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 at least three times more effective than the unemployed in job search; and (3) the employed receive better job offers than the unemployed. We set up a general equilibrium model of on-the-job search with endogenous search effort, calibrate it to fit our new facts, and find that the search effort of the employed is highly elastic. We show that search effort substantially amplifies labor market responses to productivity shocks over the business cycle.

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

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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 plays in search theories of the labor market, evidence on its extent and nature remains scant, much in contrast with the abundance of evidence on the job search behavior of the unemployed.

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

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

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

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

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

Our calibration replicates the empirical elasticity between search effort and wages observed in the data, which uniquely identifies the curvature of search costs in the model. In particular, we find that job search effort is more elastic than suggested by a quadratic search cost function—the most common assumption in the literature (e.g., Christensen et al., 2005; Hornstein et al., 2011). The elasticity we identify using our data has direct implications for how search intensity responds to changes in labor market conditions. To quantify the macroeconomic implications of this higher elasticity, we consider the economy's response to a negative aggregate productivity shock, which then reverts back to its initial level over time following Shimer (2005). We find that the resulting decline in employed workers' search effort in our experiment is over six times larger relative to a model with quadratic search costs, leading to substantial amplification of the declines in vacancies, labor market tightness and job-to-job transitions. As in Eeckhout and Lindenlaub (2019), the amplification is the result of a circular feedback between employed workers' search effort and firms' vacancy creation. Search effort also responds more strongly as labor market conditions improve, increasing the speed of reallocation to better jobs on the job ladder. Overall, our quantitative exercise highlights the importance of modeling search effort endogenously and with the appropriate elasticity to characterize labor market dynamics.

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

1.1 Related Literature

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

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

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

2 Survey Design and Data

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

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

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

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

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

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

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

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

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

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

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

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

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

3 Evidence on Job Search Behavior and Outcomes

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

3.1 Extensive and Intensive Margins of Job Search

We begin with evidence on the basic characteristics of individual job search effort. It is useful to analyze the extensive and intensive margins of job search separately since the distribution of total search effort along both dimensions is informative to appropriately measure search inputs. Table 1 reports the incidence of job search by labor force status at the time of the survey interview, which we interpret as the *extensive margin* of job search. By definition, all unemployed, save for those on temporary layoff, search. We employ a search-based definition of unemployment that is somewhat broader than the CPS definition, so we find that only a minimal fraction of those out of the labor force engage in search.[5] Among the employed, over 21 percent can be classified as searchers regardless of the criteria we employ to define job search. Over 22 percent of the employed looked for work in the last four weeks, with 21 percent applying to at least one job and a similar amount searching at least once in the last seven days. Around 22 percent of those searching on the job report looking for only part-time jobs. Among the employed, 36 percent of those actively searching (representing 9 percent of all employed) report only looking for an additional job, with no intention of leaving their current job. This is a notably large fraction since this type of job search is absent from nearly all models of on-the-job search. Though the fraction of those out of the labor force searching for work is small by definition, the majority of those that do seek work (51 percent) are only looking for part-time work. This is also notable since it suggests that individuals who transition to employment from out of the labor force are likely hired to different types of jobs than those hired while already in the labor force.

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 3.4 percent of the employed reported that they searched because they had been given advance notice, while 11.7 percent cited job instability. Another 7.9 percent cited a need to relocate. Note that respondents can cite more than one reason, so these percentages do not need to add up to 100. Overall, these answers are consistent with the notion that workers seek to move to more productive, better paid jobs through job-to-job transitions.

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

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

Table 1: Basic Job Search Statistics by Labor Force Status

	Employed	**Unemployed**	**Out of Labor Force**
Percent that actively searched for work	22.4	99.6	2.4
	(0.7)	(0.8)	(0.6)
Percent that actively searched and are available for work	13.2	99.6	0.0
	(0.6)	(0.5)	(0.0)
Percent reporting no active search or availability, but would take job if offered	5.9	0.2	6.1
	(0.4)	(0.3)	(0.9)
Percent applying to at least one vacancy in last four weeks	21.4	92.8	2.2
	(0.7)	(1.7)	(0.6)
Percent with positive time spent searching in last seven days	21.3	86.7	2.3
	(0.7)	(2.3)	(0.6)
Conditional on Active Search			
Percent only searching for an additional job	36.0	—	—
	(1.7)		
Percent only seeking part-time work	21.7	22.5	50.9
	(1.5)	(2.8)	(12.9)
Percent only seeking similar work (to most recent job)	25.3	7.4	33.7
	(1.7)	(1.8)	(14.3)
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.

about 8.5 applications in the *last four weeks*, on average.[6]

We can use a range of current and retrospective questions on labor force history to generate a labor force status for respondents four weeks prior to the survey interview. This allows us to deal with a selection issue whereby some employed at the time of the interview may report search activity that they performed while unemployed prior to their current job. This is particularly important for our measure on job applications sent, which reports all applications sent in the previous four weeks.[7] Using this measure of prior labor force status, we find that the differences in search intensity between the employed and unemployed are more stark. The employed who actively looked for work sent 4.1 applications in the subsequent four weeks while the unemployed sent 10.4 applications in the subsequent four weeks. If we ignore applications sent by the em-

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

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

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

	Employed			Unemployed	Out of Labor Force
	Looking for Work	Not Looking	All		
A. Labor Force Status at Time of Survey					
Hours spent searching, last 7 days	4.40	0.07	1.16	9.19	0.10
	(0.29)	(0.01)	(0.08)	(0.69)	(0.04)
Mean applications sent, last 4 weeks	4.17	0	1.06	8.50	0.09
	(0.31)	(—)	(0.08)	(1.01)	(0.04)
N	804	2,498	3,302	228	706
B. Labor Force Status in Prior Month					
Mean applications sent	4.08	0.00	1.03	10.39	0.47
	(0.30)	(0.00)	(0.08)	(1.37)	(0.09)
Mean applications sent, ignoring applications to additional jobs	3.06	0.00	0.77	10.39	0.47
	(0.29)	(0.00)	(0.08)	(1.37)	(0.09)
N	822	2,526	3,348	166	721

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

ployed only looking for additional work (i.e., work does not involve leaving their current job), the difference between the employed and unemployed is even more stark. These findings are remarkably similar to the statistics reported by Barron and Gilley (1981), who use a special survey of the unemployed in the CPS from May 1976. They find that the typical unemployed individual contacted over three employers *per week* and spent approximately eight and two-thirds hours *per week* to make such contacts.

