Job Search Behavior among the Employed and Non-Employed*

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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 about four times more efficient than the unemployed in job search; and (3) the employed receive better job offers than the unemployed. We set up an on-the-job search model 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 job separation and matching efficiency shocks over the business cycle.

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

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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 and outcomes, the incidence of informal recruiting methods, 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 looking for work in the prior four weeks, and with similar fractions applying to at least one job in the last month or searching at least once in the last seven days. Their search intensity declines strongly with their current wage, consistent with a central prediction of models that include on-the-job search. In these models, workers with low wages search harder as they attempt to climb the job ladder. Controlling for observable worker characteristics, we estimate an elasticity of search intensity with respect to the current wage that is 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 *search efficiency* as job offers received per unit of search effort and estimate that the employed are about four times more efficient at job search. If we were to rely only on transition rates—a common approach in the literature due to lack of data on job search effort—we would find the opposite result: that the unemployed are about seven times more efficient. The contrast in implications underscores the value of collecting data on search behavior for both employed and non-employed individuals. The search efficiency of the employed is a key statistic in models of on-the-job search and has important implications for aggregate wage and productivity growth.

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). The finding that employed workers receive better wage offers suggests that factors that are unique to employment status are important determinants of the hiring process. An obvious concern about this interpretation, 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. Consequently, an individual's prior work history provides a useful proxy for unobserved heterogeneity that may be correlated with one's current labor force status. We have survey data on such labor force histories over an individual's previous five years, but 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 an on-the-job search model with endogenous search effort. The model is in the spirit of Christensen, Lentz, Mortensen, Neumann, and Werwatz (2005), though we enrich the framework with various additional features supported by our data. These include differential search efficiency and search costs, unobserved heterogeneity in worker productivity, and differential censoring of job offers among the employed and unemployed. We parameterize the model carefully by matching it to a number of key moments from our survey data. Our model provides a good fit to the various features of the data: search behavior, search efficiency, and wage offer differentials between employed and unemployed job seekers. Two implications follow immediately from our calibration exercise. First, the unemployed are willing to accept low-paying job offers despite a relatively high value of nonemployment. Given the high relative search efficiency of the employed we identify in the data, the unemployed are better off accepting a low-paying job so they can enjoy the efficiency of on-the-job search. Second, most, but not all, of the residual wage offer premium enjoyed by the employed is due to differences in unobserved heterogeneity by labor force status. Our calibration suggests that about one-quarter of the residual wage offer premium (4 log points), and only ten percent of the unconditional wage offer premium, is attributable to factors outside of our model.

We also calibrate our model to replicate the negative empirical elasticity between search effort and wages. This elasticity uniquely identifies the elasticity of search costs in the model and has direct implications for how search intensity responds to changes in aggregate labor market conditions. 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, Krusell, and Violante, 2011).[1] To quantify the macroeconomic implications of this higher elasticity, we consider the economy's response to a recession where job separations increase and matching efficiency decreases. Both shocks reduce the return to search and lower job search activity. We find that the decline in search effort in our experiment is about 50 percent larger relative to a model with quadratic search costs, leading to substantial amplification of the declines in the job-finding rate 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.[2] Our experiment thus highlights the importance of modeling job search effort endogenously and with the appropriate degree of responsiveness to business cycle shocks.

In sum, our paper breaks new ground along several dimensions: First, we design and implement a unique new survey, which administers questions about job search behavior and job search outcomes regardless of employment status. Second, we use the survey to 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

[1] Christensen et al. infer the value of the elasticity from how job-to-job transitions relate to the current wage, which is challenging due to the fact that not all transitions are related to movements up the job ladder. Our approach is different as we relate search behavior directly to the current wage of the job.

[2] Highly elastic search effort would likely lead to further amplification in the presence of feedback effects of search behavior on vacancy postings, as in Eeckhout and Lindenlaub (2019).

unobservable in data available thus far. We find that on-the-job search dominates search while unemployed along several key dimensions. Finally, we examine our findings through the lens of a job-ladder model and show that search effort is more elastic than typically assumed in the literature, with important implications for the response of the economy to aggregate shocks that affect the returns to search.

1.1 Related Literature

The majority of the literature 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; Aguiar, Hurst, and Karabourbanis, 2013; and Mukoyama, Patterson, and Şahin, 2018) or job applications sent by a survey group (Krueger and Mueller, 2011). 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 of the ATUS and its lack of data on job offers do not allow it to provide a complete picture of on-the-job search. 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 are not based on detailed surveys, so they typically lack information on labor force status and 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.

Eeckhout and Lindenlaub (2019) provide an elegant theory where the search behavior of employed workers generates large labor market fluctuations even in the absence of other shocks through a strategic complementary between on-the-job search and vacancy posting. Elsby, Michaels and Ratner (2015) carefully characterize the implications of on-the-job search for the Beveridge curve, and Moscarini and Postel-Vinay (2019) and Faccini and Melosi (2019) link on-the-job search to inflation. The latter two studies argue that when employment is concentrated at the bottom of the job ladder, typically following a recession, employed workers search harder to find a better job. As workers climb the job ladder, the labor market tightens and generates inflation pressures. We conclude that, given the growing interest in the job ladder implications of business cycle fluctuations, 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 on-the-job search behavior and job search 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

Our data are 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.[3] We designed the supplement ourselves and first administered it in October 2013. We have administered it annually since then, and present results 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 portion of the SCE survey.

The survey asks a variety of questions that are tailored to an individual's employment status and job search behavior. For the employed, the survey asks questions about their wages, hours,

[3]See Armantier et al. (2017) for a description of the survey design of the SCE. The survey draws from a nationally-representative sample of households. Respondents are paid to complete the survey online. They remain in the sample rotation for 12 months. Armantier et al. (2017) report an initial survey response rate of 54 percent, with response rates in subsequent months ranging between 59 and 72 percent. They also report that the sample closely mirrors the demographics of the American Community Survey. We also evaluate the representativeness of the sample with a comparison to the Current Population Survey in Table 1.

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 survey asks a range of detailed questions on their most recent employment spell and their reasons for non-employment. The survey 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 preceding job of the currently employed.

Regardless of employment status, the survey asks all individuals 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). It also 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, including any offers within the last six months, 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 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.

Many of the survey questions follow a format similar to the Current Population Survey (CPS), with some notable differences. The survey identifies the labor force status of respondents at several different points in their employment history: at the time of the survey, at the time of their hiring (if currently employed), and at the time of their job offer (if they reported receiving one). We also impute a labor force status for individuals four weeks prior to the survey. Our ability to identify labor force status at these different points allows us to deal with time aggregation and related issues when comparing the search and job-finding behavior of the employed and non-employed.

We define a respondent's labor force status at the time of the survey in a manner similar to the CPS, but because we ask about search effort more broadly than the CPS, we can generate two measures of unemployment. The Bureau of Labor Statistics (BLS) definition classifies someone as unemployed if they "do not have a job, have actively looked for work in the prior four weeks, and are currently available for work." Those on temporary layoff are also included regardless of search effort or availability. We employ the same definition, but due to the skip logic of the CPS survey design, there are some non-employed in the CPS who are never asked whether they searched for work. These are primarily retired individuals who state that they do not want a job (and are therefore assumed to be unavailable for work). Our survey, however, captures search effort regardless of whether a non-employed individual states that they want work. We define a respondent's labor force status at the time of the survey using the broader "job search" definition of unemployment since we aim to capture overall search activity and its effectiveness within the aggregate economy. In online Appendix A, however, we show that we obtain similar results using the BLS definition.[4]

At the time of their hiring or receipt of a job offer, we identify individuals as either employed or non-employed. The survey allows for some greater disaggregation of these labor force statuses and we obtain results similar to those in our main analyses when using the more detailed definitions.[5]

[4] The difference in definitions is that the "job search" definition includes non-employed individuals who stated that they actively searched and are available, while the stricter "BLS definition" includes only those who additionally state that they want work. The results in the appendix show that those included in the broader "job search" definition represent about 10 percent of those considered out of the labor force under the BLS definition. Given the well-known observation that even individuals who have not searched and state that they are not available for work transition from nonparticipation to employment in the CPS, we view our broader "job search" definition of unemployment as a reasonable one.

[5] Specifically, the labor force status at the time of hiring distinguishes between those who quit from a previous job and those who lost their job immediately prior to starting the current job. The majority of the employed quit from their current job, so the results for this group are very similar to those reported in our analysis. The labor force status at the time of job offer distinguishes between those who were employed either full-time or part-time at the time of the offer. Most individuals were employed full-time, and consequently their results are similar to what we report in our analysis. The vast majority of the non-employed under both definitions report actively searching.

Table 1: Summary Statistics, SCE Job Search Supplement vs. Current Population Survey

Labor Force Status	**SCE Job Search Supplement** *Job Search Definition*	*BLS Definition*	**Current Population Survey**
Employment-population ratio	0.765	0.765	0.714
	(0.006)	(0.006)	(0.001)
Unemployment rate	6.8	4.5	5.1
	(0.4)	(0.3)	(0.04)
Labor force participation rate	82.1	80.1	75.3
	(0.6)	(0.6)	(0.1)
Demographics			
Percent male	48.3		51.3
	(0.7)		(0.1)
Percent white, non-Hispanic	72.4		63.0
	(0.7)		(0.1)
Percent married	64.5		51.0
	(0.7)		(0.1)
Percent with college degree	33.7		34.7
	(0.7)		(0.1)
Percent aged 18-39	35.1		39.2
	(0.7)		(0.1)
Percent aged 40-59	49.7		48.9
	(0.7)		(0.1)
Percent aged 60+	15.2		11.9
	(0.5)		(0.1)

Notes: Estimates come from authors' tabulations from the SCE Job Search Supplement and the Current Population Survey (CPS) for data pooled across October 2013 through 2017. Both samples are for heads of household ages 18 to 64. Job search definition of unemployment includes all non-employed who actively searched and are available for work, regardless of reporting whether they want work. Standard errors are in parentheses.

We also impute a labor force status four weeks prior to the survey for individuals using a range of their responses on employment status, job tenure, non-employment duration, job offer incidence and timing, etc. We detail our imputation methodology in online Appendix B. Having a labor force status for individuals one month prior to the survey is useful for when we apply our empirical findings to the model because the model characterizes a job seeker's search behavior using their labor force status prior to exerting search effort or receiving any job offers.[6]

Our analysis uses a sample from the SCE of individuals aged 18 to 64 pooled across the 2013-17 surveys. This provides just under 4,700 observations. Individuals are only in the SCE for,

[6]We evaluate the performance of our measure of labor force status along several dimensions in the online appendix. We also merge the SCE labor market module to the SCE monthly survey, which does allow for some longitudinal analysis, and use the labor market status from the most recent monthly survey data available for a given individual, in either September or August of the same year. The results using prior labor force status from the SCE monthly survey are very similar. See Table B2 in the appendix.

at most, one year, so our sample is a panel of repeated cross sections rather than longitudinal. 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. Table 1 presents basic summary statistics for our analysis sample and a comparable sample using the same months of data from the CPS. The demographic makeup of the samples have some notable differences, which are discussed in more detail by Armentier et al. (2016). Notably, the SCE sample over-represents white, married, and older individuals. Since these individuals tend to have greater labor force attachment, the SCE also has a higher employment-to-population ratio and labor force participation rate, and a somewhat lower unemployment rate (under its comparable BLS definition) than its CPS counterpart. 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 online Appendix C. These results differ little from those reported in the main text. It is also worth noting that including the additional job seekers in the "job search" definition of unemployment increases the unemployment rate considerably, from 4.5 percent to 6.8 percent, suggesting that the BLS definition of unemployment misses some search activity in the economy.

In addition to our main sample, we also focus on a subsample of all 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, the sample has 1,054 observations. We use this sample to examine a range of job offer characteristics, including the offer wage distribution, as well as the characteristics of accepted job offers. Note that we first ask respondents whether they received any offer in the last month, and only if not, do we ask about offers received in the last 6 months. Thus the data allow us to determine the monthly offer rate.

3 Evidence

We now turn to our empirical analysis. We can summarize our main findings 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 their observable characteristics, but despite receiving higher-quality offers, the employed 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 for thinking about the efficiency of job search.[7] Table 2 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. Since we employ a search-based definition of unemployment, only a minimal amount of those out of the labor force engage in search.[8] 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.

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. 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 15 percent of the employed reported that they searched because they had been given advance notice or otherwise expected to lose their job. This is consistent with the notion that workers move to more productive, better paid jobs through job-to-job transitions.

Empirical evidence on the incidence of on-the-job search is scarce and mostly comes from outdated surveys, so it is hard to provide a good comparison for our estimates of search intensity.

[7] We borrow this distinction from the well-established literature on labor supply.

[8] By both the "job search" definition and the BLS definition of unemployment, no one outside of the labor force is available for work.

Table 2: 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.

The American Time Use Survey (ATUS) is a recent, timely survey that measures time spent on job search, but there are reasons to believe that the ATUS understates job search intensity, particularly for the employed. First, the survey is based on a time diary for a single day, so it may miss intermittent search activity. Second, the time diary only captures time spent on primary activities. If the employed literally search while on the job, then it would be a secondary activity and not captured by the ATUS. In our online Appendix A.2, we compare the estimates of time spent looking for work from the ATUS to our estimates from the SCE. ATUS data pooled over the 2013-2017 period suggest that, on average, only around 0.6 percent of the employed actively search for work. The corresponding fraction is only 16.5 percent for the unemployed, revealing the difficulty of comparing daily diary-based measures with traditional surveys.[9] The ATUS data suggest that the employed only spend about 0.8 minutes per day looking for work, while the

[9] See a detailed discussion of this comparison in online Appendix A.2. In particular, Table A4 provides a comprehensive comparison of the SCE and ATUS measures of job search activity.

unemployed spend 26.7 minutes per day looking for work, implying that on-the-job search is only about 3 percent as intensive as search while unemployed. In contrast, we find that 21.3 percent of the employed and 97.4 percent of the unemployed searched in the last *seven* days in the SCE. Furthermore, the total reported time spent searching in the SCE implies that on-the-job search is 10 percent as intensive as unemployed search. This is more than triple the ATUS implication and suggests that the ATUS misses a great deal of on-the-job search because it is likely a secondary activity for many ATUS respondents. Such a misspecification of relative search intensity can have considerable aggregate implications, made clear in models such as Moscarini and Postel-Vinay (2019) and discussed in our Appendix A.2.

The SCE estimates are more in line with older studies of job search activity that do not use diary-based information. For example, according to Black (1980), 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). Similarly, 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. Unfortunately, the main source of labor market statistics for the U.S., the CPS, does not ask questions about job search to employed individuals, but its recent Computer and Internet Use Supplements asked 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 last six months in the 2015 survey. We also asked a question about whether an individual searched in the last *twelve months*. Around 45 percent employed reported searching in the last twelve months using any active search method, including online job search. Given that we designed our survey to cast a wide net to identify any "search activity," we find our estimates of search intensity reasonable.

Table 3 reports the amount of effort spent on the job search process, the *intensive margin* of job search. We categorize the employed by whether or not they actively looked for work.[10] This distinction emphasizes 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

[10]The estimates exclude the self-employed.

