in the main paper. Figure D2 also shows that the dynamic labor market responses to an aggregate productivity shock are very similar when we simulate the responses for an economy *without* ex-ante worker heterogeneity, showing that amplification is not driven by compositional shifts in x in the pool of job seekers.

Calibration of γ: The search-wage gradient is strongly increasing in the parameter γ, as shown by comparing columns (2) and (4) in the table. This shows that the search-wage gradient is a highly informative moment to identify the parameter γ.

Roles of censoring, bargaining, and endogenous search: Columns (5), (6), (7) and (8) demonstrate how the model behaves if we gradually turn off key features of our model such as censoring, bargaining and endogenous search effort. More precisely, in column (5) we do not allow for censoring both in the model and the targeted moments. This implies that the total offer rate (formal + censored offers) is substantially lower for the employed, reducing their relative search efficiency. The relative search efficiency also declines because the reallocation parameter δ_0 is estimated to be higher, leaving less room for offers arising due to endogenous search effort. In column (6), we also set $\tau_e = \tau_u = 0.5$, allowing for equal bargaining power of the employed. In column (7), we set $\tau_e = \tau_u = 1$, effectively eliminating the role of bargaining in the model and setting the wage equal to the marginal product. Note that with $\tau_e = \tau_u = 1$ the general equilibrium is not well defined for $c > 0$ as firms have no incentive to post vacancies, but the results can be viewed as identical to a partial equilibrium model where the wage is equal to productivity and where θ is set to 1. In column (8), we also set $\beta_e = \beta_u = 0$, which effectively shuts down endogenous search effort in the model. In this model, we calibrate α_i to match the offer rate by employment status, though the model cannot match the targeted moments exactly.[11] The model's implied flow value of unemployment gradually decreases from columns (5) to (8), with a values of z of 0.55, 0.48, 0.29, and 0.15 compared to 0.66 in our baseline model. These results show that the resolution of the wage dispersion puzzle in our baseline model is due to all of these model ingredients.

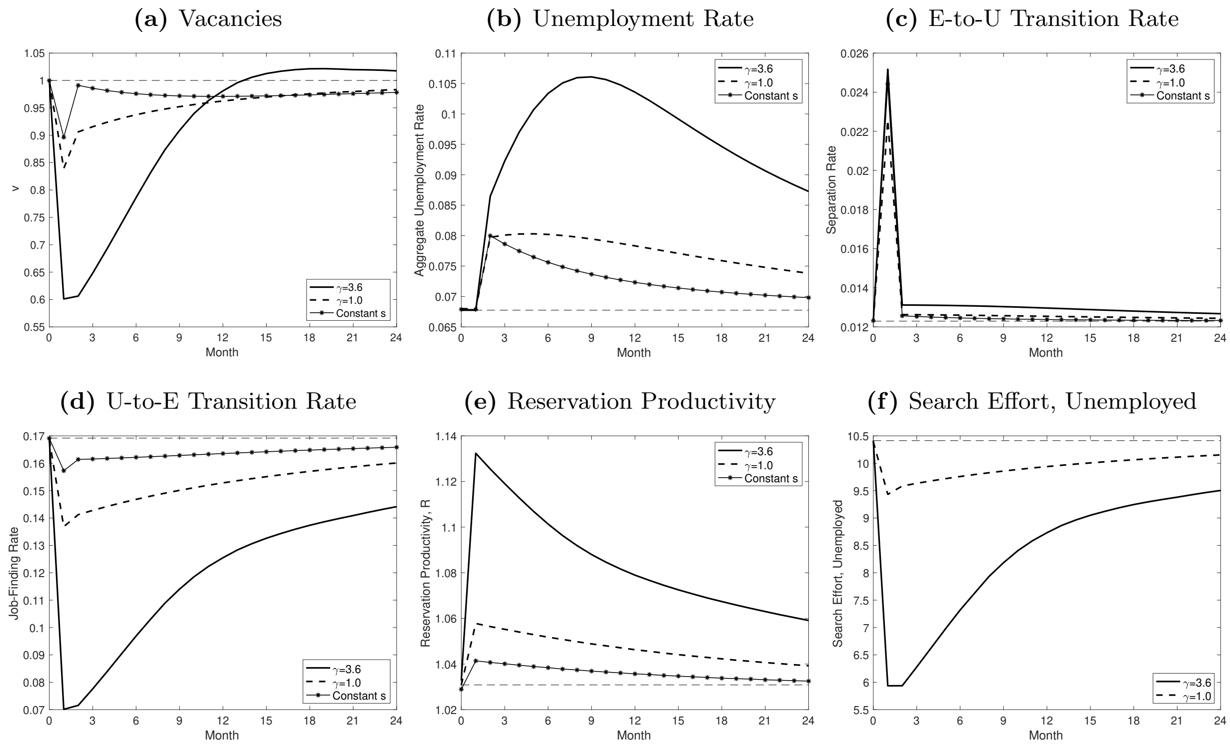
[11] The model requires a high value of δ_0 to match the acceptance rate of the employed, but since δ_0 also leads to more separations, this implies that, for high values of δ_0, the estimated value of $\delta(x_{med}) = 0$. Thus, we are no longer able to match both the separation rate and the employed's acceptance rate. In any event, the model moments are still close to the targeted moments.