Figure 1 shows the distributions of search time in the last seven days and the number of applications sent in the last four weeks for job seekers employed and unemployed at the time of the survey interview, conditional on searching in the last four weeks.[8] The left panel of the figure shows that the majority of employed job seekers (58 percent) sent two or fewer applications in the previous four weeks, while just over 26 percent of the unemployed sent more than 10 applications. The right panel of the figure shows that over 42 percent of employed job seekers searched for one hour or less within the last seven days, while over 81 percent of the unemployed searched for two

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

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

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

hours or more, with 37 percent searching 10 hours or more (compared to 13 percent of employed job seekers that searched for 10 hours or more). Despite both groups defined as actively looking for work, 25 percent of the employed and 13 percent of the unemployed performed no search within the last seven days, highlighting the intermittent nature of job search effort.

Comparison with other surveys. Empirical evidence on the incidence of on-the-job search is scarce and mostly comes from outdated surveys, making it hard to provide a good comparison for our estimates of search intensity. The American Time Use Survey (ATUS) is a recent survey that provides estimates of time spent on job search in the *prior day*, but there are reasons to believe that the ATUS understates job search intensity, particularly for the employed. Most importantly, time use surveys do not prompt participants to report their search activity, but instead simply ask participants to report how they spent their previous day, which likely leads respondents to underreport shorter episodes of job search. This issue seems particularly relevant for the employed, consistent with the large discrepancy that we find in the extensive margin for the employed between the ATUS and the SCE. In addition, the ATUS does not account for job search activity unless it is the respondent's primary activity, which may lead to understating search intensity, especially for the employed.

In Online Appendix C, we provide a detailed comparison of the ATUS data pooled over the 2013-2017 period with the SCE. We find that, in the ATUS, the employed only spend about 0.95 minutes per day (or 6.7 minutes per week) looking for work, while the unemployed spend 26.9 minutes per day (or 188 minutes per week) looking for work. These estimates contrast sharply with the evidence we report in Tables 1 and 2 for the SCE. We also find that only around 0.6 percent of the employed actively search for work on any given day according to the ATUS. The corresponding fraction is only 16.5 percent for the unemployed (who by definition had searched in the last four weeks), revealing the intermittent nature of search that makes it difficult to derive corresponding estimates of the extensive margin at the weekly horizon.

In Online Appendix C, we examine data from the ATUS, combined with supplemental evidence from the United Kingdom Time Use Survey (UKTUS), which reports job search activity on two consecutive days as well as time spent on secondary activities. The correlation of job search on two consecutive days allows us to infer the prevalence of intermittent search and derive a measure of the extensive margin at the weekly horizon. We use these data to derive weekly estimates of job search for the ATUS, which also include secondary activities. We find that differences in the weekly extensive-margin incidence of job search for the unemployed is comparable in the ATUS and SCE, but the ATUS estimates are still well below what we observe in the SCE data for the employed. Adjusting for secondary activities raises the average minutes of job search in the ATUS slightly from 6.7 to 8.0 minutes per week for the employed and from 188 to 213 minutes per week for the unemployed, which is still lower than the estimates in the SCE, particularly for the employed. We conclude that the survey instrument and to a lesser extent search as a secondary activity likely lead to a downward bias in estimates of search activity in time use surveys, especially for the employed. This is consistent with studies of time use survey measurement, which highlight the difficulty of accurately capturing intermittent and secondary activities in the context of home production (e.g., Floro and Miles, 2003).

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

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

activity," we find our estimates of search intensity reasonable and broadly in line with the limited comparable evidence on on-the-job search.

3.2 Search Intensity and Wages

A key implication of job ladder models is that workers near the bottom of the job ladder search harder for a better job while those near the top of the job ladder do not search as hard since their chances of improving upon their current job are smaller (see, for example, Christensen et al., 2005; Bagger and Lentz, 2019; and Moscarini and Postel-Vinay, 2019). While this relationship is at the heart of job-ladder models, one could not measure it empirically with a direct, reliable measure of search effort until the development of our survey.[10] Measurement error and unobserved worker heterogeneity in wages make it difficult to assess the exact position of a worker on the job ladder, but a worker's wage relative to her peers with similar observable characteristics should still provide a useful proxy. Therefore, we estimate a linear regression of the relationship between a worker's search behavior and her (log) current wage controlling for observable worker characteristics. Our estimates are in Table 3 and show that workers with lower wages in their current job are more likely to engage in search regardless of the measure of search activity that we use. In addition, the overall intensity of search activity, measured by the total number of applications in the last four weeks or the total hours spent searching the last seven days, is higher for workers with lower wages.[11] The estimates in the right columns of Table 3 imply a search effort-wage elasticity of -0.36 using applications sent and -0.52 using hours spent searching.

We also explore potential non-linearities in the search-wage relationship. Figure 2 shows the estimates from a locally weighted regression (LOWESS) between the different measures of search effort and the residualized current wage, i.e., the wage conditional on the controls from Table 3. The figure highlights the negative wage-search effort relationship in Table 3 for both the total number of applications and hours of search, and illustrates the quantitatively large decline in search effort from low to high residual wages.[12] There is some nonlinearity in the relationship for

45 percent of the employed report searching in the last twelve months using any active search method, including online job search.