Table 3: Intensive Margin: Search Effort by Labor Force Status

	Employed			**Unemployed**	**Out of Labor Force**
	Looking for Work	**Not Looking**	**All**		
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
Labor Force Status in Prior Month					
Mean applications sent			1.03	10.39	0.47
			(0.08)	(1.37)	(0.09)
Mean applications sent, ignoring applications to additional jobs			0.77	10.39	0.47
			(0.08)	(1.37)	(0.09)
N			3,349	166	721

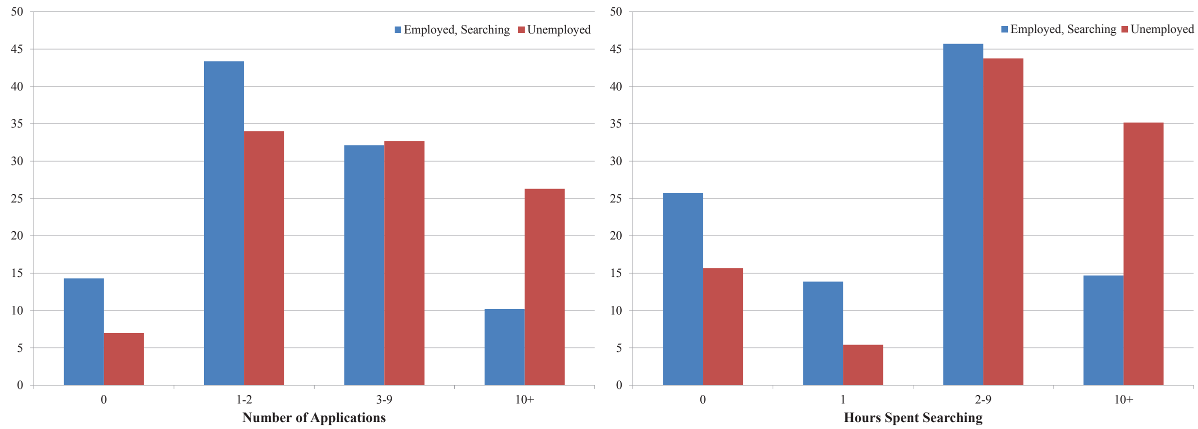
Notes: Estimates come from authors' tabulations from the October 2013-17 waves of the SCE Job Search Supplement, for all individuals aged 18-64, excluding the self-employed, by detailed labor force status. The top panel reports results by labor force status at the time of the survey, while the bottom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

8.5 applications in the *last four weeks*. 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 within the last seven days and the number of applications sent within the last four weeks for employed and unemployed job seekers, conditional on searching in the last four weeks.[11] About 44 percent of the employed and about 31 percent of the unemployed apply to either one or two jobs. About 11 percent of employed job seekers sent more than 10 applications, while just over 26 percent of the unemployed sent more than 10 applications. The right panel of the figure shows the distribution of search time. The differences between the employed and unemployed are more pronounced when we consider the distribution of search time. Over 42 percent of employed job seekers report searching for one hour or less within the last seven days, but over 81 percent of the unemployed searched for two hours or more. Moreover, searching for longer than 10 hours a week is relatively more common among

[11] Recall from Table 2 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.

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.

the unemployed than the employed (37 percent vs. 13 percent). Interestingly, 25 percent of the employed and 13 percent of the unemployed did not search at all within the last seven days. This observation highlights the intermittent nature of search effort and reinforces our view that the ATUS, which is based on a time diary reported at the daily frequency, greatly understates the extensive margin of job search. Given that the employed are likely to search as a secondary activity (and therefore not report it in the ATUS), the bias is likely to be more pronounced for the employed.

3.2 Search Intensity and Wages

A key implication of related 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 obtaining an offer better than 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 of search effort until the development of our survey.[12] Measurement error and unobserved worker heterogeneity in wages make it difficult to assess the exact position

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

Table 4: 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.

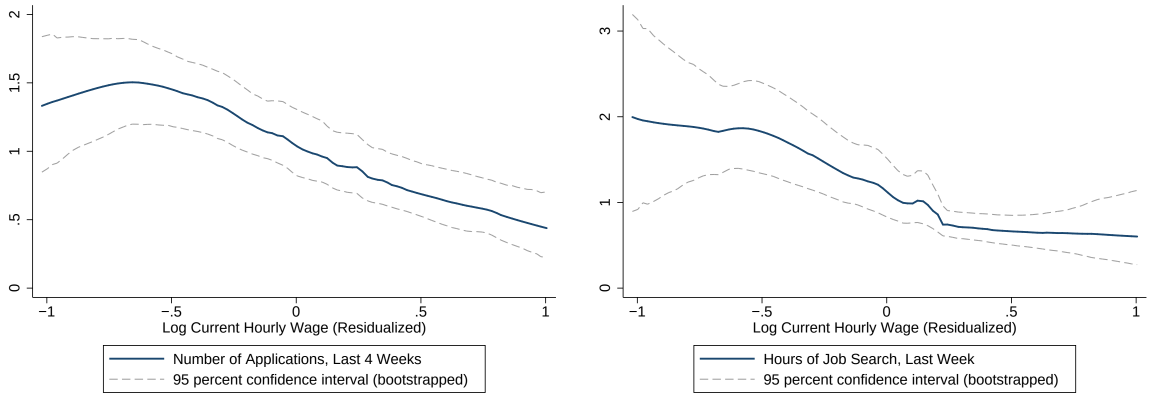
of a worker on the job ladder, but a worker's wage relative to her peers with similar observable characteristics should still provide a useful proxy. Therefore, we estimate a linear regression of the relationship between a worker's search behavior and her current wage controlling for observable worker characteristics. Our estimates are in Table 4 and show that workers with lower wages in their current job are more likely to engage in search regardless of the definition 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.[13] The estimates in the right columns of Table 4 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 4. The figure highlights the negative wage-search effort relationship in Table 4 for both the total number of applications and hours of search, and illustrates the quantitatively large decline in search effort from low to high residual wages.[14] There is some nonlinearity in the relationship for low wages, but otherwise the relationship is close to linear. These plots provide direct evidence

[13] 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.

[14] Figures C1 and C2 in the Appendix show that similar patterns hold for measures of the incidence of search as well as when we do not control for observable characteristics in the wage.

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 4 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.

of declining search intensity with respect to current wages, a key implication of the job ladder models with endogenous search effort mentioned earlier. We will return to this topic in the model section.

3.3 Search Outcomes by Labor Force Status

We have shown that there is considerable job search activity among the employed. We now move on to show how search effort translates into employer contacts, job offers, and new job matches. The fact that our data contain exhaustive information on both search effort and search outcomes at different stages of the process puts us in a unique position to assess the relative effectiveness of employed versus unemployed search.

The top panel of Table 5 reports search outcomes by labor force status at the time of the survey and shows that those who are employed and looking for work receive the greatest number of employer contacts and interviews, and nearly the most offers, despite the fact that their search effort is about half that of the unemployed. They also receive the most unsolicited employer contacts. These are employer contacts that did not result from a job seeker's search efforts. Overall, those searching on the job receive about 5 percent more contacts and 14 percent fewer job offers than the unemployed. Those who are employed but not looking for work receive nearly one-quarter as many contacts and offers as the unemployed despite exerting no search effort. They receive about one-quarter of the offers of those searching on the job as well.

A potential concern with our estimates is that the outcomes are based on retrospective questions and the respondents' current labor force status may not reflect their labor force status at the time of the outcome. Non-random job acceptances by those unemployed at the time of a job offer can create a selection issue.[15] We address this issue by constructing a measure of labor force status for the prior month using a wide range of survey questions from the SCE labor supplement. In the middle panel of Table 5, we report offer outcomes by the prior month's labor force status. The results show that the fraction with at least one offer over the last four weeks decreases slightly for the employed, from 11.7 percent to 10.6 percent, but increases substantially for the unemployed, from 22.3 percent to 34.2 percent, when considering labor force status in the prior month instead of at the time of the survey, reflecting the selection of some unemployed at the time of the job offer into employment by the time of the survey. Another concern is that a substantial fraction of employed workers only seek an additional job. Job-to-job transitions, as measured in the CPS and most other household surveys, only capture changes in an individual's main job. Nearly all models of labor market search only consider this type of job-to-job transition as well. In the bottom panel of Table 5, we report offer outcomes ignoring the offers of those who reported only looking for additional work. The fraction of the employed receiving at least one offer falls to 8.1 percent in this case. We use this estimate of the offer rate in our model calibration below.

It is possible that some individuals simply do not pursue offers that they are likely to reject. In this case, the job offers we observe in the data would be *censored*. Most importantly, this type of censoring could be correlated with employment status, since the employed may be more likely to prefer their current labor market situation. 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 who did not report a formal offer over the last

[15] This selection issue is similar to the time-aggregation issue that plagues calculations of the separation rate using CPS data.

Table 5: Search Outcomes by Labor Force Status

	Employed			Unemployed	Out of Labor Force
	Looking for Work	**Not Looking**	**All**		
Labor Force Status at Time of Survey					
Mean contacts received	1.647	0.337	0.699	1.575	0.129
	(0.167)	(0.035)	(0.050)	(0.320)	(0.032)
Mean unsolicited contacts	0.795	0.341	0.455	0.764	0.105
	(0.095)	(0.032)	(0.034)	(0.279)	(0.030)
Mean job interviews (2014-17)	0.314	0.007	0.081	0.224	0.008
	(0.019)	(0.002)	(0.005)	(0.033)	(0.004)
Mean offers	0.442	0.117	0.200	0.511	0.101
	(0.033)	(0.023)	(0.019)	(0.210)	(0.027)
Mean unsolicited offers	0.069	0.068	0.068	0.063	0.061
	(0.015)	(0.022)	(0.017)	(0.019)	(0.025)
Fraction with at least one offer	0.291	0.058	0.117	0.223	0.049
	(0.016)	(0.005)	(0.006)	(0.028)	(0.008)
Fraction with at least one unsolicited	0.044	0.027	0.031	0.052	0.023
offer	(0.007)	(0.003)	(0.003)	(0.015)	(0.008)
Fraction with at least one offer,	0.350	0.098	0.162	0.252	0.062
including unrealized offers	(0.017)	(0.006)	(0.006)	(0.029)	(0.009)
N	804	2,498	3,294	228	705
Labor Force Status in Prior Month					
Fraction with at least one offer			0.106	0.342	0.079
			(0.005)	(0.037)	(0.010)
Fraction with at least one unsolicited			0.030	0.042	0.033
offer			(0.003)	(0.016)	(0.007)
Fraction with at least one offer,			0.150	0.370	0.089
including unrealized offers			(0.006)	(0.038)	(0.011)
Labor Force Status in Prior Month, Ignoring Search Outcomes for Additional Jobs					
Fraction with at least one offer			0.081	0.342	0.079
			(0.005)	(0.037)	(0.010)
Fraction with at least one unsolicited			0.026	0.042	0.033
offer			(0.003)	(0.016)	(0.007)
Fraction with at least one offer,			0.123	0.370	0.089
including unrealized offers			(0.006)	(0.038)	(0.011)
N			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 results 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 the appendix for how prior month's labor force status is determined. Standard errors are in parentheses.

Table 6: Acceptance Decisions by Labor Force Status in Previous Month

	Employed	**Unemployed**	**Out of Labor Force**
Percent of best offers accepted	32.8	49.3	19.5
	(2.7)	(6.9)	(5.2)
Percent of all offers accepted	23.0	45.6	17.2
	(1.9)	(6.7)	(4.5)
Percent of best offers accepted,	30.9	49.3	19.5
ignoring offers for an additional job	(3.0)	(6.9)	(5.2)
Percent of all offers accepted,	20.6	45.6	17.2
ignoring offers for an additional job	(2.0)	(6.7)	(4.5)
N	314	53	58

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. See the appendix for how prior month's labor force status is determined. Standard errors are in parentheses. The additional work distinction only applies to the employed.

four weeks, 4.4 percent of the employed indicated that they rejected or did not pursue such an unrealized offer, compared to only 2.8 percent of the unemployed. The middle panel of Table 5 reports the fraction of individuals who received at least one offer, including these unrealized offers. Accounting for unrealized offers raises the fraction receiving a job offer to 15.0 percent for the employed (12.3 percent when excluding offers for additional work) and to 37.0 percent for the unemployed. The share of unrealized offers among all offers is thus substantially higher among the employed (28 percent) than among the unemployed (8 percent).

Table 6 reports the acceptance rate for offers received within the last four weeks by labor force status in the prior month. The results show that the unemployed are much more likely to accept a given offer, with 45 to 49 percent of their offers accepted, depending on whether we include their best formal offers, or their best offer including any unrealized offers in the denominator of the acceptance rate. In contrast, the employed accept 20 to 33 percent of their offers, depending on the measure used. Note, however, that despite accepting a substantially higher fraction of their job offers than the employed, the unemployed still reject nearly half of all offers received. This is notable because most models of labor market search imply that, in equilibrium, the unemployed accept *all* job offers. Our evidence suggests that a sizable number of unsuitable offers do in fact exist. In our calibration, we focus on the acceptance rates of the best offers, excluding offers for additional work, which is 30.9 percent for the employed and 49.3 percent for the unemployed.

Finally, we present the distribution of search effort and search outcomes across the differ-

Table 7: Distribution of Search Effort and Outcomes by Labor Force Status

	Employed			**Unemployed**	**Out of Labor Force**
	Looking for Work	**Not Looking**	**All**		
Pct. of population	18.8	55.4	74.2	6.2	19.7
Job Search over Last Four Weeks					
Pct. of total applications	59.1	0.0	59.1	39.6	1.3
Pct. of contacts received	48.3	32.6	80.9	15.2	4.0
Pct. of unsolicited contacts	36.6	46.7	83.2	11.7	5.1
Pct. of interviews (2014-17 only)	77.0	2.2	74.3	18.8	2.0
Pct. of offers received	41.7	32.6	74.3	15.8	9.9
Pct. of unsolicited offers received	19.6	56.7	76.3	5.8	17.9

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 at the time of the survey.

ent labor force categories. Examining these distributions provides another way of assessing the relative efficiency of employed and unemployed job seekers. Table 7 reports the distribution of respondents, job applications, and job search outcomes by labor force status. The unemployed make up just over 6 percent of our sample, but account for nearly 40 percent of all job applications sent. At the same time, they only receive 16 percent of all offers made. In stark contrast, the employed who report not looking for work send no applications by construction but account for nearly 33 percent of all employer contacts and receive around 33 percent of all job offers. This is due, in part, to the fact that they also account for 47 percent of all unsolicited employer contacts and 57 percent of all unsolicited offers. Those actively searching on the job account for another 42 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 employer contacts and job offers. The employed, on the other hand, do fairly well regardless of whether they are actually looking for work. Though the unemployed are seemingly less effective in their job search efforts, they are also more likely to accept the offers that they do receive.

3.4 Search Efficiency by Labor Force Status

Having detailed data on all stages of job search allows us to quantify the relative *efficiency* of the employed in job search, which is a key input for search and matching models with on the job search. Let the offer arrival rate be λ_i for a worker with labor force status i, where $i \in \{e, u\}$ denotes the employed or unemployed, respectively. Let it depend on search effort, s, according to $\lambda_i(s) = \alpha_i + \beta_i s$, where α_i represents unsolicited offers and β_i is *search efficiency*, defined as the offers generated per unit of search effort. This generalized specification applies to a broad range of labor search models going back to Mortensen (1977) and detailed in Pissarides (2000).[16] Thus, our data and generalized offer arrival rate allow a calculation of relative search efficiency for a broad range of search models.