Table D1: Alternative Calibrations of Model

			Alternative Models:							
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Calibrated parameter values		**Baseline Model**	$n_x = 2$	$\gamma = 1$	$\gamma_u < \gamma$	$\gamma = 10$	$\chi_i = 0$	$\chi_i = 0$ $\tau_i = 0.5$	$\chi_i = 0$ $\tau_i = 1$	$\beta_i = 0$ $\chi_i = 0$ $\tau_i = 1$
γ		3.6	3.6	1	3.6	10	3.6	3.6	3.6	3.6
γ_u		3.6	3.6	1	1	10	3.6	3.6	3.6	3.6
τ_u		0.4	0.4	0.4	0.4	0.4	0.4	0.5	1	1
τ_e		0.5	0.5	0.5	0.5	0.5	0.5	0.5	1	1
n_x		10	2	10	10	10	10	10	10	10
σ_x		0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57
σ_y		0.273	0.273	0.273	0.273	0.273	0.273	0.273	0.273	0.273
κ_u		0.014	0.014	0.003	0.003	0.019	0.018	0.023	0.038	0
κ_e		0.062	0.062	0.058	0.062	0.066	0.039	0.039	0.069	0
α_u		0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.331
α_e		0.026	0.026	0.027	0.026	0.026	0.027	0.027	0.027	0.058
β_u		0.032	0.032	0.032	0.032	0.032	0.029	0.029	0.029	0
β_e		0.115	0.115	0.108	0.115	0.116	0.046	0.046	0.046	0
χ_u		0.139	0.139	0.139	0.139	0.139	0	0	0	0
χ_e		0.458	0.457	0.465	0.458	0.465	0	0	0	0
z		0.662	0.662	0.583	0.667	0.654	0.552	0.482	0.293	0.149
δ_0		0.010	0.010	0.016	0.010	0.009	0.021	0.021	0.022	0.026
δ		0.007	0.007	0.004	0.007	0.008	0.002	0.001	0.001	0.000
δ_x		0.002	0.002	0.003	0.002	0.003	0.002	0.002	0.005	0.000
c		0.937	0.933	1.052	0.935	0.889	1.492	1.342	—	—
Targeted moments	**Data**									
Search-wage elasticity	-0.36	-0.36	-0.36	-0.21	-0.36	-0.45	-0.29	-0.31	-0.40	—
Wage offer differential (E-U)	0.194	0.193	0.193	0.164	0.193	0.224	0.092	0.084	0.075	0.000
St. dev. log wage offers	0.678	0.678	0.680	0.677	0.679	0.674	0.673	0.675	0.689	0.689
Search effort U	10.39	10.39	10.39	10.39	10.40	10.39	10.39	10.39	10.39	0
Search effort E	0.769	0.769	0.769	0.769	0.769	0.769	0.769	0.769	0.769	0
Unsol. offer rate U	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0
Unsol. offer rate E	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0
Censored offer rate U	0.028	0.028	0.028	0.028	0.028	0.028	0	0	0	0
Censored offer rate E	0.041	0.041	0.041	0.041	0.041	0.041	0	0	0	0
Formal offer rate U	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.331
Formal offer rate E	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.083
Acceptance rate U	0.493	0.493	0.493	0.493	0.493	0.494	0.494	0.494	0.494	0.523
Acceptance rate E	0.309	0.309	0.309	0.309	0.309	0.309	0.309	0.309	0.309	0.299
Unemployment rate	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.067
Prior wage diff. (E-U)	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.000	-0.038
Additional moments										
Wage offer differential		0.193	0.193	0.164	0.193	0.221	0.092	0.084	0.075	0
... due to composition		0.118	0.118	0.082	0.117	0.135	0.063	0.065	0.074	0
... due to censoring		0.036	0.036	0.035	0.036	0.037	0	0	0	0
... due to bargaining		0.039	0.040	0.048	0.039	0.048	0.029	0.019	0	0
Unempl. rate of low-x types		0.083	0.086	0.077	0.079	0.097	0.076	0.076	0.077	0.067
Unempl. rate of high-x types		0.053	0.050	0.059	0.057	0.039	0.060	0.060	0.059	0.067
Mean-min ratio		1.556	1.557	1.500	1.556	1.573	1.418	1.418	1.414	1.350