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

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

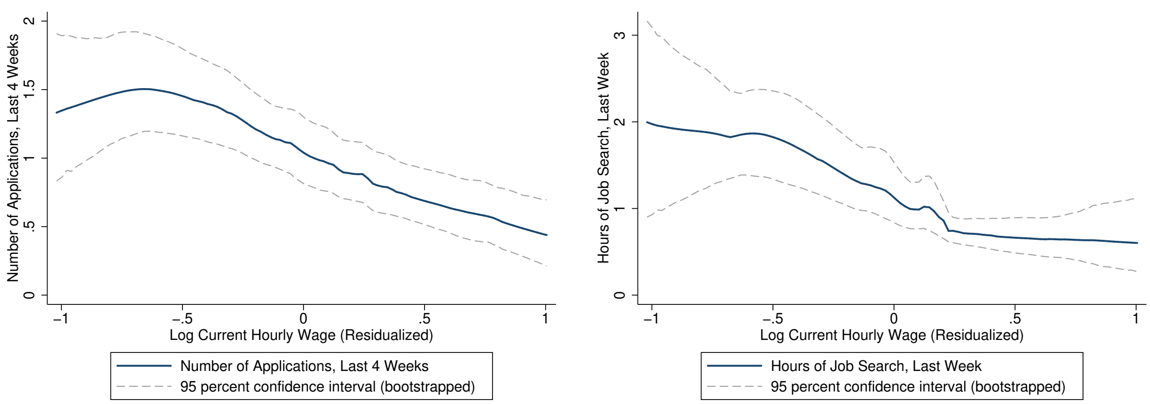
[12] In Supplemental Appendix S-B, we show that similar patterns hold for our measures of search intensity when

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

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

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

Figure 2: Job Search Effort by the Current Wage



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

low wages, but otherwise the relationship is close to linear. These plots provide direct evidence of declining search intensity with respect to current wages, a key implication of the job ladder models with endogenous search mentioned earlier.[13]

we do not control for observable characteristics in the wage.

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

Table 4: Job Search Outcomes by Labor Force Status

	Employed				Out of
	Looking for Work	Not Looking	All	Unemployed	Labor Force
A. All Search Outcomes					
Mean offers	0.417	0.115	0.191	0.666	0.130
	(0.033)	(0.023)	(0.019)	(0.286)	(0.024)
Fraction with at least one formal offer,	0.261	0.053	0.105	0.342	0.078
including unsolicited offers	(0.015)	(0.004)	(0.005)	(0.037)	(0.010)
Fraction with at least one	0.044	0.025	0.030	0.042	0.033
unsolicited offer	(0.007)	(0.003)	(0.003)	(0.016)	(0.007)
Fraction with at least one formal	0.318	0.094	0.150	0.370	0.089
or unrealized offer	(0.016)	(0.006)	(0.006)	(0.038)	(0.011)
Fraction of best formal offers accepted	0.460	0.111	0.328	0.493	0.195
	(0.036)	(0.027)	(0.027)	(0.069)	(0.052)
B. Ignoring Search Outcomes for Additional Jobs					
Mean offers	0.258	0.111	0.148	0.666	0.130
	(0.024)	(0.023)	(0.018)	(0.286)	(0.024)
Fraction with at least one formal offer,	0.173	0.051	0.081	0.342	0.079
including unsolicited offers	(0.013)	(0.004)	(0.005)	(0.037)	(0.010)
Fraction with at least one	0.030	0.024	0.026	0.042	0.033
unsolicited offer	(0.006)	(0.003)	(0.003)	(0.016)	(0.007)
Fraction with at least one formal	0.217	0.091	0.123	0.370	0.089
or unrealized offer	(0.014)	(0.006)	(0.006)	(0.038)	(0.011)
Fraction of best formal offers accepted	0.488	0.106	0.309	0.493	0.195
	(0.046)	(0.028)	(0.030)	(0.069)	(0.052)
N	822	2,526	3,348	166	721

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

3.3 Search Outcomes by Labor Force Status

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

Table 4 reports job offer estimates by labor force status in the prior month.[14] In Panel B, we also report estimates that exclude offers to those only looking for additional work. These estimates are most relevant for current models of labor market search since these models usually focus on job offers that lead to a job-to-job transition.

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

Panel A of Table 4 reports mean offers received in the last four weeks by labor force status in the prior month. The unemployed receive a somewhat higher number of offers than the subset of employed actively looking for work, on average, though the difference is not statistically significant. Keep in mind, too, that the unemployed search more than twice as much as those employed and actively looking. The employed not looking for work also receive a fair number of job offers, on average. In the data, the vast majority of respondents receive either zero or one offer, so outliers skewing the mean estimate is a concern.[15] Therefore, we also report the fraction of each labor force state that received any offer in the last four weeks. These estimates also show that a somewhat lower fraction of the employed actively looking for work received a formal job offer in the last four weeks than the unemployed, 26 percent compared to 34 percent, respectively. About 5 percent of the employed who were not looking for work and 8 percent of those out of the labor force also received a formal job offer in the last four weeks.

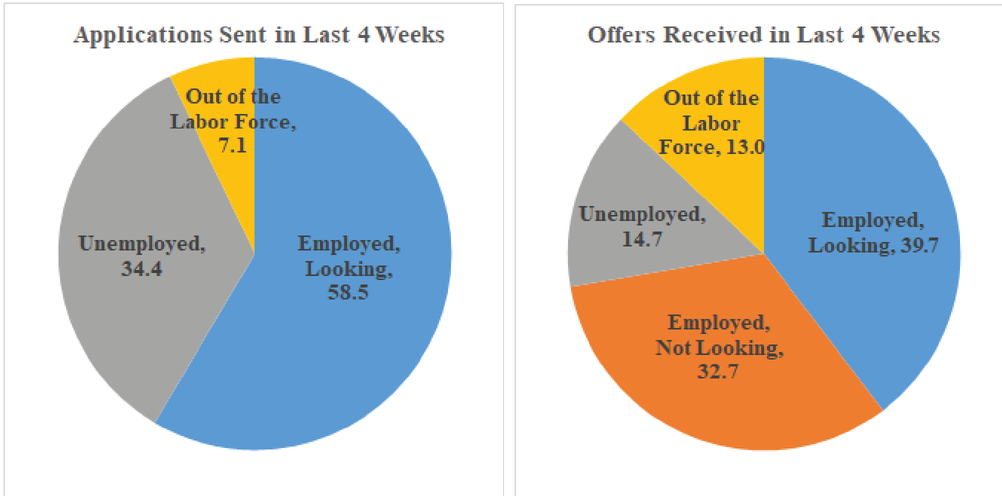
Just over 4 percent of both the employed looking for work and the unemployed received an *unsolicited* job offer. These are job offers that came about without a direct application by the job seeker. While these estimates are comparable in their arrival rates, they are quite different in terms of their share of all formal offers—they make up 17 percent of offers received by the employed looking for work, and 28 percent of offers received by all employed, but only 12 percent of offers received by the unemployed.