We define the relative search efficiency of the employed as the ratio, β_e/β_u. Before we quantify this measure, however, it is useful to illustrate how wrong an estimate one obtains from data available prior to our survey. The most common way of imputing search efficiency is to use data on transition rates.[17] In our data, transition rates are the product of the offer arrival rate and the job acceptance rate. Let EE denote the job-to-job transition rate and UE denote the unemployment-to-employment transition rate. Applying this calculation, we get:

$$\beta_e/\beta_u = \frac{EE}{UE} = \frac{(0.081)(0.309)}{(0.342)(0.493)} = \frac{0.025}{0.168} = 0.148.$$

The underlying assumptions in this calculation are that the employed and unemployed exert the same level of search intensity and have identical job acceptance rates—neither of which are supported by our data. The calculation implies that the employed are only 15 percent as efficient as the unemployed in job search, or inversely, that the unemployed are 6.8 times more efficient at search.[18]

It is arguably better to infer search efficiency from offer arrival rates alone, which allows for differences in acceptance rates but still assumes that search intensity is equal for the employed and unemployed. In this case, the calculation of relative search efficiency is:

$$\beta_e/\beta_u = \frac{\lambda_e(s)}{\lambda_u(s)} = \frac{0.081}{0.342} = 0.237.$$

The calculation implies that the employed are now 24 percent as efficient as the unemployed at job search, or that the unemployed are 4.2 times as efficient.

Since we can measure the search effort directly, and can identify unsolicited and unrealized offers, we are in a unique position to disentangle the differences in search efficiency from search

[16]Exceptions are offer arrival rates that allow for substitutability between search effort and market conditions, as in Shimer (2004) and Mukoyama, Patterson, and Şahin (2018).

[17]See Eeckhout and Lindenlaub (2018), Moscarini and Postel-Vinay (2019).

[18]Transition rates from the CPS 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 efficient at search than the employed.

effort. Now consider the relative search efficiency in the generalized formulation for the offer arrival rate, $\lambda_i(s) = \alpha_i + \beta_i s$ and add *unrealized* offers to the observed offer arrival rate assuming that these offers are part of search efficiency. In this case, we subtract unsolicited offers and calculate the relative search efficiency as

$$\beta_e/\beta_u = \frac{(\lambda_e(s) - \alpha_e)s_u}{(\lambda_u(s) - \alpha_u)s_e} = \frac{(0.082 + 0.041 - 0.026)(10.39)}{(0.342 + 0.028 - 0.042)(0.77)} = 3.99.$$

This calculation shows that taking account of differences in search intensity (measured here as job applications sent), unsolicited offers, and unrealized offers paints a very different picture of search efficiency. The employed are now four times more efficient than the unemployed at job search. If we were to interpret the receipt of unsolicited job offers as part of search efficiency, it would imply an even higher relative search efficiency of the employed, increasing the estimate further, to 4.49, since the employed receive a higher share of these as well. Therefore, using our data to gain a proper estimate of relative search efficiency shows that the unemployed have an incentive to accept low wage offers, since, once employed, they will be able to search more efficiently while on the job and therefore move up the job ladder more quickly to better job offers. One would wrongly get the opposite implication if they relied on an estimate of search efficiency implied by transition rates alone.

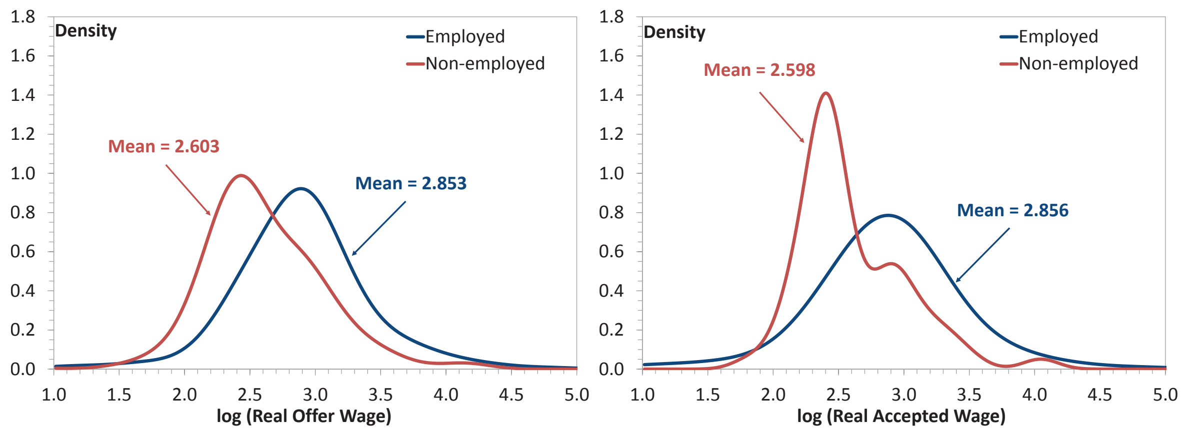
3.5 Characteristics of Job Offers and Accepted Jobs

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 examine this next. Our survey asks individuals about any offers they received in the last four weeks. For those who received no offer within the last four weeks, it probes further to elicit information on any offers received within the last six months. The survey also elicits the respondent's labor force status at the time of the job offer. It asks a variety of questions about the characteristics of the job offer, including information about the search and bargaining process. It also asks if the offer was accepted (and if it represents their current job).

Table 8 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.[19] Note that

[19]Starting in 2014, we added a question to the survey that identifies those who searched prior to the receipt

Figure 3: Distribution of All Wage Offers (left panel) and Accepted Wage Offers (right panel)



Notes: Figures report kernel density estimates of residual log(real wage offer) by labor force status after controlling for observable worker and job characteristics. Estimates are for all (best) job offers received within the last six months by individuals in the October 2013-17 waves of the SCE Job Search Supplement.

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 employed receive wage offers that are about 36 log points (44 percent) higher than the wage offers of the non-employed.[20] Even after conditioning on the observable characteristics of the worker and the job offer, the employed enjoy wage offers that are 19 log points (21 percent) higher than the wage offers of the non-employed.[21] The left panel of Figure 3 shows that, even after accounting for these controls, the distribution of wage offers for the employed stochastically dominates the distribution of wage offers for the non-employed.

The middle panel of Table 8 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 employed are nearly 60 percent more likely to have received their offer through an unsolicited

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.

[20]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).

[21]Our conditional estimates of the offered wage and the subsequent accepted 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 online Appendix C.

Table 8: 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 respondents with at least a good	60.1	57.5	2.6
idea of pay	(1.7)	(3.1)	(5.0)
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 (best) job offers accepted	35.0	50.9	-15.9
	(1.7)	(3.1)	(5.1)
Pct. of offers accepted as only option,	7.7	26.5	-18.8
conditional on acceptance	(1.6)	(3.9)	(7.8)
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.

contact. The employed and non-employed are roughly equally likely to have had a "good idea" of what the job paid prior to receiving the offer. Potentially contributing to the differences in offer wages between the two groups, the employed are 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.[22] Counter-offers by the current employer, defined 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 offer from an outside firm.

Despite their relatively poor job offers, the non-employed are nearly one-and-a-half times more likely than the employed to accept a job offer, with 51 percent of offers accepted by the non-employed versus 35 percent by the employed. These acceptance rates are very close to those we obtain using the prior month's labor force status. A primary reason the non-employed are more likely to accept their relatively poor job offers is a perceived lack of alternative options– about 27 percent of the non-employed cite a lack of other alternatives as the main reason for accepting an offer, while only 8 percent of the employed cite that as their primary reason. The right panel of Figure 3 shows that, even after controlling for observed worker and job characteristics, the accepted wage distribution of the employed stochastically dominates the accepted wage distribution of the non-employed.

The bottom panel of Table 8 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, but conditional on observables the difference is essentially zero. That is, despite our finding of a large differential in offered wages by labor force status, we find almost no difference in residual prior wages. In our model calibration, we use the negligible residual wage differential in prior wages to discipline the degree of unobserved heterogeneity in the model.

3.6 Accounting for Differences in Job Offers

We can dig deeper into the wage offer differential between the employed and non-employed using responses to a rich set of questions from our survey. Table 8 shows that observable worker and job characteristics explain 46 percent of the raw wage offer difference. 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

[22]These estimates 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.

by employers but are unobserved in our data. For example, workers may differ in unobserved characteristics such as communication or time-management skills. Those with better skills of this nature would be more likely to be employed and earn a higher wage. This creates a selection effect that naturally generates a wage gap between the job offers received by the employed versus the non-employed. 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 has detailed questions that allow us to control for an individual's labor force history over the previous five years. As Table 9 shows, controlling for the fraction of the last five years 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 goes down somewhat more to 0.127, implying that labor force history can account for an additional 19 percent of the wage offer gap.

Even after these controls, about one-third of the unconditional wage gap remains unexplained. As we noted earlier, prior wages of workers can also provide additional information regarding workers' unobserved skills. We add the *prior* wage of workers as an additional control in Table 9. We find that the prior wage does not close the gap. On the contrary, the gap widens. We discuss this issue below in the model section.

The remaining gap may also arise because of differences in the job search process between the employed and non-employed. 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 better non-wage benefits. In the last row of Table 9, 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

Table 9: 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 8 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.

our estimate of the wage offer differential.[23] Thus, while controlling for observable worker and job 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 possibility is that human capital depreciates 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. Accounting for the work history of the employed and non-employed would reduce the gap. We already showed that controlling for the previous five-year work history (specifically, the fraction of the prior five years spent employed, unemployed, etc.) reduces the wage gap from 0.19 to 0.13. This suggests that human capital depreciation can explain only a limited fraction of the wage offer gap. Moreover, questions about five-year work histories also capture fixed unobserved differences in worker productivity even in

[23] If we re-estimate the last row of Table 9 excluding the prior wage, we obtain a wage offer gap of 0.119.

the absence of human capital depreciation.

Finally, the presence of bargaining and counter-offers represents another way the search process can affect the wage offer gap. We find that 38 percent of offers to the employed, while only 26 percent of offers to the non-employed, involved some bargaining between the individual and the potential employer. In general, a greater propensity to bargain with the potential employer should increase the reported wage offer, all else equal. Moreover, 12 percent of the employed with an outside offer 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 raises the mean wage offers for the employed even when no such offer occurs in equilibrium. Regardless of its source, any such penalty on job search while unemployed would imply that the employed and unemployed draw from seemingly different wage offer distributions, an issue we take up in the next section.

4 Job Search On and Off the Job: A Theoretical Framework

In this section, we set up a partial equilibrium model of on-the-job search 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, which provides empirical support for recent papers such as Eeckhout and Lindenlaub (2019), Moscarini and Postel-Vinay (2019) and Faccini and Melosi (2019). These studies highlight on-the-job-search behavior as a driving force of business cycles or as a propagation mechanism of aggregate shocks. Moreover, our model provides insights on the implications of efficient on-the-job search and the employed wage offer premium, and does remarkably well in generating a plausible amount of frictional wage dispersion.

4.1 Framework

Our model builds on earlier models of on-the-job search with endogenous search effort in the spirit of Christensen et al. (2005) and Hornstein et al. (2011), with four important extensions to accommodate the salient features of our survey.[24] First, we allow for differences in search efficiency by employment status. Second, we allow the employed and unemployed to draw from potentially different wage offer distributions. Third, we allow workers to differ in *ex ante* productivity. Fourth, we allow for censoring of potential job offers by workers—that is, we allow workers to reject offers before they are realized in line with a question that we directly asked our survey respondents.

In the model, workers are either employed or unemployed. We denote their employment status with the subscript $i \in \{e, u\}$. Workers are *ex ante* heterogeneous in their productivity, x. This reflects the unobserved heterogeneity that remains in our data after controlling for observable characteristics. Time is discrete and its discount rate is r.

As in our exercise on search efficiency, individuals receive a job offer with probability $\lambda_i(s) = \alpha_i + \beta_i s$, where $s \in [0, \frac{1-\alpha_i}{\beta_i}]$ is the endogenously-chosen level of search effort. The constant α_i reflects the probability of an *unsolicited offer*, which occurs absent any search effort, and the constant β_i reflects *search efficiency*, i.e., the probability of an offer per unit of search effort. Both the unsolicited offer rate and search efficiency may vary by employment status.

Search effort has an increasing, convex cost that depends on *ex ante* worker productivity and may also vary by employment status. We assume that search costs are proportional to unobserved productivity, $c_i(x, s) = xc_i(s)$, with $c_i', c_i'' > 0$ and $c_i(0) = c_i'(0) = 0$. Existing matches end exogenously at an average rate $\delta(x)$, which also depends on *ex ante* worker productivity. The piece-rate wage, w, is drawn from a wage offer distribution, $F_i(w)$, which we assume depends on employment status, is identically distributed across worker types x, and has upper support $\bar{w}$.

Given this setup, the Bellman equation for the employed is

$$\begin{aligned} W(x, w) \quad = \quad & \max_{\bar{s}_e \geq s \geq 0} \left\{ wx - c_e(s)x + \frac{1-\delta(x)}{1+r} \Big[W(x, w) + \right. \\ & \left. \lambda_e(s) \int_w^{\bar{w}} [W(x, y) - W(x, w)] dF_e(y) \Big] + \frac{\delta(x)U(x)}{1+r} \right\}, \end{aligned} \tag{1}$$

where $\bar{s}_e = \frac{1-\alpha_e}{\beta_e}$. The first term on the right-hand side reflects the wage net of search costs. The second term on the right-hand side reflects the continuation value of the job, accounting

[24] Richer models with similar features exist, such as Bagger and Lentz (2019). Our model provides a parsimonious framework to evaluate the quantitative importance of our empirical findings and can be extended to accommodate richer features.

for the potential separation to either a new job or unemployment and the last term reflects the expected value of a separation to unemployment. It is easy to show that the value of employment is increasing in the wage and derive the first order condition for an employed worker.[25] Since the cost of search effort is increasing and convex, search effort will decline with the wage, i.e., as workers move up the job ladder.

The Bellman equation for the unemployed is similar in structure:

$$\begin{aligned} U(x) &= \max_{\bar{s}_u \geq s \geq 0, R} \Bigg\{ bx - c_u(s)x + \\ &\quad \frac{1}{1+r}\Big[U(x) + \lambda_u(s)\int_{R(x)}^{\bar{w}} [W(x,y) - U(x)]dF_u(y)\Big]\Bigg\}, \end{aligned} \tag{2}$$

where $\bar{s}_u = \frac{1-\alpha_u}{\beta_u}$ and $b(x) = bx$ is the flow value of unemployment.[26] The first term on the right-hand side reflects the flow value net of search costs and the second term on the right-hand side reflects the continuation value of unemployment, accounting for the probability of finding a job. The unemployed of type x have an optimal reservation wage, $R(x)$, that solves $W(x, R(x)) = U(x)$ and represents the wage at which the unemployed are just indifferent between a job that pays $R(x)$ and unemployment.

Finally, we allow for censoring of job offers. We model censored offers by assuming that job seekers observe the terms of the offer prior to receiving a formal offer with probability χ_i, and do not pursue the offer further (i.e., reject) if the wage is below their reservation wage.[27] This is consistent with our finding in the SCE data that the employed appear to reject many offers before they are made, on the order of 50 percent of formal offers made, compared to 8 percent for the unemployed. Note that we do not allow for censoring of unsolicited offers. For a worker with productivity x and reservation wage R_i, one can thus write

$$\tilde{\lambda}_i(x, R_i) = \alpha_i + \beta_i s_i(x)(\chi_i(1 - F_i(R_i)) + 1 - \chi_i), \tag{3}$$

where $s_i(x)$ is the optimal search effort and $\lambda_i(s_i(x)) = \alpha_i + \beta_i s_i(x)$ is the "true" probability of

[25] We derive the first-order conditions for both employed and unemployed workers in online Appendix D.

[26] Similar to our assumption for the employed, 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). It also consistent with our evidence in Appendix Table C2, which shows that controlling for observable characteristics does little to affect the likelihood of receiving a job offer.