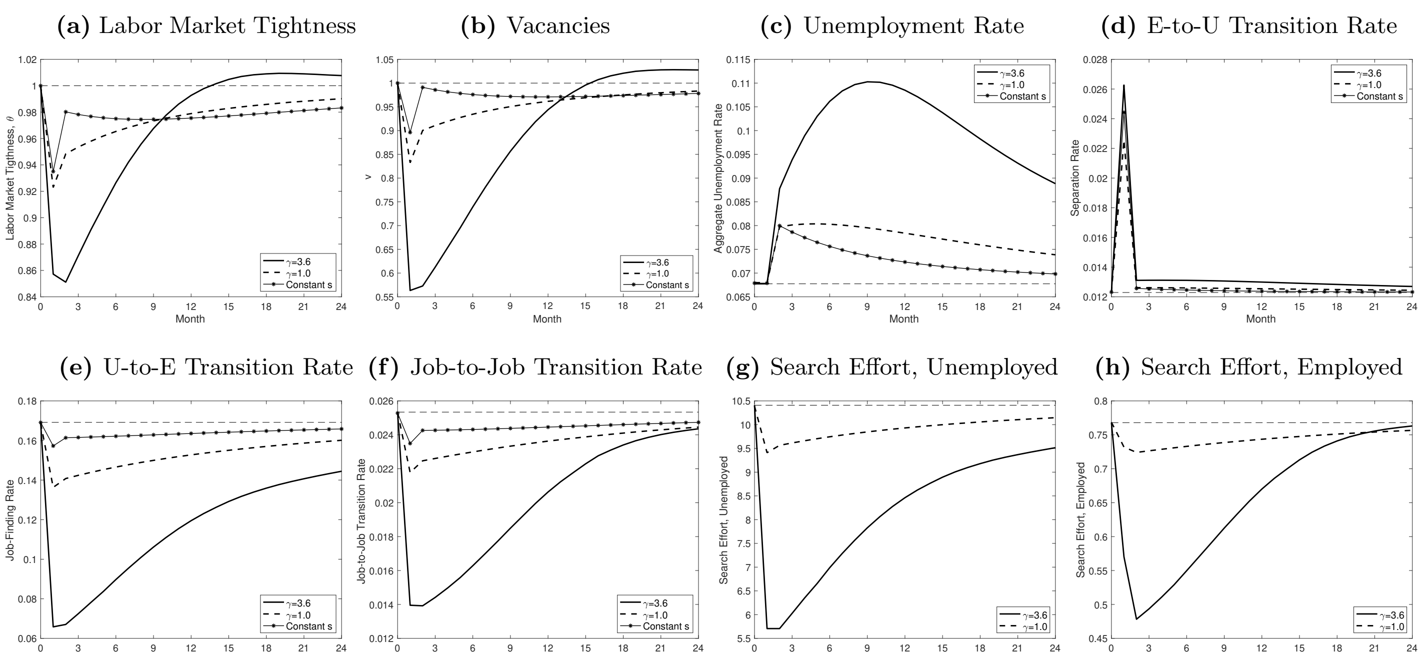
Notes: All moments referring to wages are based on residualized wage data as described in the paper. Note that unless otherwise noted, for the alternative models, we do not re-calibrate the parameters γ, τ_u, and σ_x and thus these calibrations do not necessarily match the search-wage elasticity, the wage offer differential and the standard deviation of log wages in the data. The other parameters are re-calibrated to match the targeted moments in the data. Column (1) shows the results for the model with 2 x-types instead of 10; column (2) shows results for the model where we set $\gamma = 1$; column (3) shows results for the model where we allow for $\gamma_u < \gamma$; column (4) shows results for the model where set $\gamma = 10$; column (5) shows results for the model without censoring ($\chi_u = \chi_e = 0$); column (6) shows results for the model without censoring and where $\tau_u = \tau_e = 0.5$; column (7) shows results for the model without censoring and with $\tau_u = \tau_e = 1$; column (8) shows results for the model without censoring, with $\tau_u = \tau_e = 1$ and without endogenous search effort, which amounts to setting $\beta_u = \beta_e = 0$. Note that in columns (7) and (8) the general equilibrium is not well defined for $c > 0$ as firms have no incentive to post vacancies, but the results can be viewed as identical to a partial equilibrium model where the wage is equal to productivity and where θ is set to 1.