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

There are also notable differences in the rates at which the employed and unemployed *accept*

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

Figure 3: Distribution of Search Activity by Labor Force Status



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

formal job offers. The unemployed accept 49 percent of their best offers. In contrast, the employed accept 33 percent of their best offers. Table 4 shows that much of this difference is driven by low acceptance rates among the employed who did not look for work. Notably, however, the unemployed reject half of all offers received, suggesting that the unemployed actually receive a sizable number of unsuitable job offers.[16] The large fraction of rejections among the employed also suggests substantial randomness in the job search process. This is inconsistent with models of directed search, which imply an acceptance of all best offers.

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

Finally, we present the distribution of job applications sent and formal job offers received by labor force status in the prior month and search incidence.[17] These distributions provide

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

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

another way of characterizing the stark differences in search effort and search outcomes between the employed and unemployed. Figure 3 presents pie charts of the distributions. The unemployed make up just over 4 percent of our sample, but account for over 34 percent of all job applications sent. At the same time, they only receive 15 percent of all offers made. In stark contrast, the employed who report not looking for work send no applications by construction but receive around 33 percent of all job offers. In Supplemental Appendix S-B, we show that they receive an even higher share of *unsolicited* offers (59 percent). Those actively searching on the job account for 40 percent of all job offers. Thus, the job search behavior of the unemployed can be characterized by high effort but relatively low returns in terms of job offers. The employed, on the other hand, do fairly well regardless of whether they actually look for work. While the unemployed are seemingly less effective in their job search efforts, they are more likely to accept the offers they receive.

3.4 The Offer Yield by Labor Force Status

The differences in search effort and the returns to search between the employed and unemployed are stark. To quantify these differences, we introduce the concept of the *offer yield*, which we define as the incidence of an offer received per unit of search effort. We illustrate how important it is to have detailed data on search effort and search outcomes to properly compute the offer yield by computing the offer yield step by step. We then present differences in offer yields for different groups of workers. Note that our concept of offer yield does not take into account the quality of job offers, which we analyse in depth in the next subsection.[18]

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

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

The calculation implies that the employed are only 15 percent as effective as the unemployed in job search, or inversely, that the unemployed have a 6.8 times higher yield to their search effort.[19]

[18] One can interpret the offer yield as the job-search analog to the vacancy yield in Davis, Faberman and Haltiwanger (2013), which provides a similar reduced-form construct for examining employer recruiting behavior.

[19] Note that transition rates from the CPS would suggest an even higher level of search efficiency for the unem-

This calculation assumes that the employed and unemployed exert the same level of search effort and have identical job acceptance rates—neither of which are supported by our data. Our data allow us to directly observe the incidence of offer arrivals that we can use instead of realized transition rates. In this case, let λ_e be the offer arrival rate of the employed and λ_u be the offer arrival rate of the unemployed. The calculation of the relative offer yield is then:

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

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

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

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

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

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

ployed over this period. In the CPS, the job-finding rate of the unemployed is 24.0 percent while the job-to-job transition rate is 1.9 to 2.3 percent (depending on the estimation method used, see Fujita et al., 2019), implying that the unemployed are 10.4 to 12.6 times more effective at search than the employed.

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

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

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

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

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

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

	Number of Applications Sent, s	**Fraction with an Offer, λ**	**Offer Yield, λ/s**	**Relative Offer Yield, $\frac{\lambda_e/s_e}{\lambda_u/s_u}$**
Panel A. Employment Status				
All Employed				
All formal offers	1.03	0.106	0.103	3.13
...excluding search for addl. work	0.77	0.081	0.106	3.22
All formal and unrealized offers	1.03	0.150	0.146	4.48
...excluding search for addl. work	0.77	0.123	0.160	4.12
Part-Time Employed				
All formal offers	1.91	0.181	0.094	2.87
...excluding search for addl. work	1.00	0.130	0.130	3.96
All formal and unrealized offers	1.91	0.217	0.113	3.19
...excluding search for addl. work	1.00	0.165	0.165	4.62
Unemployed				
All formal offers	10.4	0.342	0.033	—
All formal and unrealized offers	10.4	0.370	0.036	—
Panel B. Demographics				
Age 18 to 39	1.26	0.102	0.080	2.94
Age 40 to 54	1.29	0.101	0.078	3.33
Age 55 to 64	0.76	0.070	0.093	3.84
Male	1.05	0.088	0.084	3.06
Female	1.20	0.096	0.080	3.33
White	0.93	0.082	0.088	3.82
Non-White	1.67	0.121	0.072	2.52
Less than college	1.08	0.098	0.091	3.30
College or more	1.13	0.077	0.068	3.52

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

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

3.5 Characteristics of Job Offers and Accepted Jobs

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

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

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

3.5.1 Job Offer Characteristics by Employment Status

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

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

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

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

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

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

	Employed at Offer	**Non-Employed at Offer**	**Difference, E - NE**
Percent of job offers	72.1	27.9	
Offer Wage Estimates			
log real offer wage,	2.977	2.615	0.362
unconditional	(0.031)	(0.047)	(0.101)
Controlling for worker & job	2.933	2.739	0.194
characteristics	(0.026)	(0.031)	(0.048)
Additional Job Offer Characteristics			
log offer usual hours	3.396	3.269	0.126
	(0.025)	(0.038)	(0.059)
Pct. of offers with no benefits	40.5	62.0	-21.5
	(1.7)	(3.0)	(4.8)
Pct. of offers through an unsolicited	25.0	15.9	9.1
contact	(1.5)	(2.3)	(3.5)
Pct. of offers with some counter-offer	12.3	—	—
given	(1.2)		
Pct. of offers that involved bargaining	38.0	25.8	12.2
	(1.7)	(2.7)	(4.3)
Pct. of offers accepted as only option,	7.7	26.5	-18.8
conditional on acceptance	(1.6)	(3.9)	(8.0)
Accepted Wage Estimates			
log real accepted wage,	3.000	2.542	0.458
unconditional	(0.042)	(0.068)	(0.170)
Controlling for worker & job	2.906	2.710	0.195
characteristics	(0.029)	(0.033)	(0.065)
Prior-Job Wage Estimates			
log real prior wage,	2.881	2.758	0.122
unconditional	(0.041)	(0.053)	(0.088)
Controlling for worker & job	2.840	2.832	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. Robust standard errors are in parentheses.

raise, or some added job benefit, occurred for about 12 percent of the employed who received an offer from an outside firm.