[27] Hall and Mueller (2018) introduce censoring of offers in a similar way in their appendix to capture partially directed search.

receiving an offer, including unrealized offers, $\tilde{\lambda}_i(x, R_i)$ is the probability of receiving a formal offer, and $1 - F_i(R_i(x))$ is the likelihood a potential offer is above the reservation wage threshold, which is $R_e = w$ for the employed and $R_u = R(x)$ for the unemployed.

4.2 Parameterization and Targeted Moments

We calibrate our model to the 2013-2017 period and parameterize our model as follows. We set its frequency to be monthly and match the monthly discount rate to an annual interest rate of 4 percent. We match most parameters directly to key moments computed using our survey, as shown in Table 10. 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.

We take the unsolicited offer rates and formal offer rates of the employed and unemployed directly from the estimates in Table 5. We match the average rate of censored offers by employment status, $E(\beta_i s_i(x) \chi_i F_i(R_i(x))|i)$, to the average rate of unrealized offers by employment status in our data. Given that the offer arrival rate is of the form $\lambda_i(s) = \alpha_i + \beta_i s$, we can calculate β_i directly from the offer arrival rates, $\lambda_i(s)$ and α_i, and average search intensity, s, in the data.

We assume a search cost function of the form $c_i(s) = \kappa_i s^{1+(1/\gamma)}$, as in Christensen et al. (2005) and Hornstein et al. (2011). We calibrate each κ_i to match the average search effort by labor force status in Table 3. The high level of search efficiency and low level of search effort among the employed implies a high cost of search for the employed in our calibration. We set γ to match a search effort-wage elasticity of -0.36, which is estimated from the empirical relationship implied from results in Table 4 for applications. This results in a value of 2.8 for γ. This is substantially higher than what is typically assumed in the literature, which is $\gamma = 1$ (i.e., a quadratic cost function). The estimated elasticity of search hours with respect to the current wage is -0.52, which implies an even higher estimate of γ. We set γ to 2.8 and present robustness results in Table D2 and Figure D1 for models with higher levels of γ.

We define the flow value of unemployment as a fraction of the average wage net of average search costs, $z = \frac{b - c_u(s)}{E(w) - c_e(s)}$, and set it to match the average acceptance rate of the unemployed, implicitly pinning down a value for the parameter b. This allows our model, by construction, to match their job-finding rate, as both the acceptance rate and the offer rate of the unemployed

Table 10: Moments in the Data and in the Model

A. Targeted Moments	Data	Model
Search-wage elasticity	[-0.515, -0.364]	-0.365
Search effort U	10.39	10.39
Search effort E	0.769	0.769
Unsolicited offer rate of U	0.042	0.042
Unsolicited offer rate of E	0.026	0.026
Censored offer rate U	0.028	0.028
Censored offer rate E	0.041	0.041
Offer rate of U	0.342	0.342
Offer rate of E	0.082	0.082
Acceptance rate of U	0.493	0.494
Stdev. of log residual offered wages	0.678	0.678
Residual offered wage differential (E - U)	0.194	0.195
Residual prior wage differential (E - U)	0.008	0.008
Unemployment rate	0.068	0.068
B. Additional Moment		
Acceptance rate of E	0.309	0.244

are targets in the calibration.[28]

We parameterize the extent of heterogeneity in our model by assuming that there are 10 types of workers who differ by a wage-shifting parameter x. The distribution of types approximates a normal distribution with standard deviation σ_x over the interval $[-3\sigma_x, 3\sigma_x]$. 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. Specifically, we assume that our observed offered wage, $\tilde{y}$, satisfies $log(\tilde{y}) = log(y) + log(x) + \varepsilon_y$, where $log(y) \sim N(\mu_i, \sigma_y)$, $log(x) \sim N(0, \sigma_x)$, and $\varepsilon_y \sim N(0, \sigma_{\varepsilon_y})$ are independently distributed, and thus, $\sigma_{\tilde{y}} = \sqrt{\sigma_y^2 + \sigma_x^2 + \sigma_{\varepsilon_y}^2}$. We assume that the wage offer distribution is log normal, normalize the mean of the log offered wages to the unemployed to zero, and calibrate the standard deviation of the wage offer distribution to be 0.24 as in Hall and Mueller (2018).[29] We parameterize the mean of the offer distribution of the employed to match the gap in residualized wages between the employed and non-employed. We assume a moderate degree of measurement error equal to 13 percent of the unconditional

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

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

Table 11: Calibrated Parameter Values

A. Internally calibrated parameters

Symbol	Parameter Description	Value	Target
γ	Elasticity of search cost	2.80	Search-wage elasticity
κ_u, κ_e	Search cost parameter	0.012, 0.076	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, 0.126	Return to search by LFS
χ_u, χ_e	Censoring parameter	0.156, 0.520	Censored offer rate by LFS
z	Flow value of unemployment	0.642	Acceptance rate of U
σ_x	Dispersion in unobs. het.	0.553	Stdev. of log resid. wage offers
$\mu_{y,e}$	Mean of offer distr. for E	0.040	Resid. offered wage (E-U)
$\delta(x_{med})$	Separation rate for median	0.0123	Unemployment rate
$\delta(x_{min}) - \delta(x_{max})$	Separation rate dispersion	0.0106	Resid. prior wage (E-U)

B. Externally calibrated parameters

Symbol	Parameter Description	Value	Source/Target
r	Interest rate	0.34%	Annual interest rate of 4%
σ_y	Dispersion in wage offers	0.24	Hall and Mueller (2018)
σ_ε	Dispersion in measur. error	0.31	Bound and Krueger (1991)

Note: The return to search is defined as the sum of the offer rate and the censored offer rate divided by the average search effort.

variance in offered wages, consistent with Bound and Krueger (1991). Given our calibration of both $\sigma^2_{\varepsilon_y}$ and σ^2_y, we get an estimate for $\sigma_x = \sqrt{\sigma^2_{\tilde{y}} - \sigma^2_y - \sigma^2_{\varepsilon_y}}$.

We target the average separation rate to match an unemployment rate of 0.068, which is the sample average for 2013-2017 in the SCE, but allow separation rates to vary by worker type x in the calibration. This yields an average separation rate across all types of 0.0123. This is consistent with the well-known fact that differences in unemployment rates across skill groups are driven by separations and not job finding. We linearly interpolate the separation rates for the 8 types between the lowest and highest type, x_{min} and x_{max}, and parameterize the difference between $\delta(x_{min})$ and $\delta(x_{max})$ by matching the difference in residual prior wages between the employed and unemployed. Intuitively, as the difference between $\delta(x_{min})$ and $\delta(x_{max})$ gets larger, there is greater negative selection among the unemployed, which lowers the average prior wage of the unemployed. We use an estimate of this difference from Table 8, which reports prior wages for those who received a job offer in the last six months. The estimated log difference in residual prior wages within this sample is 0.008, i.e. prior wages are nearly the same between the employed and unemployed.[30]

[30] If we were to ignore negative selection and set $\delta(x_{min}) = \delta(x_{max})$, the simulation of our model would predict

Before moving on to the results, note that the offer rate and the acceptance rate of the employed that we target from the SCE data imply a target job-to-job transition rate of 2.5 percent (Table 10). This rate is above the average employer-to-employer transition rate in the CPS, which is 1.9 percent for our sample period. However, Fujita, Moscarini, and Postel-Vinay (2019) provide convincing evidence that the CPS understates the job-to-job transition rate during our sample period. Their corrected measure implies a job-to-job transition rate of 2.3 percent which is very close to the SCE estimate.

4.3 Model Fit and Micro Implications

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

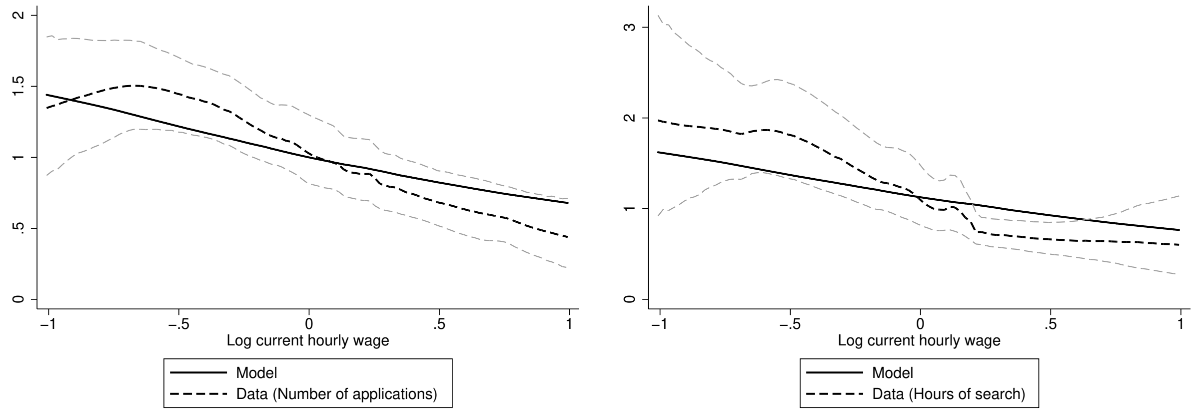
Fit of the Search Effort-Wage Relationship. A key implication of on-the-job search models with endogenous search effort is that employed workers will reduce their search effort as they climb the job ladder. We explicitly target the search-wage elasticity, which identifies the elasticity of search costs 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 current wage of the worker. 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-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. This would make search effort even more responsive to labor market conditions, strengthening one of our key findings.[31] Overall, we view this as clear evidence in support of models with endogenous search effort.

Wage Offer Premium of the Employed. In Subsection 3.6, we examined how much of the wage offer differential between the employed and unemployed could be accounted for by a rich set

that prior wages are higher for the unemployed by about 10 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 of the unemployed are from jobs prior to a separation and thus further up on the wage ladder.

[31] See Appendix Figure D1 and Appendix Table D2 for results with higher levels of γ.

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).

of controls. We match this differential in our model by incorporating unobserved heterogeneity and censoring, and calibrating them to match the moments in the SCE data. This 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, unexplained component. Panel I of Table 12 shows that the model attributes 15.3 log points (78 percent) of the 19.4 log point residual wage offer differential to unobserved heterogeneity. This represents 42 percent of the 36.2 log point unconditional wage offer differential. The contribution of censoring is small because job offers are concentrated among employed workers who are at the bottom of the ladder. The exogenous, residual offer differential is estimated to be positive but only at 4 log points. This represents 21 percent of the residual wage offer gap and 11 percent of the unconditional wage offer gap. The important takeaway is that selection into unemployment by workers with relatively low unobserved productivity accounts for a large fraction of the wage offer differential observed in the data, leaving only a small unexplained part.

Additionally, our model predicts a correlation between *ex ante* unobserved heterogeneity and labor force histories, which can provide guidance for addressing unobserved heterogeneity in 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 9, controlling for the fraction of the last five years that someone was employed reduces the residual wage offer

Table 12: Wage Offer Differentials in the Data and the Model

I. Decomposition of wage offer differential	Data	Model
Wage offer differential	0.194	0.195
- due to worker-heterogeneity	—	0.153
- due to censoring	—	0.002
- due to exogenous differential	—	0.040
II. Decomposition of wage offer differential		
Wage offer differential	0.194	0.195
Controlling for prior employment history	0.132	0.118
Additionally controlling for prior labor force history	0.127	—

Notes: Panel I decomposes the wage offer differential in the model into three sources shown in the Table. Panel II reports the coefficient estimates of a dummy for employment status at the time of the offer in regressions without and with additional controls such as the fraction of time non-employed over the last five years (employment history) or the fraction of time unemployed, in school or otherwise non-employed (labor force history). See Table 9 for further details on the regressions in the data.

gap from 0.194 to 0.132, and to 0.127 when we additionally control for the share of time spent unemployed or as a student. We can implement the same regression analysis on model-generated data from a simulation and compare it to these results. Panel II of Table 12 shows that when we do so, the model-generated wage offer gap falls from 0.195 to 0.118, which is very similar to what we observe empirically. Controlling for work history in our simulation-based regressions thus accounts for about half of the 15 log point contribution of differences in x and shows the usefulness of labor force history as a control for unobserved heterogeneity.[32]

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 1.54, 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

[32]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.

a reasonable value for the flow utility of unemployment (net of search costs) of 0.64, comparable to the 0.71 value found by Hall and Milgrom (2008). Attempts to match the observed wage dispersion typically require very low or even negative values for this parameter (see Hornstein et al., 2011).[33] 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 continue to sample better offers and search more efficiently while employed. Consequently, they are willing to accept lower-wage offers despite a relatively high value of unemployment. This increases 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 search effort to changes in labor market conditions. In particular, we consider how changes in the job separation rate and matching efficiency affect aggregate search activity and the job-to-job transition rate. We find that fluctuations in search effort amplify the effects of these shocks.

To illustrate the amplification of business cycle shocks through search effort, we expose our model to a large unexpected shock to search efficiency and job separation for a period of six months and then assume the parameters return to their previous levels, which again is not anticipated by agents in the economy. More precisely, we assume that all search efficiency parameters α_i and β_i decrease by 33 percent (40.6 log points) and the separation rate increases by 50 percent (40.6 log points) during the six-month period.[34]

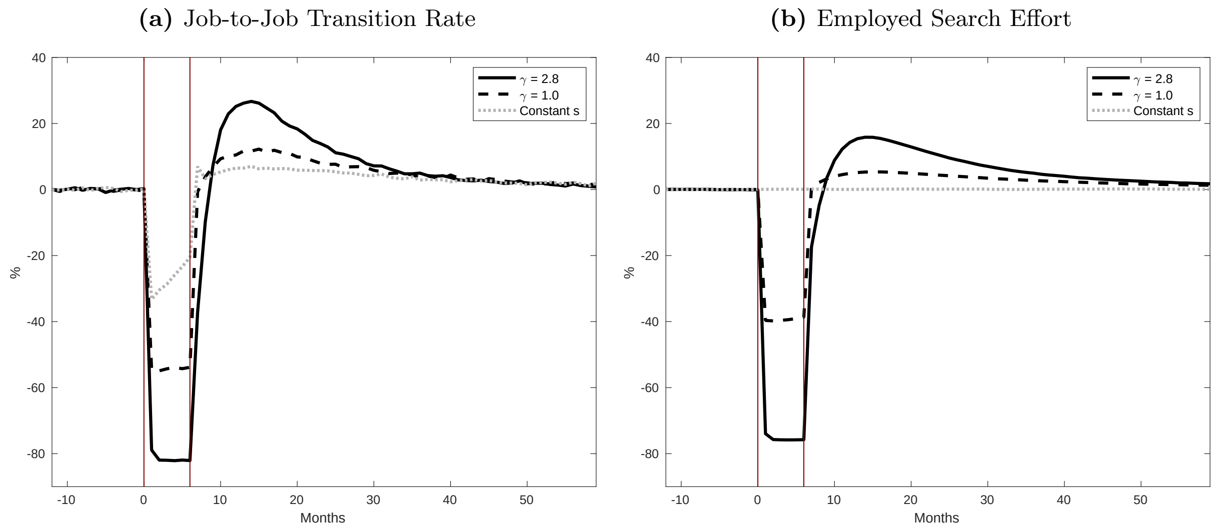
Figure 5 shows the effect of the six-month recessionary period on the search effort of the employed and job-to-job transitions for three different specifications: (1) our baseline specification with $\gamma = 2.8$, (2) a specification with $\gamma = 1$ (i.e., quadratic search costs), and (3) a specification with exogenous search.[35] The parameters in our alternative specifications are recalibrated to

[33] We evaluate the performance of alternative models for the wage dispersion puzzle in online Appendix D3. To underscore our point, shutting down endogenous search effort and other features implied by our empirical results yields a mean-min ratio of 1.39 and a flow value of unemployment (net of search costs) of 0.13.