Figure D1: Labor Market Responses to Aggregate Productivity Shock—Additional Variables



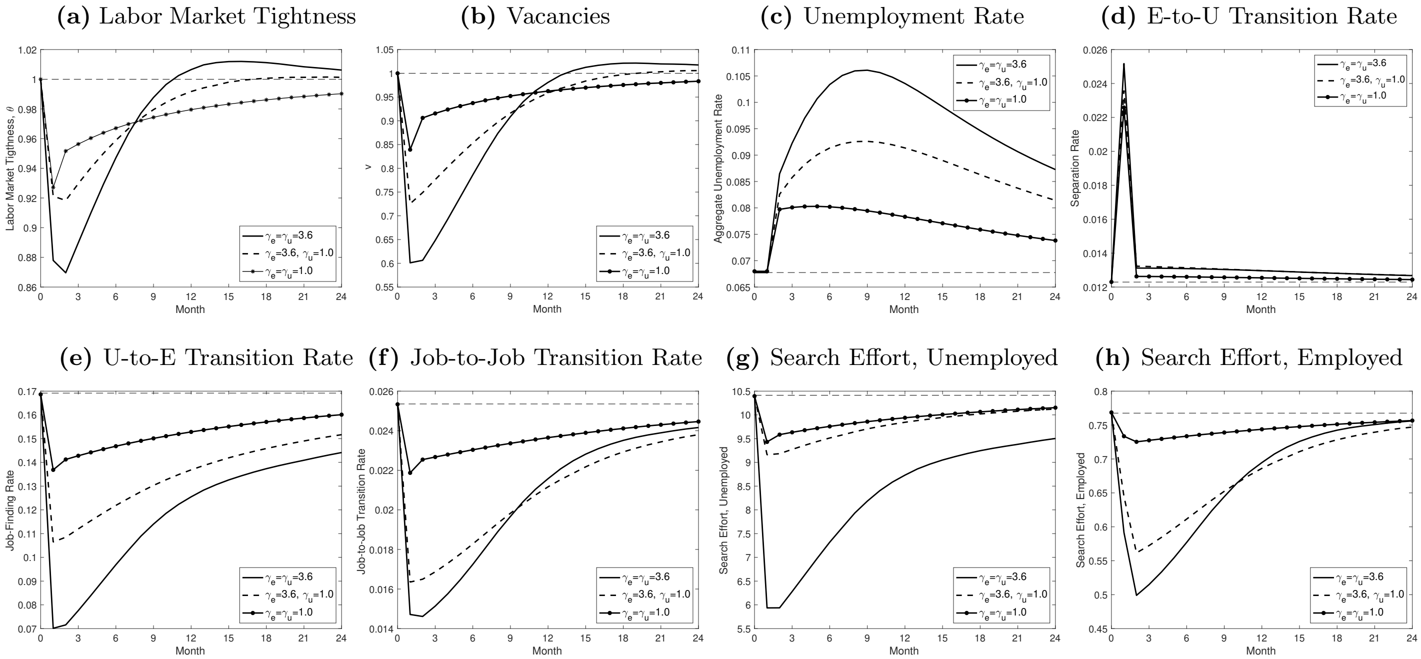
Note: The figures show the response of the economy to an unexpected 4% decline in aggregate labor productivity with a monthly auto-correlation of 0.95 and with the economy starting out in steady state in month 0. Vacancies are normalized to 1 in month 0.

Figure D2: Labor Market Responses to Aggregate Productivity Shock—Economy Without Ex-Ante Worker Heterogeneity (x)



Notes: Responses of the economy to an unexpected 4% decline in aggregate labor productivity with a monthly auto-correlation of 0.95 and with the economy starting out in steady state. Vacancies are normalized to 1 in month 0.

Figure D3: Labor Market Responses to Aggregate Productivity Shock—Comparing Responses of Economies where $\gamma = \gamma_u = \gamma_e$ to Responses of an Economy where $\gamma_e = 3.6$ and $\gamma_u = 1.0$



Notes: Responses of the economy to an unexpected 4% decline in aggregate labor productivity with a monthly auto-correlation of 0.95 and with the economy starting out in steady state. Vacancies are normalized to 1 in month 0.

References

[1] Abraham, Katharine G., John C. Haltiwanger, and Lea E. Rendell, 2020. "How Tight is the U.S. Labor Market?" Brookings Papers on Economic Activity, Spring 2020.

[2] Armantier, Olivier, Giorgio Topa, Wilbert van der Klaauw, and Basit Zafar, 2017. "An Overview of the Survey of Consumer Expectations", Economic Policy Review, Vol. 23(2): 51-72.

[3] Braun, Christine, 2021. "Revisiting Unemployment with an Intensive Margin," University of Warwick, mimeo.

[4] Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin, 2006. "Wage Bargaining with On-the-job Search: Theory and Evidence," Econometrica 74(2): 323-364.

[5] Eeckhout, Jan, and Ilse Lindenlaub. 2019. "Unemployment Cycles," American Economic Journal: Macroeconomics, 11(4): 175-234.

[6] Floro, Maria Sagrario, and Marjorie Miles, 2003. "Time Use, Work and Overlapping Activities: Evidence from Australia," Cambridge Journal of Economics, Vol. 27(6): 881-904.