As we showed in Table 4, the unemployed are about one-and-a-half times more likely than the employed to accept a job offer. Table 6 shows that a primary reason the unemployed are more likely to accept what turn out to be relatively poor job offers is a perceived lack of alternative options—nearly 27 percent of those non-employed when they receive an offer cite a lack of other alternatives as the main reason for their acceptance; only 8 percent of the employed cite this as their primary reason. If we focus on accepted wages instead of offered wages, we find similar wag gaps in favor of the employed. They accept wages that are 46 log points (58 percent) higher than the accepted wages of the non-employed, unconditionally, and 20 log points (22 percent) higher than the accepted wages of the non-employed when controlling for observed worker and job characteristics, nearly identical to the residual offered wage gap.

The bottom panel of Table 6 reports prior-job wages for those who received an offer, with and without controls for observable characteristics. For the employed, it is the wage earned *prior to* their current job, while for the non-employed, it is the wage earned in their most recent job. Unconditionally, the prior wages of the employed are 12 log points (13 percent) higher than the prior wages of the non-employed, but conditional on observables the difference is essentially zero. That is, despite our finding of a large differential in offered wages, we find almost no difference in residual prior wages. This suggests that unobserved worker heterogeneity cannot explain entirely the differential in offered wages, though differences in prior wages could also be driven by unobserved match quality. In our model's calibration, we use the residual prior-wage differential to discipline the difference in unobserved worker quality between the employed and unemployed, taking into account that the prior wage reflects additional factors such as the quality of the match of the prior job.

3.5.2 Accounting for Differences in Offered Wages

We can dig deeper into the wage offer differential between the employed and non-employed using a rich set of additional survey questions. Our estimates in Table 6 imply that observable worker and job characteristics account for 46 percent of the unconditional wage offer differential. For clarity, we show these results again in Rows (a) and (b) of Table 7. Differences in worker characteristics such as education and age are the most important observables in accounting for the wage offer gap. The differential that remains after controlling for both worker and job characteristics may reflect differences that are observed by employers but unobserved in our data. For example, workers may differ in communication or time-management skills that make them more likely to be employed and earn a higher wage. This creates a selection effect that would naturally generate a wage offer gap. An individual's prior work history can provide a useful proxy for such unobserved heterogeneity because it reflects repeated labor market outcomes determined at least partly by their unobserved skills. Our survey asks about an individual's labor force history over the previous five years. As Row (c) of Table 7 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 in Row (d), the difference falls somewhat more to 0.127, implying that labor force history can account for an additional 19 percent of the (unconditional) wage offer gap. As we noted, prior wages of workers can also reflect workers' unobserved skills. Additionally controlling for the prior wage of workers in Row (e) of Table 7 actually *widens* the wage offer gap. In our model calibration, we show that this occurs because most of the employed who receive a job offer are near the bottom of the job ladder. Thus, the model implies that controlling for the prior wage does not fully account for unobserved differences in productivity since the prior wage also captures the position on the job ladder.

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

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

Table 7: Offer Wage Gap Estimates, Additional Controls.

Offer Wage Gap Estimates	**E-NE**
(a) Log real offer wage, unconditional	0.362
	(0.101)
(b) Log real offer wage, controlling for observable worker & job characteristics	0.194
	(0.048)
(c) Log real offer wage, controlling for observable worker & job characteristics,	0.132
and employment history	(0.047)
(d) Log real offer wage, controlling for observable worker & job characteristics,	0.127
and labor force (LF) history	(0.047)
(e) Log real offer wage, controlling for observable worker & job characteristics,	0.193
LF history, and prior wage	(0.058)
(f) Log real offer wage, controlling for observable worker & job characteristics,	0.186
LF history, prior wage, 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. Observable worker and job characteristics controlled for in the conditional wage estimates include fixed effects for survey year and state, demographic controls such as 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, two-digit SOC occupation of the job and six categories of the firm size of the potential employer. 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. Robust standard errors are in parentheses.

reduces the offered wage gap by about two-thirds, a substantial gap between the wages offered to the employed and non-employed remains.

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

Finally, bargaining and counter-offers are additional ways the search process can affect the wage offer gap. We find that the employed are more likely to bargain with the potential employer and 12 percent of them received some form of counter-offer from their current employer. While the latter estimate falls short of the rate of counter-offers in models such as Postel-Vinay and

Robin (2002) and Cahuc, Postel-Vinay, and Robin (2006), it is possible that the threat of such counter-offers could affect the wage offer gap. We quantify how much bargaining and other aspects of the job offer process affect this gap in our quantitative framework in the next section.

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

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

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

4.1 Model Setup

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

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

Job Search and Production. Matching between firms and workers is random across both labor force status i and productivity x of the worker and is governed by a matching function $M(S;v)$ which satisfies the standard properties.[28] Labor market tightness, $\theta = v/S$, is defined as vacancies, v, per effective number of searchers, S, which weighs job seekers as defined further below (where we characterize firms' vacancy posting decision). Workers receive offers at a rate $\lambda_i(s)\lambda(\theta)$ which depends on their labor force status, search effort, s, and the equilibrium arrival rate of offers per unit of search, $\lambda(\theta) = M(1;\theta)$. Search effort has an increasing, convex cost, $c(\cdot)$, that may vary by labor force status, with $c_i', c_i'' > 0$ and $c_i(0) = c_i'(0) = 0$. When a worker and a firm meet, a match-specific productivity y is drawn from a distribution $F(\cdot)$, which is assumed to be fixed over the duration of the match. The output of the match is pyx, where p is aggregate productivity and is assumed to be constant.[29] Job matches are subject to exogenous separation shocks, $\delta(x)$, which depend on a worker's productivity and an exogenous job reallocation shock, δ_0. Workers who are subject to a reallocation shock sample an outside offer from the offer distribution $F(\cdot)$ and flow into unemployment if they reject the offer.