[34] We abstract from compositional changes in the pool of unemployed over the business cycle and simulate the model for the median type x.

[35] In Appendix Figure D2, we show the effects of these shocks on the job-finding rate and search effort of the unemployed, the unemployment rate, and the average wage in the economy. All four measures have an amplified response to our shocks when we use the search cost elasticity implied by our empirical findings. Notably, movements in the average wage reflects compositional changes in wages earned that occur as workers move across the job ladder.

Figure 5: Job-to-Job Transition Rate and Employed Search Effort in Response to 6-Month Recession



Note: The figure shows the response to a decline of search efficiency parameters α_i and β_i by 40.6 log points (or 33.3%) and increase in exogenous separation rates δ by 40.6 log points (or 50%) for a period of 6 months.

match the same data moments reported in Table 10.[36] The response of the job-to-job transition rate varies considerably across specifications during the recession and the subsequent recovery. While the job-to-job transition rate goes down in all specifications, endogenous search effort amplifies the decline in job-to-job transitions. The strength of amplification depends on the value of γ because the decline in search efficiency and increase in the separation rate both reduce the returns to search. Higher values of γ imply a more elastic response of search effort to this reduction (see online Appendix D for a formal exposition). The value of γ implied by our empirical results (2.8) produces a decline in the job-to-job transition rate that is about 1.5 times larger than the decline implied by quadratic search costs ($\gamma = 1$). Note also that these are partial equilibrium responses. Recent work by Eeckhout and Lindenlaub (2019) suggests that equilibrium vacancy-posting behavior would amplify the response of job-to-job transition rates even further by reducing a firm's incentive to post vacancies.

Once search efficiency and the job separation rate return to their pre-recession values, the job-to-job transition rate and employed search effort gradually overshoot their previous levels, peaking

[36]The parameters and model fit for model (2) are reported in column 1 of Table D2. Model (3) sets $\kappa_i = \beta_i = \chi_i = 0$ for both the employed and unemployed and calibrates the remaining parameters to match the same transition rates (separation, job finding and job-to-job) as in the other two models.

eight months after the recession's trough then gradually converging back to their steady-state level. The overshooting and gradual convergence occur because of changes in the distribution of workers across positions along the job ladder. As the economy recovers, more unemployed workers find jobs, but they are predominantly at the bottom of the ladder. This shifts the distribution of job seekers towards low-paying and consequently high-search effort jobs (Figure 5). These workers search for and gradually find better jobs, moving up the job ladder and eventually returning the distribution of job seekers to its steady state. 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. On the positive side, highly elastic search effort also suggests that workers reallocate to better jobs more quickly than what is implied by quadratic search costs or models that ignore endogenous search effort altogether.

4.5 Robustness and Further Results

In this subsection, we briefly describe a series of robustness analyses we conducted and relegate the details to online Appendix D. First, we evaluate how different model features affect the fit of our model. Table D1 shows that the search-wage gradient is similar for versions of the model that do not allow for censoring or an exogenous wage offer differential. Of course, without these features, the model does not fit the observed wage offer differential between the employed and unemployed as well. Second, Table D2 shows how different values of γ affect the search-wage gradient in the model. The model with $\gamma = 1$ implies an elasticity of -0.25, which is clearly above our target range of $[-0.52, -0.36]$, whereas a model with $\gamma = 10$ implies an elasticity of -0.45, which is closer to the lower end of the target range. The table also shows that these conclusions are robust to assuming a slightly lower value for the degree of frictional wage dispersion, $\sigma_w = 0.20$, which is more in line with some other estimates in the literature (Tjaden and Wellschmied, 2014). Finally, we also explore the sensitivity of our results on amplification by looking separately at shocks to search efficiency (Figure D3) and shocks to separations (Figure D4) and find that the amplification channel responds very similarly to both shocks. We also report results with both shocks, but with a value of $\gamma = 10$ (Figure D5). The results are as expected, with the higher search cost elasticity implying greater amplification. We also consider experiments with *permanent* shocks to parameters instead of temporary shocks: a permanent decline in search efficiency, a permanent increase in the job separation rate, and a permanent decline in offered wages (see Table D4). Relative to the case of quadratic search costs ($\gamma = 1$), our estimates with $\gamma = 2.8$ imply a larger response of search effort, job-to-job transitions and the unemployment rate. In summary, our model's implications for the fit of the search-wage gradient and the amplification of shocks to the returns to search are robust to various alternative specifications.

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 expect it to be crucial in assessing the labor market impacts of future downturns, including the current and unprecedented Covid-19 crisis.

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 about four times as efficient in generating job offers compared to job search while unemployed. Third, the employed receive better offers than the unemployed, and a significant wage offer premium for the employed exists even after applying a variety of controls. In summary, our results show that on-the-job search is pervasive, elastic and dominates job search while unemployed along several margins.

We end our paper by developing a 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. Only a small fraction of the gap is left unexplained. The model also highlights the importance of a high relative search efficiency among the employed by showing that it leads the unemployed to accept relatively low wage offers despite a relatively high flow utility of unemployment. This finding itself provides a simple resolution of the *wage dispersion puzzle* introduced to the literature by Hornstein et al. (2011). The model also highlights important macroeconomic implications. 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. The model suggests that aggregate search effort is more elastic than implied by a quadratic cost function. Consequently, we obtain greater amplification of on-the-job search effort and job-to-job transition rates in response to shocks to search efficiency and the job separation rate. Clearly, the responsiveness of search effort affects labor reallocation in the economy through its impact on transition rates. Therefore, variations in worker search effort provide an important amplification mechanism. Given the growing interest in the job ladder implications of business cycle fluctuations such as Moscarini and Postel-Vinay (2019), Faccini and Melosi (2019) and Eeckhout and Lindenlaub (2018), and the focus on their implication for the Beveridge curve (Elsby, Michaels, Ratner, 2015), these findings are particularly important.

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Appendix - For Online Publication

A Comparison of SCE Labor Survey to External Data

A.1 Results using CPS Definition of Unemployment

Our survey allows for a broader measure of job search among the non-employed than what is possible using the Current Population Survey (CPS). In the CPS, the unemployed are the non-employed who either were on temporary layoff or had actively searched within the last four weeks and were available for work. We use the same definition. The difference in scope between the two surveys is that the CPS does not follow up with certain non-employed individuals (predominantly the retired and disabled) who report that they either do not want work or cannot work, to ask if they had searched.

Our survey suggests that many of these individuals actively search and are available for work. Table A1 shows that they represent just over 12 percent of those counted as out of the labor force under the CPS definition. A similar fraction of those out of the labor force sent at least one application in the prior four weeks or spent some time searching in the previous seven days. As Table 1 in the main text shows, including these individuals in our job search measure increases the measured unemployment rate by 2.4 percentage points. Further analysis (not reported here) suggests that the majority of the difference is due to retired individuals seeking only part-time work. In fact, almost half of all individuals actively searching from out of the labor force are only seeking part-time work. Conditional on actively searching, just under 9 percent are looking for work similar to their most recent job.

Tables A2 and A3 replicate our job search analysis using the CPS scope and definition of unemployment using the SCE data. This counts those non-employed who do not explicitly report wanting work as out of the labor force, regardless of whether they later report that they actively searched and are available. The tables correspond to Tables 3 and 5 in the main text, though we only report the replicated results by labor force status at the time of the survey since the difference in the unemployment definition only matters for this period. We determine labor force status in the previous month using responses from a variety of other survey questions that do not directly correspond to the CPS definition. Note also that the results for the employed (regardless of whether they actively searched for work) are the same under both definitions.

The tables show that moving from our job search measure to the CPS measure of unemployment has only a minor effect on our estimates for the intensive margin of search effort and

Table A1: Basic Job Search Statistics by Labor Force Status, CPS Measure of Unemployment

	Employed	**Unemployed**	**Out of Labor Force**
Percent that actively searched for work	22.4	99.4	12.2
	(0.7)	(0.6)	(1.2)
Percent that actively searched and available for work	13.2	99.4	10.1
	(0.6)	(0.6)	(1.1)
Percent reporting no active search or availability, but would take job if offered	5.9	0.3	5.5
	(0.4)	(0.5)	(0.8)
Percent applying to at least one vacancy in last four weeks	21.4	96.3	10.7
	(0.7)	(1.5)	(1.1)
Percent with positive time spent searching in last seven days	21.3	97.4	8.9
	(0.7)	(1.3)	(1.0)
Conditional on Active Search			
Percent only searching for an additional job	36.0	—	—
	(1.7)		
Percent only seeking part-time work, conditional on active search	21.7	9.8	46.4
	(1.5)	(2.4)	(5.3)
Percent only seeking similar work (to most recent job), conditional on active search	25.3	9.0	8.8
	(1.7)	(2.3)	(3.4)
No. of Observations	3,725	153	781

Note: 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 using the CPS definition of unemployment. Standard errors are in parentheses.

search outcomes for the unemployed. The CPS definition implies a somewhat higher level of search effort. The number of applications rises by 22 percent, to 10.35 per month, and time spent searching rises by 25 percent, to 11.47 hours per week. The number of employer contacts, job interviews, and job offers received all rise somewhat as well, though the differences between the estimates in Table A3 and Table 5 in the main text are not statistically significant. The job search definition and the CPS definition of employment also imply similar ratios of employer contacts per application and mean job offers per application.

Finally, note that the definitions used here have no bearing on our model calibration since it uses job search effort and outcome estimates based on labor force status in the prior month.

A.2 Search Effort Estimates in the SCE and ATUS

Next, we compare our estimates of the time spent searching for work to comparable estimates from the time diaries of the American Time Use Survey (ATUS). We use the ATUS because

Table A2: Intensive Margin: Search Effort by Labor Force Status, CPS Measure of Unemployment

	Employed			Unemployed	Out of Labor Force
	Looking for Work	Not Looking	All		
Labor Force Status at Time of Survey					
Hours spent searching, last 7 days	4.40	0.07	1.16	11.47	0.60
	(0.29)	(0.01)	(0.08)	(0.81)	(0.13)
Mean applications sent, last 4 weeks	4.17	0.00	1.06	10.35	0.60
	(0.31)	(—)	(0.08)	(1.35)	(0.17)

Note: 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 using the CPS definition of unemployment. Standard errors are in parentheses.

Table A3: Search Outcomes by Labor Force Status, CPS Measure of Unemployment

	Employed			Unemployed	Out of Labor Force
	Looking for Work	Not Looking	All		
Labor Force Status at Time of Survey					
Mean contacts received	1.647	0.377	0.699	2.033	0.192
	(0.167)	(0.035)	(0.050)	(0.477)	(0.033)
Mean unsolicited contacts	0.795	0.341	0.455	1.089	0.113
	(0.095)	(0.032)	(0.034)	(0.422)	(0.028)
Mean job interviews (2014-17)	0.314	0.007	0.081	0.267	0.024
	(0.019)	(0.002)	(0.005)	(0.043)	(0.006)
Mean offers	0.442	0.117	0.200	0.560	0.133
	(0.033)	(0.023)	(0.019)	(0.317)	(0.027)
Mean unsolicited offers	0.069	0.068	0.068	0.082	0.057
	(0.015)	(0.022)	(0.017)	(0.027)	(0.023)
Fraction with at least one offer	0.291	0.058	0.117	0.208	0.072
	(0.016)	(0.005)	(0.006)	(0.033)	(0.009)
Fraction with at least one unsolicited	0.044	0.027	0.037	0.064	0.023
offer	(0.007)	(0.003)	(0.003)	(0.020)	(0.005)
Fraction with at least one unsolicited	0.350	0.098	0.162	0.234	0.084
offer, including unrealized offers	(0.017)	(0.006)	(0.006)	(0.034)	(0.010)
N	804	2,498	3,302	153	780

Note: 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 using the CPS definition of unemployment. Standard errors are in parentheses. Job interview data are only available for 2014 forward.

Table A4: Time Spent Searching for Work, ATUS and SCE Labor Survey Data

	Employed	**Unemployed**	**Out of Labor Force**
American Time Use Survey			
Percent reporting time spent searching for work, prior day	0.6	16.5	0.9
Average minutes spent searching, prior day, all respondents	0.8	26.7	1.4
Relative search intensity	0.03	1	0.05
SCE			
Percent reporting time spent searching for work, last seven days	21.3	97.4	98.9
Average minutes spent searching, last seven days, all respondents	69.6	687.9	36.1
Relative search intensity	0.10	1	0.05

Note: 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.

existing measures of search effort are rare, particularly when one wants to measure on-the-job search.

Table A4 reports our results. We focus on individuals age 18-64 in both surveys and report the average time spent searching for work by labor force status (employed, unemployed, or out of the labor force). We use the CPS definition of unemployment to maintain consistency across the surveys. There are differences between the frequencies over which each survey measures search time, for which we cannot control. The ATUS measures search time for a single day using a detailed time diary, while the SCE asks respondents the number of hours they spent searching for work over the previous seven days.

The differences are clear for both the extensive and intensive margins of search. 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. Even among the unemployed, who are defined as actively looking for work, the ATUS estimates suggest that only 16.5 percent looked for work on the previous day, while the SCE estimates suggest that 97.4 percent searched within the last seven days. The ATUS also suggests that the employed only spend less than 1 minute per day on job search, while the SCE data suggest they spend nearly 70 minutes per week on job search. Among the unemployed, the ATUS suggests they spend 27 minutes per day on job search, while the SCE data suggest they spend 11 *hours* per week on job search. There are reasons to believe that the ATUS misses a large degree of search activity, particularly among the employed. First, if search activity is intermittent, then a daily time diary will fail to capture some job search. Second, the ATUS only records a respondent's time spent on their primary activity. Thus, if an individual is literally searching while on the job, it will likely show up as work time rather than search time. Given these issues, we believe that our estimates of search effort provide a more comprehensive and reliable measure than the ATUS.

This latter point has aggregate implications since it suggests that the ATUS may give 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 3 percent as intensely as the unemployed, while the SCE estimates of job search imply that they search 10 percent as intensely as the unemployed. Define S 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. Aggregate efficiency units of job search in this case are

$$S = s^e E + U + s^n N.$$

In the CPS over the 2013-17 period, there are 148.7 million employed, 8.8 million unemployed, and 93.0 million out of the labor force, on average. If we combine these numbers with the relative search intensities from the ATUS, it implies that on-the-job search makes up only 25 percent of aggregate search effort, while search among the unemployed makes up 49 percent of aggregate search effort. If we instead use 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 measurement.

B Measuring Labor Force Status in the Previous 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 labor 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.

To determine labor force status in the prior month, 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 that this is a reasonable assumption given the relatively short time interval. In the 2014 and 2015 waves of the survey, we have additional information on whether an individual 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, we have to make some modest assumptions to determine whether someone was unemployed or out of the labor force. If an individual who was non-employed at the time of the job offer was employed at the time of the 2013 labor 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.

For the remaining individuals (who are the vast majority of respondents), we determine their prior month's labor force status starting with their labor force status at the time of the survey. If an individual did not receive a job offer in the last four weeks but was employed at the time of the survey, we determine their prior month's labor force status as follows: if they report that their current job tenure is at least one month, or if they report tenure of less than a month but with less than two weeks between jobs, we count them as employed in the previous month. Otherwise, we assume that these individuals were actively searching for work and count them as unemployed in the previous month.

If an individual was unemployed at the time of the survey and did not receive an offer in the last four weeks, we count them as employed in the previous month if they were on temporary layoff for less than one month or if their current non-employment spell was one month or less. We count them as unemployed in the prior month if they were on temporary layoff for more than one month or if they report actively searching for work for more than one month. Otherwise, we count them as out of the labor force.