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

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

where $\tilde{\delta}_0(x,\theta) = (1-\delta(x))\delta_0\lambda(\theta)$ and $\tilde{\lambda}_e(s,x,\theta) = (1-\delta(x))(1-\delta_0)\lambda_e(s)\lambda(\theta)$.[31] A worker who receives an exogenous separation shock flows into unemployment. If a worker receives a

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

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

[30] The reason is that with jointly optimal search and separation behavior, the standard linear Nash-Bargaining rule applies, see Supplemental Appendix S-C.1.2. We also consider a partial equilibrium model where the worker unilaterally chooses search effort in an earlier version of our paper in Faberman et al. (2017).

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

reallocation shock δ_0, she samples an outside offer and accepts it if the offered wage is above the optimal reservation productivity $R_\delta(x)$. In the absence of separation or reallocation shocks, the worker samples an outside offer with probability $\tilde{\lambda}_e(s, x, \theta)$ from the distribution $F(\cdot)$ and accepts the offer if its match-specific productivity is above the optimal reservation productivity, $R_e(y, x)$.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

4.2 Parameterization and Targeted Moments

We calibrate the model to our 2013-2017 data and set its frequency to be monthly, with the discount rate set to match an annual interest rate of 4 percent. Table 9 lists the calibrated parameters as well as their respective calibration targets. Panel A lists the parameters that were normalized or parameterized based on an external target, whereas Panel B lists the 15 parameters that were chosen to match the 15 moments listed in Table 8. While the latter are jointly calibrated, there is one moment for each parameter that varies strongly with that parameter and thus the system is exactly identified.[34]

Search Technology. We match parameters that govern search technology to key moments computed using our survey, as shown in Table 8.[35] We use the total formal and unsolicited offer rates of the employed and unemployed from Table 4 to match the intercept and slope of a linear job offer arrival function, $\lambda_i(s) = \alpha_i + \beta_i s$. The aggregate matching function is Cobb-Douglas, $M(S; v) = \mu S^{(1-\eta)} v^{\eta}$. We set the censoring parameter χ_i to match the average rate of censored/unrealized offers by employment status in the data.

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

Productivity and Wages. Match-specific productivity, y, is assumed to follow a log-normal distribution with a standard deviation of 0.27, which—conditional on individual-specific produc-

[34]See the Appendix D.3 and the Supplemental Appendix S-C.3 for details.

[35]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.

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

Moment	Data	Model	Moment	Data	Model
Search effort (U, E)	10.39, 0.769	10.39, 0.769	Search-wage elasticity	-0.36	-0.36
Unsolicited offer rate (U, E)	0.042, 0.026	0.042, 0.026	Stdev. of wage offers	0.679	0.678
Formal offer rate (U, E)	0.342, 0.081	0.342, 0.081	Offer wage diff. (E-U)	0.194	0.193
Censored offer rate (U, E)	0.028, 0.041	0.028, 0.041	Prior wage diff. (E-U)	0.008	0.008
Acceptance Rate (U, E)	0.494, 0.309	0.494, 0.309	Unemployment rate	0.068	0.068

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

tivity x—yields a standard deviation of log wage offers of 0.24 as in Hall and Mueller (2018).[36] We also assume that observed wages are subject to i.i.d. measurement error $\varepsilon_w \sim N(0, \sigma_{\varepsilon_w})$. Consistent with Bound and Krueger (1991), we assume a moderate degree of measurement error and set $\sigma^2_{\varepsilon_w}$ to 13 percent of the unconditional variance in offered wages. We set the elasticities of the matching function and the bargaining share to 0.5 following Petrongolo and Pissarides (2001) and consider deviations of the unemployed's bargaining share from this value.

We parameterize the extent of heterogeneity in our model by assuming that there are 10 types of workers who differ by a productivity-shifting parameter x. The distribution of types approximates a log-normal distribution with standard deviation σ_x over the interval $[-2\sigma_x, 2\sigma_x]$. We parameterize σ_x to match the standard deviation of our residual wage offer estimates since our goal is to quantify the role of *unobserved* heterogeneity. We set the unemployed worker's bargaining share, τ_u, to match the gap in residualized wages between the employed and non-employed.[37] Note that even with $\tau_u = \tau_e = 0.5$, the model predicts a wage offer premium for the employed due to their better outside options. Our estimate of $\tau_u = 0.4$ implies that the differences in outside options alone are insufficient to match the observed wage offer differential. This estimate is in line with our evidence in Table 6 that shows that unemployed workers engage less frequently in bargaining compared to the employed. Not surprisingly, our calibration of the χ_i parameters imply a much larger fraction of censored offers among the employed, as their unrealized offer rate in the data is much higher relative to their formal offer rate (see Table 4).

Separation and Reallocation Shocks. We target the average separation rate to match an

[36]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.

[37]Note that our target of the wage offer differential controls for two-digit occupation effects. While an occupation may represent a position on the job ladder, which would argue against controlling for it, it also represents heterogeneity in skills required to perform a job. The latter connects better to the notion of job ladder in our model, which is the productivity of the match, conditional on worker skills.

Table 9: Calibrated Parameter Values in Model

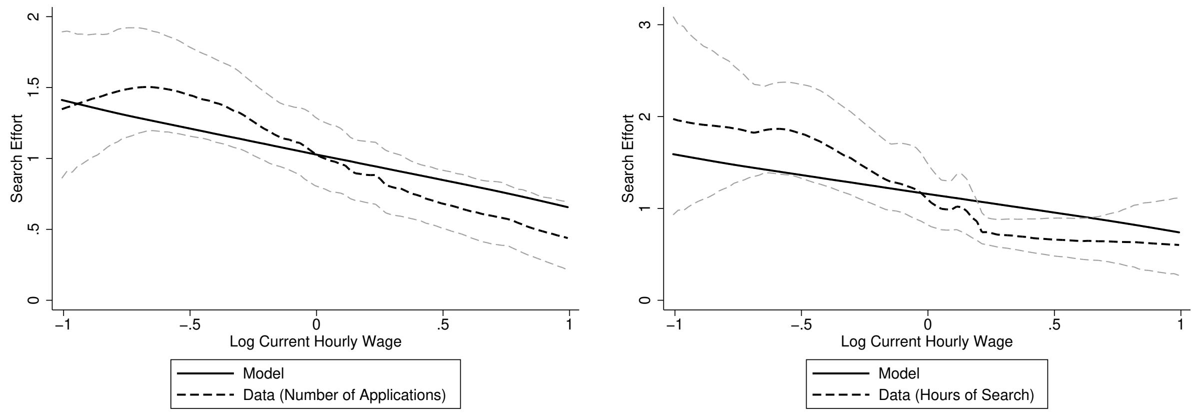
Symbol	Parameter Description	Value	Source/Target
A. Externally calibrated parameters and normalizations			
Symbol	Parameter Description	Value	Source/Target
r	Monthly interest rate	0.34%	Annual interest rate of 4%
c	Vacancy posting cost	0.80	$\theta = 1$
μ	Matching efficiency	1.00	Normalization
η	Elasticity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

unemployment rate of 6.8%, which is the sample average for 2013-2017 in the SCE. We allow separation rates to vary by worker type x, which is consistent with the well-known fact that differences in unemployment rates across skill groups are driven primarily by separations rather than job finding. We assume $\delta(x) = \delta - \delta_x \ln(x)$, which results in a value of 0.0123 for the average separation rate, δ. We parameterize δ_x by matching the difference in residual prior wages of 0.008 between the employed and unemployed in Table 6. Intuitively, as δ_x increases, there is greater negative selection among the unemployed and thus a lower average prior wage of the unemployed.[38]

We calibrate the reallocation shock, δ_0, to match the acceptance rate of employed workers in the data, which is 0.309. For a given formal offer rate, this strategy implicitly targets the job-to-job transition rate of 0.025 in the data and implies a relatively modest rate of reallocation

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

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



Notes: We rescale search effort in the model such that averages are the same in the model and data. The dashed lines show the 95 percent confidence interval (bootstrapped with 500 replications).

of 1% per month, corresponding to about 8 percent of all employed offers.[39] This number is in line with our data, where 11 percent of employed searchers indicate that their main reason for on-the-job search was either a relocation or advance notice of a layoff. We believe our approach to identifying the reallocation rate is more plausible than in the literature, which typically relies on matching the fraction of job-to-job transitions associated with a wage decline which could also be due to measurement error, differences in wage-tenure profiles (e.g., Cahuc et al., 2006) or non-wage amenities (e.g., Sorkin, 2018).

Flow Value of Unemployment. We define the flow value of unemployment as the fraction of average productivity net of average search costs, $z = E(b - c_u(s_u(x)))/E(py - c_e(s_e(y, x))$, and set it to match the acceptance rate of the unemployed, implicitly pinning down a value for the parameter b. By construction, this strategy matches the job-finding rate of 0.169 in the data.[40]

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

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

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

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

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

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

4.3 Model Fit and Micro Implications

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

Fit of the Search Effort-Wage Relationship. A key implication of on-the-job search models with endogenous search effort is that employed workers will reduce their search effort as they climb the job ladder. We explicitly target the search-wage elasticity, which identifies the elasticity of search costs with respect to search effort through γ. The evidence in Figure 2 shows that the fit of the relationship is clearly negative between different measures of search effort and the worker's current wage. In Figure 4, we compare the relationship implied by a simulation of our model to its counterpart from our survey data. The model produces a good fit to the data with the model-implied relationship generally lying within the 95 percent confidence interval. Note that the fit is particularly good for applications, which is our target measure of search effort. Adjusting γ to further improve the fit in Figure 4 would imply an even higher value for γ and thus make search effort even more responsive to labor market conditions.[41] Overall, we view this as clear evidence in support of models with endogenous search effort.

Wage Offer Premium of the Employed. In Section 3.5.2, we examined how much of the wage offer differential between the employed and unemployed could be accounted for by a rich set of controls. We match this differential in our calibrated model, which allows us to decompose the differential into three parts: the part due to unobserved heterogeneity, the part due to censoring of the wage offer distribution, and a residual that we attribute to bargaining. Table 10 shows that the model attributes 11.8 log points (61 percent) of the 19.3 log point residual

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

wage offer differential to unobserved heterogeneity. This represents 33 percent of the 36.2 log point unconditional wage offer differential. The contribution of censoring is smaller because job offers are concentrated among employed workers who are at the bottom of the job ladder. The contribution of bargaining accounts for the remaining 3.9 log points, which is due to both better outside options of employed workers and the lower bargaining weight of unemployed workers. This represents 20 percent of the residual wage offer gap and 11 percent of the unconditional wage offer gap. The main takeaway is that negative selection into unemployment accounts for over 60 percent of the wage offer differential observed in the data but leaves a non-trivial fraction accounted for by censoring and bargaining.