Finally, if an individual was out of the labor force at the time of the survey and did not receive an offer in the last four weeks, we count them as employed if their current non-employment spell is one month or less. We count them as unemployed if they report actively searching for more than one month and they are not currently disabled. Otherwise, we count them as out of the labor force.

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 roughly comparable to the CPS estimates and the SCE labor supplement estimates (using the CPS definition of unemployment) in Table 1 of the main text.

Second, Table B1 reports labor force transition rates for two data sources. The first source is the SCE labor supplement, which estimates the transition rates using our measure of labor force status in the prior month and labor force status at the time of survey (using the CPS definition described in Appendix A). The second source is the monthly CPS, which measures the transition rates between September and October of each year (2013-17) for individuals in the survey during both months. The transition rates for the SCE are generally very comparable to the transition rates for the CPS. The job-separation rates into unemployment and out of the labor force are nearly identical. The SCE labor supplement has a slightly lower job-finding rate for the unemployed and a notably lower job-finding rate for those out of the labor force. Transitions between unemployment and being out of the labor force are roughly comparable between the two surveys.

B.2 Prior Month's Labor Force Status Based on Monthly SCE Data

Another way to test the validity of our estimates of labor force status in the prior month is to compare it to results based on labor force status for individuals in the regular, monthly SCE for the previous month. The monthly SCE data's measure of labor force status in the previous month is generally not consistent with the timing of the SCE labor supplement because individuals may respond to the labor supplement anywhere from a few days to nearly two months after their

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**	**Out of the LF**
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**	**Out of the LF**
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.

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 timing between the supplement and their September SCE interview. If the gap between interviews is 22 days or more, we use their September labor force status. 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 Tables 3 and 5 of the main text using the prior month's labor force status measure derived from the monthly SCE data. The table shows that the estimates are very similar to those estimated using our prior month's labor force status measure derived from the labor supplement. Some minor exceptions exist for the unemployed. For example, application and offer rates are somewhat lower using the monthly SCE measure. Otherwise, the two measures produce nearly identical estimates of search effort and search outcomes.

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

	Employed	**Unemployed**	**Out of Labor Force**
Labor Force Status in August/September, Monthly SCE			
Search Effort			
Mean applications sent	1.08	7.76	0.79
	(0.09)	(1.09)	(0.18)
Mean applications sent, ignoring applications to additional jobs	0.84	7.76	0.79
	(0.09)	(1.09)	(0.18)
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

Note: 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.

C Additional Empirical Results

C.1 Results Conditional on Observable Characteristics

In the main analysis, we explore how much wage differentials between the employed and non-employed change when we add controls for observable worker and job characteristics to the offer wage, the wage at the time of hiring, and the previous wage of the currently employed. This subsection examines how much of a gap exists for other job characteristics, and how much differences in search effort and search outcomes by labor force status persist, after controlling for observable worker and job characteristics for these estimates as well.

Table C1: Search Effort by Labor Force Status, Conditional on Observable Worker and Job Characteristics

	Employed				
	Looking for Work	**Not Looking**	**All**	**Unemployed**	**Out of Labor Force**
Labor Force Status at Time of Survey					
Hours spent searching, last 7 days	4.31	0.11	1.17	8.86	0.07
	(0.27)	(0.02)	(0.07)	(0.66)	(0.07)
Mean applications sent, last 4 weeks	4.21	-0.07	1.00	8.78	0.33
	(0.33)	(0.02)	(0.08)	(1.07)	(0.06)
N	797	2,477	3,274	210	617
Labor Force Status in Prior Month					
Mean applications sent			0.96	10.70	0.73
			(0.08)	(1.42)	(0.09)
Mean applications sent, ignoring applications to additional jobs			0.77	10.69	0.72
			(0.08)	(1.42)	(0.09)
N			3,288	157	656

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 results 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. Standard errors are in parentheses. See appendix text for set of observable worker characteristics used as controls. Observable job characteristics include two-digit SOC occupation, two-digit NAICS industry, and six categories of firm size. Controls also include fixed effects for survey year and state.

We begin by examining the differences in search effort and search outcomes by labor force status after controlling for observables. Throughout the exercise, our worker controls include sex, age, age squared, four education categories, four race categories, a dummy for homeownership, the number of children under age six in the household, marital status, and marital status interacted with sex. The job controls include the two-digit SOC occupation of the job, six categories of the job's firm size, and, when available, the two-digit NAICS industry of the firm. State and year fixed effects are included throughout as well.

Tables C1, C2, and C3 correspond to Tables 3, 5, and 6 in the main text. In general,

Table C2: Search Outcomes by Labor Force Status, Conditional on Observable Worker and Job Characteristics

	Employed			Unemployed	Out of Labor Force
	Looking for Work	**Not Looking**	**All**		
Labor Force Status at Time of Survey					
Mean contacts received	1.612	0.347	0.664	1.506	0.273
	(0.165)	(0.035)	(0.050)	(0.293)	(0.040)
Mean unsolicited contacts	0.768	0.308	0.423	0.703	0.235
	(0.094)	(0.032)	(0.033)	(0.249)	(0.035)
Mean job interviews (2014-17)	0.549	0.001	0.133	0.422	0.018
	(0.048)	(0.003)	(0.012)	(0.099)	(0.012)
Mean offers	0.434	0.120	0.199	0.449	0.108
	(0.033)	(0.023)	(0.019)	(0.222)	(0.031)
Mean unsolicited offers	0.071	0.063	0.065	0.089	0.077
	(0.016)	(0.022)	(0.017)	(0.021)	(0.029)
Fraction with at least one offer	0.293	0.063	0.121	0.189	0.034
	(0.015)	(0.005)	(0.005)	(0.027)	(0.009)
Fraction with at least one unsolicited offer	0.049	0.027	0.032	0.054	0.021
	(0.007)	(0.003)	(0.003)	(0.015)	(0.006)
Fraction with at least one offer, including unrealized offers	0.354	0.101	0.165	0.212	0.055
	(0.016)	(0.006)	(0.006)	(0.028)	(0.010)
N	797	2,477	3,274	210	617
Labor Force Status in Prior Month					
Fraction with at least one offer			0.109	0.313	0.067
			(0.005)	(0.036)	(0.010)
Fraction with at least one unsolicited offer			0.031	0.045	0.030
			(0.003)	(0.016)	(0.007)
Fraction with at least one offer, including unrealized offers			0.153	0.344	0.085
			(0.006)	(0.037)	(0.011)
Labor Force Status in Prior Month, Ignoring Search Outcomes for Additional Jobs					
Fraction with at least one offer			0.092	0.318	0.069
			(0.004)	(0.036)	(0.010)
Fraction with at least one unsolicited offer			0.029	0.047	0.030
			(0.003)	(0.016)	(0.007)
Fraction with at least one offer, including unrealized offers			0.140	0.348	0.085
			(0.006)	(0.037)	(0.011)
N			3,288	157	656

Notes: Estimates come from tabulations from the October 2013-17 waves of the SCE Job Search Supplement, for all individuals aged 18-64, excluding the self-employed, with at least one job offer in the last six months. Standard errors are in parentheses. See appendix text for set of observable worker characteristics used as controls. Observable job characteristics include two-digit SOC occupation, two-digit NAICS industry, and six categories of firm size. Controls also include fixed effects for survey year and state.

Table C3: Acceptance Decisions by Labor Force Status in Previous Month, Conditional on Observable Worker and Job Characteristics

	Employed	**Unemployed**	**Out of Labor Force**
Percent of best offers accepted	33.1	54.0	30.7
	(2.1)	(5.1)	(4.3)
Percent of all offers accepted	27.4	51.8	27.6
	(2.0)	(5.1)	(4.0)
Percent of best offers accepted,	32.8	52.8	30.3
ignoring offers for an additional job	(2.2)	(5.1)	(3.7)
Percent of all offers accepted,	27.5	50.7	26.0
ignoring offers for an additional job	(2.1)	(5.2)	(3.7)
N	293	48	52

Notes: Estimates come from tabulations from the October 2013-17 waves of the SCE Job Search Supplement, for all individuals aged 18-64, excluding the self-employed, with at least one job offer in the last six months. Standard errors are in parentheses. See appendix text for set of observable worker characteristics used as controls. Observable job offer characteristics include two-digit SOC occupation, and six categories of firm size. Controls also include fixed effects for survey year and state.

controlling for observable characteristics does little to alter the original results in the main text. Table C1 shows that search effort is practically unchanged regardless of the measure used or timing of the measurement of labor force status. The search effort of the employed relative to the unemployed, ignoring search for additional work (our preferred measure of relative effort for our model calibration) is essentially unchanged, at 0.92, compared to 0.91 unconditionally.

Tables C2 and C3 show that search outcomes and acceptance rates also change little after controlling for observables. If we ignore the effects of censoring, we can infer the relative search efficiency of the employed to the unemployed directly from the data as $\lambda_i(s) = \alpha_i + \beta_i s$. Using the unconditional estimates from Table 5 in the main text suggests that relative efficiency measured this way is about 2.48. If we were to instead use the estimates from Table C2, the estimates suggest that the relative efficiency under this method is somewhat higher, at 3.23.

Finally, Table C4 reports the characteristics of the best job offer for the employed and non-employed after controlling for observable characteristics. Controlling for observables leads to only modest reductions in the observed gaps in job offer characteristics between the employed and non-employed and a somewhat larger gap in job offer acceptance rates.

C.2 Search Effort-Wage Gradient with Different Measures of Job Search

Figure C1 replicate our estimates of the search effort-wage gradient with measures for the incidence of search such whether an individual sent any applications in the last four weeks, spent any time looking for work in the last seven days or searched actively in the last 4 weeks. Figure C2

Table C4: Characteristics of Best Job Offer by Labor Force Status, Conditional on Observable Worker and Job Characteristics

	Employed at Offer	**Non-Employed at Offer**	**Difference, E - NE**
log offer usual hours	3.382	3.301	0.080
	(0.020)	(0.033)	(0.053)
Pct. of offers with no benefits	42.0	57.4	-15.4
	(1.4)	(2.5)	(3.8)
Pct. of offers through an unsolicited contact	24.2	18.3	5.9
	(1.4)	(2.0)	(3.4)
Pct. of respondents with at least a 'good idea' of pay	60.2	57.8	2.4
	(1.6)	(2.8)	(4.5)
Pct. of offers with some counter-offer given	11.5		
	(1.1)		
Pct. of offers that involved bargaining	37.6	26.1	11.5
	(1.6)	(2.6)	(4.1)
Pct. of job offers accepted	34.4	52.7	-18.3
	(1.5)	(2.6)	(4.0)
Pct. of offers accepted as only option	9.2	23.9	-14.7
	(1.4)	(2.9)	(4.6)
N	797	257	

Notes: Estimates come from tabulations from the October 2013-17 waves of the SCE Job Search Supplement, for all individuals aged 18-64, excluding the self-employed, with at least one job offer in the last six months. Standard errors are in parentheses. See appendix text for set of observable worker characteristics used as controls. Observable job offer characteristics include two-digit SOC occupation and six categories of firm size. Controls also include fixed effects for survey year and state.

replicate our estimates of the search effort-wage gradient for raw wages, again finding a similar negative relationship as shown in the figure in the paper.

C.3 Differentials between the Starting and Previous Wage

As an auxiliary analysis of the differences in prior job's earnings observed in Table 8, our survey allows us to examine job search retrospectively for those employed at the time of the survey interview by asking them how they came about their current jobs. We perform this analysis using the sample of the currently employed, excluding the currently self-employed. After removing respondents with missing data, this sample includes 2,892 respondents. The advantage of this approach is that we are able to examine their starting wages and previous earnings as a function of their labor force status at their time of hiring.

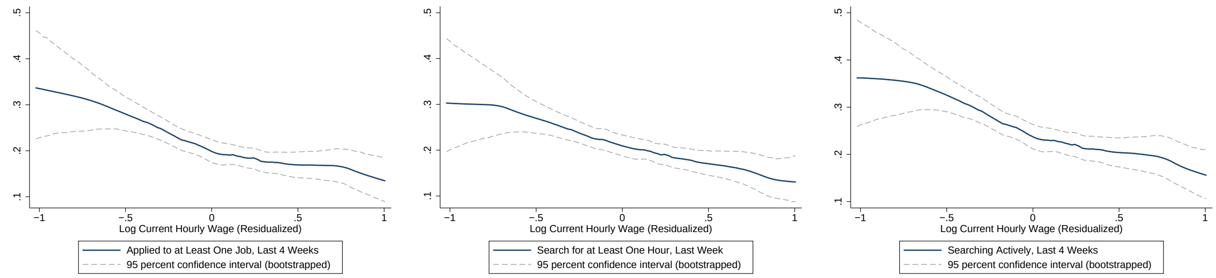
Table C5 presents the characteristics of the current job and the previous job's wage by labor force status at the time of hire. We focus on the comparison of the non-employed to those who move directly from employment to their current job. At the time of the survey interview, those

Table C5: Characteristics of Current and Previous Job, by Labor Force Status at Time of Hire

	Hired from Employment	**Hired from Non-Employment**	**Difference, E - NE**
Share of Employment	67.9	32.1	
Characteristics of Current Job			
log real current wage	3.172	2.937	0.236
	(0.015)	(0.024)	(0.047)
log usual hours	3.673	3.521	0.153
	(0.008)	(0.017)	(0.025)
Pct. with no benefits	14.6	28.0	-13.4
	(0.8)	(1.5)	(2.7)
Median tenure (mos.)	54.0	45.0	9.0
	(2.2)	(2.9)	(4.8)
Characteristics of Current Job, Controlling for Observable Characteristics			
log real current wage	3.132	3.030	0.101
	(0.011)	(0.017)	(0.026)
log offer usual hours	3.656	3.556	0.099
	(0.007)	(0.015)	(0.020)
Pct. with no benefits	16.4	23.9	-7.5
	(0.7)	(1.2)	(1.9)
Median tenure (mos.)	76.0	74.1	-1.9
	(1.9)	(2.7)	(4.2)
Starting Wage Estimates			
log real starting wage,	2.988	2.738	0.250
unconditional	(0.015)	(0.023)	(0.045)
Controlling for observable	2.953	2.816	0.137
characteristics	(0.012)	(0.017)	(0.027)
Previous Wage Estimates			
log real previous wage,	2.903	2.874	0.029
unconditional	(0.018)	(0.028)	(0.042)
Controlling for observable	2.885	2.921	-0.036
characteristics	(0.015)	(0.023)	(0.033)
N	2,003	889	

Note: Estimates come from authors' tabulations from the October 2013-17 waves of the SCE Job Search Supplement, restricted to currently employed individuals aged 18-64, excluding the self-employed, with a reported labor force status at the time of hire and reported current, starting, and previous-job wages and hours. 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 current job, as well as the two-digit NAICS industry and six categories of firm size for the current employer. Standard errors are in parentheses.

Figure C1: Incidence of Job Search Effort by the Current Wage

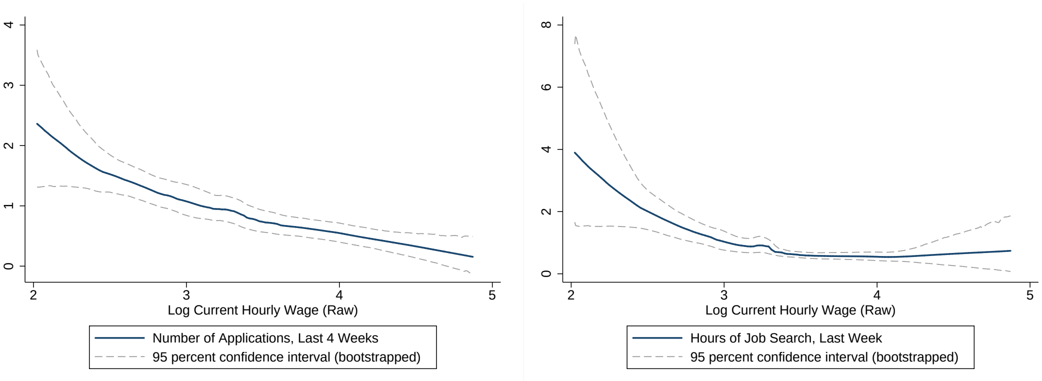


Note: Figure reports the LOWESS estimates (with smoothing parameter 0.8) of the relationship between the measures of search effort listed on each vertical axis and the (log) real current wage of the employed, residualized after controlling for observable worker characteristics (see Table 4 for the list of specific variables). 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. Dashed lines represent 95 percent confidence intervals.

hired from non-employment are paid lower wages, have fewer work hours, and are much less likely to have any benefits than those hired from another job. Controlling for observables in this case leads to reductions in the observed gaps in job characteristics, but most gaps remain statistically significant. The residual gap in current wages falls from 24 to 10 log points, while the residual gap in current hours falls from 15 to 10 log points.

Estimates reported in the middle of Table C5 show that most of the current wage differences stem from wage differences at their time of hiring. The real starting wage of those hired from non-employment is 25 log points (28 percent) lower than the real starting wage of those hired from employment, on average, and about 14 log points (15 percent) remains after conditioning on

Figure C2: Job Search Effort by the Current Wage (Raw)

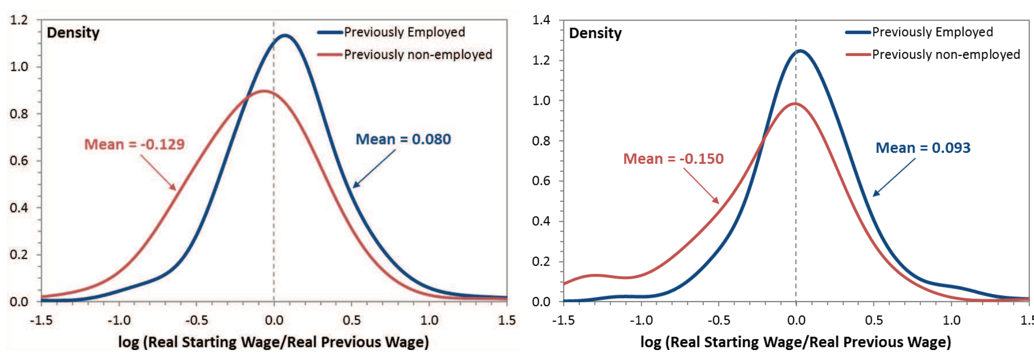


Note: Figure reports the LOWESS estimates (with smoothing parameter 0.8) of the relationship between the measures of search effort listed on each vertical axis and the (log) real current wage of the employed. The confidence intervals are based on a bootstrap with 500 replications. The estimates use all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

observable characteristics.[37] Similar to the evidence from prior wages in Table 8, the differences in previous jobs' wages between those hired from employment vs. non-employment are small and statistically insignificant. This is true for both the unconditional real wage and the wage that controls for observable characteristics. Note that the smaller difference in the premium in starting wages compared to the premium in offered wages is likely due to selection: poor job offers are less present in the cross-section of current jobs, as individuals accepting these jobs are more likely to quit and to move to better-paying jobs. If the non-employed get worse offers than the employed, this explains why the gap is smaller among starting wages compared to job offers.

Finally, Figure C3 illustrates the wage differences between those hired from employment and those hired from non-employment for their full wage distributions. It plots the (log) differences in the real starting wage, relative to the real previous wage, for each group, after controlling for observable worker and job characteristics. The relative wage distribution of those hired from employment stochastically dominates the distribution of those hired from non-employment. The left panel of the figure shows that, after conditioning out our controls, those who transition directly from employment receive an 9 log point increase in their wage, on average, while those who were non-employed receive a 7 log point decrease in their wage, on average. The right panel shows that, without any controls for observable worker and job characteristics, the average (log) wage increase for those hired from employment rises from 9 to 10 log points and the average (log) wage decrease for those hired from non-employment changes from 7 to 9 log points.

Figure C3: Distribution of Starting Wages Relative to Previous Wage among the Currently Employed Conditional on Observables (left panel) and Without Controls (right panel)



Notes: Figure reports kernel density estimates of the residual of log(real starting wage/real previous wage), where the previous wage refers to final wage of the prior job and the starting wage is for the current job. Estimates are for the sample of the currently employed (excluding self-employed) in the October 2013-17 waves of the SCE Job Search Supplement.

[37] Our conditional estimates of the starting wage and previous wage use the same worker characteristics as our conditional estimates of the offer wage. The starting wage uses the same firm and job controls, and additionally controls for two-digit industry. The previous wage only includes the two-digit occupation as a job or firm control.

D Theoretical Framework

D.1 First Order Conditions

The first order condition for an employed individual's search effort, $s_e(x, w)$, is

$$xc_e'(s_e(x, w)) \leq \beta_e \frac{1 - \delta(x)}{1 + r} \int_w^{\bar{w}} [W(x, y) - W(x, w)] dF_e(y), \tag{D1}$$

which holds with equality for optimal search effort below $\bar{s}$.

The first order condition for an unemployed individual's search effort, $s_u(x)$, is

$$xc_u'(s_u(x)) \leq \frac{\beta_u}{1 + r} \int_{R(x)}^{\bar{w}} [W(x, y) - U(x)] dF_u(y). \tag{D2}$$

The first order condition differs from (D1) in three ways: (i) the search cost function, (ii) the search efficiency parameter, and (iii) the discounted expected gain from accepting a job, which is determined by the reservation wage $R(x)$ and the shape of the wage offer distribution for the unemployed.

D.2 Main Results and Robustness

Table D1 shows the full set of results for the baseline model. In addition, it also shows the results for 4 restricted versions of the baseline model: (1) a model without an exogenous wage offer differential; (2) same as (1) but without censoring of wage offers; (3) same as (2) but without endogenous search effort; and (4) same as (3) but without worker heterogeneity in x. All parameters are re-calibrated to match the targeted moments except for γ, which is kept at a value of 2.8.

Going from the baseline model to the restricted model (1), which sets the exogenous wage offer differential to 0, shows that the model continues to match the search-wage gradient well, and if anything would require a slightly higher level γ to fit our target range in the data. All other targeted moments are still fitted (nearly) exactly, whereas the fit of the acceptance rate is somewhat worse as employed workers receive worse job offers than in the baseline model.

Going from the baseline model to the restricted model (2), which sets the exogenous wage offer differential to 0 and features no censoring, shows that the model continues to fit the search-wage gradient well, and if anything would require a slightly higher level γ to fit our target range in the data. All other targeted moments are still fitted (nearly) exactly, whereas the fit of the acceptance rate is substantially worse as all offers are uncensored and thus paying lower wages.

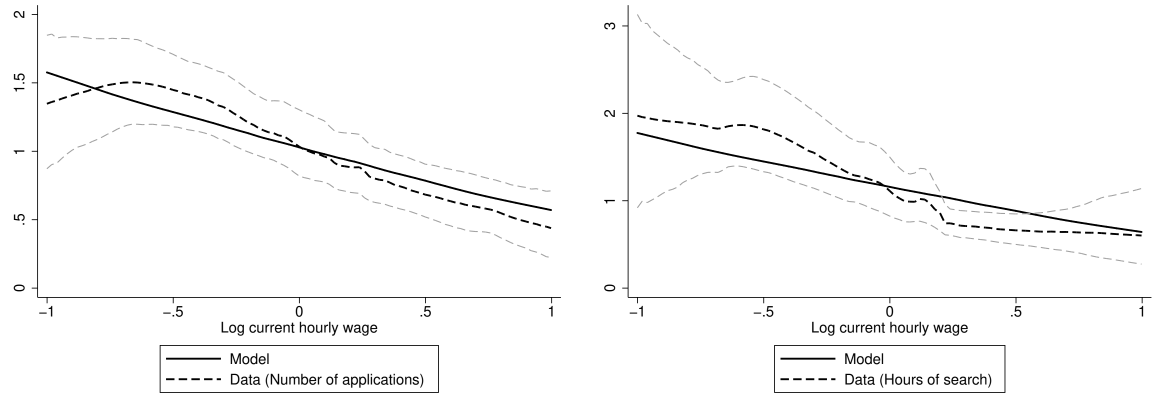
Going to the restricted model (3) without endogenous search effort shows how the model does even worse in terms of fitting the acceptance rate of the employed. The main reason is that

Table D1: Parameter Estimates and Model Outputs for Restricted Model Versions

			Restricted Models:			
	Data	**Baseline**	(1)	(2)	(3)	(4)
Calibrated parameter values						
γ		2.8	2.8	2.8	—	—
κ_u		0.01	0.01	0.02	—	—
κ_e		0.08	0.07	0.05	—	—
α_u		0.04	0.04	0.04	0.34	0.34
α_e		0.03	0.03	0.03	0.08	0.08
β_u		0.03	0.03	0.03	—	—
β_e		0.13	0.13	0.07	—	—
χ_u		0.16	0.16	—	—	—
χ_e		0.52	0.51	—	—	—
b		1.25	1.17	1.01	0.18	0.16
$\mu_e - \mu_u$		0.04	0	0	0	0
$x_{high} - x_{low}$		1.11	1.11	1.11	1.11	1.11
$\delta(x_{low}) - \delta(x_{high})$		0.0106	0.0119	0.0141	0.0130	0
Targeted moments (means)						
Search-wage elasticity	[-0.52, -0.36]	-0.36	-0.35	-0.32	—	—
Search effort U	10.39	10.40	10.40	10.39	—	—
Search effort E	0.77	0.77	0.77	0.77	—	—
Unsolicited offer rate U	0.042	0.042	0.042	0.042	0.342	0.342
Unsolicited offer rate E	0.026	0.026	0.026	0.026	0.082	0.082
Censored offer rate U	0.028	0.028	0.028	—	—	—
Censored offer rate E	0.041	0.041	0.041	—	—	—
Offer rate U	0.342	0.342	0.342	0.342	0.342	0.342
Offer rate E	0.081	0.082	0.082	0.082	0.082	0.082
Acceptance rate U	0.493	0.494	0.495	0.493	0.493	0.493
Stdev. of log residual offered wages	0.68	0.68	0.68	0.68	0.68	0.68
Residual prior wage differential (E - U)	0.01	0.01	0.01	0.01	0.01	-0.06
Unemployment rate	0.068	0.068	0.068	0.068	0.068	0.068
Additional moments						
Acceptance rate E	0.31	0.24	0.22	0.17	0.13	0.13
Residual offered wage differential (E - U)	0.19	0.19	0.16	0.11	0.07	0.00
... due to worker-heterogeneity		0.15	0.14	0.11	0.07	0.00
... due to censoring		0.00	0.02	0.00	0.00	0.00
... due to exogenous differential		0.04	0.00	0.00	0.00	0.00
Unempl. rate of low-x type		0.09	0.08	0.08	0.07	0.07
Unempl. rate of high-x type		0.05	0.05	0.05	0.06	0.07

Notes: The table shows results and estimated parameters for restricted versions of the baseline model: (1) the same as the baseline model but without an exogenous wage offer differential; (2) same as (1) but without censoring of wage offers; (3) same as (2) but without endogenous search effort; and (4) same as (3) but without worker heterogeneity in x.

Figure D1: On-the-Job Search Effort by Current Wages ($\gamma = 10$)



Note: The dashed lines show the 95 percent confidence interval (bootstrapped with 500 replications). The model simulations are based on a calibration with $\gamma = 10$.

without endogenous search effort even those at the very top of the job ladder continue to receive many offers, which they are likely to reject. Interestingly, the residual wage offer differential attributed to worker heterogeneity is substantially lower in the model without endogenous search effort. The reason is that in the absence of worker heterogeneity (see model 4), prior wages between unemployed and employed workers are more similar (-0.06) and thus the model needs less negative selection among the unemployed to fit the prior wage differential of 0.01 in the data. The comparison of column 3 and 4 also shows that the role of heterogeneity is purely to fit the prior and offered wage differential and does not affect any of the other moments and parameters.

Table D2 shows the parameter estimates and results of the baseline model and compares them to alternative models with different values of γ and σ_y. All other parameters are re-calibrated to match the data targets, except for the exogensous wage offer differential, which is kept at 0.04 as in the baseline model. The results show that the search-wage elasticity is clearly above the target range $[-0.52, -0.36]$ in the model with $\gamma = 1$, with a value of -0.25. The baseline model with $\gamma = 2.8$ matches exactly the upper bound of our target range, whereas a model with $\gamma = 10$ is closer to the lower end of the target range with a value of -0.45. Figure D1 also shows that the model with $\gamma = 10$ fits the patterns in Figure C2 well for both applications and hours of search. Finally, columns (4) and (5) show that the search-wage elasticity is lower in models with less frictional wage dispersion (i.e., lower σ_y). The reason is that with our calibration strategy a lower value of σ_y is associated with a higher dispersion in x to match the (residual) wage dispersion in the data. The higher dispersion in unobserved heterogeneity x attenuates the

Table D2: Parameter Estimates and Model Outputs for Different Levels of γ and σ_y

	Data	Baseline	Alternative Models: (1)	(2)	(3)	(4)	(5)
Calibrated parameter values							
γ		2.8	1	5	10	2.8	5
σ_y		0.24	0.24	0.24	0.24	0.20	0.20
κ_u		0.01	0.00	0.02	0.02	0.01	0.01
κ_e		0.08	0.05	0.09	0.10	0.06	0.07
α_u		0.04	0.04	0.04	0.04	0.04	0.04
α_e		0.03	0.03	0.03	0.03	0.03	0.03
β_u		0.03	0.03	0.03	0.03	0.03	0.03
β_e		0.13	0.13	0.13	0.13	0.13	0.13
χ_u		0.16	0.16	0.16	0.16	0.16	0.16
χ_e		0.52	0.5	0.53	0.53	0.52	0.53
$\mu_e - \mu_u$		0.04	0.04	0.04	0.04	0.04	0.04
b		1.25	1.08	1.31	1.34	1.22	1.26
$x_{high} - x_{low}$		1.11	1.11	1.11	1.11	1.14	1.14
$\delta(x_{low}) - \delta(x_{high})$		0.011	0.015	0.010	0.011	0.009	0.008
Targeted moments (means)							
Search-wage elasticity	[-0.52, -0.36]	-0.36	-0.25	-0.41	-0.45	-0.30	-0.34
Search effort U	10.39	10.40	10.39	10.39	10.39	10.39	10.39
Search effort E	0.77	0.77	0.77	0.77	0.77	0.77	0.77
Unsolicited offer rate U	0.042	0.042	0.042	0.042	0.042	0.042	0.042
Unsolicited offer rate E	0.026	0.026	0.026	0.026	0.026	0.026	0.026
Censored offer rate U	0.028	0.028	0.028	0.028	0.028	0.028	0.028
Censored offer rate E	0.041	0.041	0.041	0.041	0.041	0.041	0.041
Offer rate U	0.342	0.342	0.342	0.342	0.342	0.342	0.342
Offer rate E	0.081	0.082	0.082	0.082	0.082	0.082	0.082
Acceptance rate U	0.493	0.494	0.493	0.493	0.492	0.493	0.493
Stdev. of log residual offered wages	0.68	0.68	0.68	0.68	0.68	0.68	0.68
Residual prior wage differential (E - U)	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Unemployment rate	0.068	0.068	0.068	0.068	0.068	0.068	0.068
Additional moments							
Acceptance rate E	0.31	0.24	0.22	0.25	0.26	0.24	0.25
Residual offered wage differential (E - U)	0.19	0.19	0.16	0.2	0.21	0.16	0.17
. . . due to worker-heterogeneity		0.15	0.13	0.16	0.16	0.13	0.13
. . . due to censoring		0.00	0.00	0.00	0.00	0.00	0.00
. . . due to exogenous differential		0.04	0.04	0.04	0.04	0.04	0.04
Unempl. rate of low-x type		0.09	0.08	0.09	0.10	0.08	0.09
Unempl. rate of high-x type		0.05	0.05	0.04	0.03	0.05	0.05

relationship between wages and search effort and thus requires even higher values of γ to match the search-wage gradient in the data.

D.3 Frictional Wage Dispersion

Table D3 shows the implications of our model for the wage dispersion puzzle. Hornstein, Krusell, and Violante (2011) pointed out that search models suffer from an inherent tension between matching transition rates and wage dispersion in the data with reasonable values for the flow

Table D3: Implications for the Wage Dispersion Puzzle

		Alternative Models			
	Baseline	(1)	(2)	(3)	(4)
$\mu_{y,e}$	0.04	0.04	0.00	0.00	0.00
γ	2.80	1.00	2.80	2.80	2.80
Censoring	Yes	Yes	Yes	No	No
Endogenous search	Yes	Yes	Yes	Yes	No
Search cost of unemployed	0.30	0.25	0.36	0.51	—
Search cost of employed	0.08	0.05	0.07	0.05	—
$b/E(w)$	0.80	0.70	0.77	0.70	0.13
$z = b/E(w)$ (net of search costs)	0.64	0.55	0.56	0.36	0.13
Mean-min ratio (conditional on x)	1.54	1.50	1.49	1.44	1.39

value of unemployment. As already hinted at by Hornstein, Krusell, and Violante (2011), on-the-job search, particularly when combined with endogenous search effort, attenuates this tension because it allows a relatively high offer rate for those at the bottom of the job ladder while implying few transitions for the average employed person (i.e., those further up on the ladder). Table D3 shows that our model with endogenous search resolves this tension as it generates a reasonable flow value of unemployment (net of search costs) of 0.64, which is in the range of estimates in the literature, all while matching the key moments in our data and generating a Mean-min ratio (conditional on x) of 1.54. The latter is in the range of estimates in the working paper version of Hornstein, Krusell, and Violante.

The table also shows how different components of our model contribute to the resolution of the wage dispersion puzzle: (1) a model with a lower value γ does somewhat worse as it implies a lower flow value of unemployment, as does model (2) without the exogenous wage offer differential. Model (3) without censoring of wage offers performs substantially worse, mainly because it implies a lower overall offer rate while employed. Model (4) without endogenous search effort performs worst, with a flow value of unemployment of 0.13, which is clearly below reasonable estimates in the literature.

D.4 Responses to Changes in Returns to Search

D.4.1 Permanent Changes in Returns to Search

In addition to the experiment discussed in the main text, we consider here three experiments to emphasize the aggregate implications of our findings: a permanent decline in search efficiency; a permanent increase in the exogenous separation rate and a permanent decline in wages. All three experiments result in a decline in return to search and affect the search behavior as the first

Table D4: Steady-State Response to Permanent Changes in Search Efficiency, the Separation Rate and Mean Wage Offers

	Search Efficiency Decline (-10%)		Separation Rate Increase (+10%)		Average Wage Offer Decline (-1%)	
Model Outcome	$\gamma = 2.80$	$\gamma = 1.00$	$\gamma = 2.80$	$\gamma = 1.00$	$\gamma = 2.80$	$\gamma = 1.00$
Changes expressed in % of value prior to change						
Search Effort of Employed	-3.6%	-1.1%	-1.4%	-0.8%	-3.1%	-1.2%
Job-to-Job Transition Rate	-12.1%	-6.8%	-0.2%	-3.6%	-6.7%	-2.7%
Search Effort of Unemployed	-10.8%	-3.1%	-8.3%	-2.4%	-8.8%	-2.4%
Job-finding Rate	-28.0%	-14.1%	-15.4%	-3.9%	-18.2%	-6.5%
Unemployment Rate	35.2%	15.1%	27.3%	13.3%	20.3%	6.4%

Notes: The table shows steady-state elasticities with respect to an aggregate search efficiency shock and an aggregate separation rate shock. The aggregate search efficiency shock is a uniform percent decrease in the parameters α_u, α_e, β_u and β_e. The aggregate separation rate shock is a uniform percent increase in the separation rates $\delta(x)$ for all x. The aggregate wage offer shock corresponds to a uniform decline in the average wage offer for both employed and unemployed individuals.

order conditions in the Appendix D suggest. We consider the elasticity of the search effort of the employed and unemployed as well as the job-to-job and job-finding rates with respect to changes in search efficiency, the separation rate and the average wage offer in Table D4 and compare it with the common assumption of quadratic search costs in the literature.

The first two columns of Table D4 show that when search efficiency declines by 10%, the unemployment rate rises by about 15 % under the quadratic cost assumption while it rises more than twice as much with $\gamma = 2.8$, which is our preferred estimate. A useful benchmark is the mechanical response of the unemployment rate to a 10% decline in matching efficiency that does not account for the endogenous response of search effort. If search behavior had not respond the job-finding rate would decline by 10% and the unemployment rate would have increased from 6.8% to 7.5%, which is a 10% increase and is close to what the quadratic cost specification implies. The difference is due to the higher responsiveness of search effort of the unemployed. The response of employed workers' search effort is also substantially muted under quadratic search cost assumption.

The middle two columns Table D4 shows that when the separation rate increases by 10%. Similarly, to the experiment with a decline in search efficiency, search effort of the employed and unemployed declines, but somewhat less since separation rates have a less direct impact on the return to search (through the value of an employment relationship). The last two columns of Table D4 considers an experiment when there is a one percent decline in offered wages in the economy, which also discourages search behavior for both employed and unemployed workers. Similar to the experiment with search efficiency, we find that job-finding and job-to-job transition rates both exhibits almost three times stronger response relative to implied by quadratic search costs.

To summarize, the response of flows and the unemployment rate depends critically on this elasticity when labor market conditions change. The quadratic cost specification—$\gamma = 1$—underestimates the decline in search effort, the decline in transitions and the rise in the unemployment rate substantially.

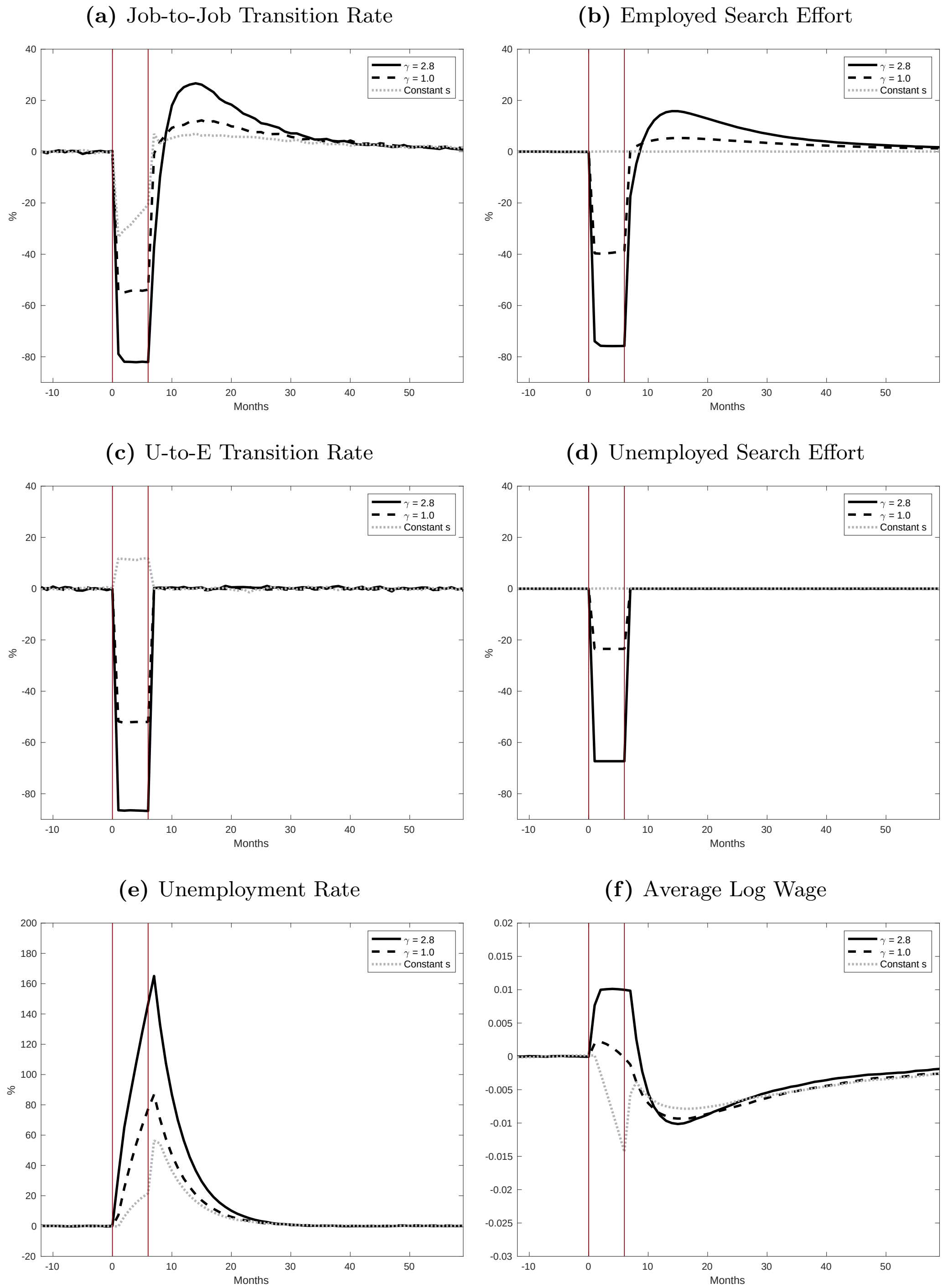
D.4.2 Temporary Changes in Returns to Search

We provide here some additional results regarding the experiment conducted in Section 4.4. First, Figure D2 shows the effects of the experiment on additional variables. It shows that the unemployed worker's search effort is highly elastic in the economy with $\gamma = 2.8$ and so the job finding rate and the unemployment rate respond much more compared to the economy with $\gamma = 1$ or the economy with constant search effort. The average wage in the economy also moves much more in the economy with $\gamma = 2.8$. Note that all changes in the average wage are due to changes in the distribution of job seekers along the job ladder (the wage for a given position on the ladder is assumed to be constant). At the beginning of the recession, the average wage increases because the reservation wage increases. As a result, workers in jobs with low wages separate, leading to an increase in the average wage. After the end of the recession, the average wage drops gradually and substantially, as more and more workers find new jobs, many of them at the bottom of the job ladder. Over time, these workers find better jobs and thus the average wage starts to increase again, moving back to its steady state value.

Figures D3 and D4 show the effects on job-to-job transitions and employed job search effort separately for shocks to matching efficiency and shocks to separations (but of the same magnitude as the experiment in the paper). The figures show that both shocks have similar effects on the employed job search effort.

Finally, Figure D5 shows the effects on job-to-job transitions and employed job search effort for the same experiment as in the paper but in an economy where we set $\gamma = 10$. As discussed earlier on, with $\gamma = 10$ we obtain a search-wage gradient of -0.45, which is closer to the lower end of our target range. The figure shows that with $\gamma = 10$, we get even more amplification as the employed job search effort drops even more sharply than in the economy with $\gamma = 2.8$.

Figure D2: Responses to 6-Month Recession



(a) Job-to-Job Transition Rate

(b) Employed Search Effort

(c) U-to-E Transition Rate

(d) Unemployed Search Effort

(e) Unemployment Rate

(f) Average Log Wage

Note: The figure shows the response to a decline of search efficiency parameters α_i and β_i by a factor of (1/1.5) and increase in exogenous separation rates δ by a factor 1.5 for a period of 6 months. The top two panels correspond to the ones in Figure 5 in the paper.

Figure D3: Responses to 6-Month Recession (Search Efficiency Only)

(a) Job-to-Job Transition Rate **(b)** Employed Search Effort

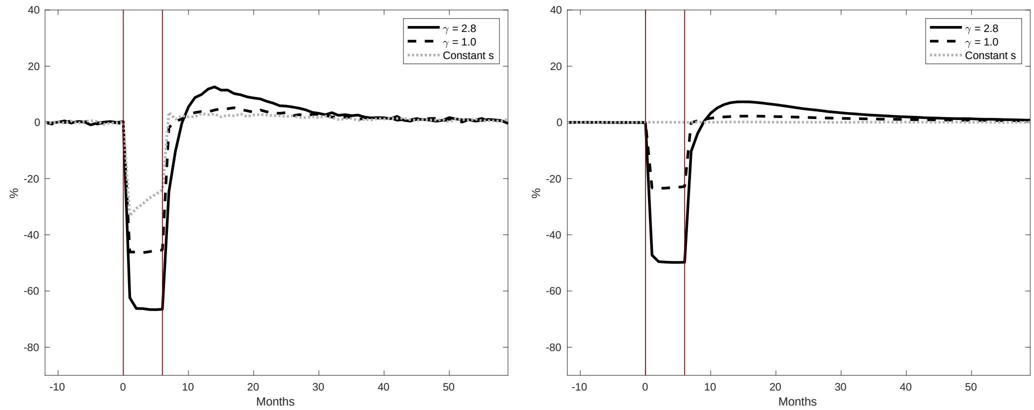


Figure D4: Responses to 6-Month Recession (Separation Shock Only)

(a) Job-to-Job Transition Rate **(b)** Employed Search Effort

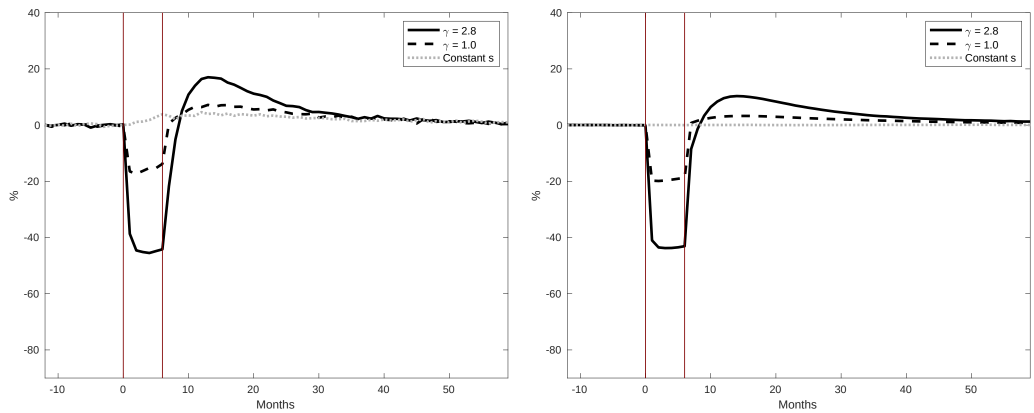


Figure D5: Responses to 6-Month Recession in Model with $\gamma = 10$

(a) Job-to-Job Transition Rate **(b)** Employed Search Effort