Additionally, our model predicts a correlation between *ex ante* unobserved heterogeneity and labor force histories, which can provide guidance for addressing unobserved heterogeneity in empirical work. The model implies that low-x workers are not only more likely to be *currently* unemployed, but also less likely to have worked *in the past*. This suggests that an individual's *work history* is a useful proxy for unobserved heterogeneity. As we showed in Table 7, controlling for the fraction of the last five years that someone was employed reduces the residual wage offer gap from 0.194 to 0.132. We implement the same regression analysis on model-simulated data and find that the wage offer gap falls from 0.193 to 0.132, which is essentially identical to what we observe empirically. Controlling for work history in our simulation-based regression accounts for about half of the contribution of differences in x and shows the usefulness of labor force history as a control for unobserved heterogeneity.[42]

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 search and matching model can only account for a tiny fraction of the wage dispersion observed in the data. They show that extending the model to include on-the-job search can generate a higher degree of wage dispersion but the success of the model depends on the *efficiency of on-the-job search* relative to unemployed search—for which we did not have data until our survey. Consistent with their intuition, our model generates a mean-min ratio of 1.56, within the range of empirical values for the mean-min ratio (see Hornstein et

[42]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.

al., 2006, who estimate a range between 1.48 and 1.83). Even though there are ongoing empirical debates about the extent of *frictional* wage dispersion because of the difficulties to parse out unobservable worker effects from empirical measures of wage dispersion, it is remarkable that our model generates substantial wage dispersion while yielding a reasonable value for the flow utility of unemployment (net of search costs) of 0.66, in line with Hall and Milgrom (2008) and Mas and Pallais (2019). Attempts to match the observed wage dispersion typically require very low or even negative values for this parameter (see Hornstein et al., 2011).[43] Intuitively, our model does well in this respect because the *higher search efficiency of the employed* implied by our findings limits the option value of unemployment. The unemployed perceive little value in waiting for a better offer if they can sample better offers and search more efficiently while employed. Consequently, they are willing to accept lower-wage offers despite a high value of unemployment, increasing the dispersion of realized wages from below.

4.4 Search Effort as an Amplification Mechanism

Finally, we use our model to quantify the responsiveness of key labor market statistics to business cycle shocks. To this purpose, we consider an economy that is in stationary equilibrium and subject it to a one-time, unexpected decline in aggregate productivity that reverts back to its initial level over time. We calibrate the productivity shock as a 4 percent drop with an auto-correlation of 0.95, as seen in Panel (a) in Figure 5. This shock corresponds to a two-standard deviation shock to productivity, as reported by Shimer (2005), and matches the quarterly auto-correlation in the same paper.[44] In Supplemental Appendix S-C, we define the equilibrium of this economy with perfect foresight of the future path of p.[45]

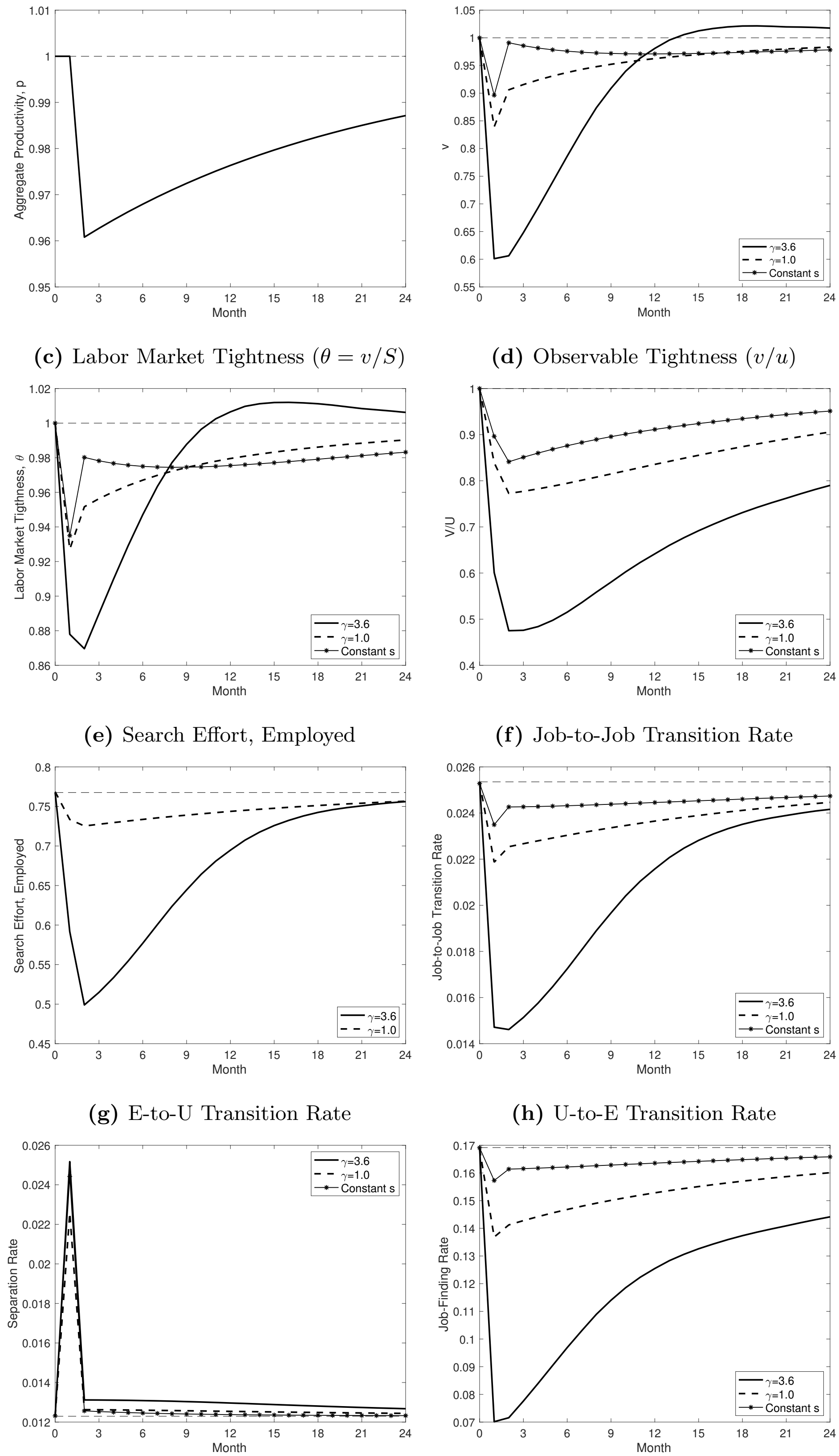
We consider the effects of an unexpected aggregate productivity shock for three different specifications: (1) our baseline model with $\gamma = 3.6$, (2) a model with quadratic search costs

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

[44] Supplemental Appendix Figure S-C1 shows that the equilibrium dynamics of the key variables in the model are approximately linear in the size and sign of the shock, which is a useful robustness check recommended by Boppart, Krusell and Mitman (2018).

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

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



(a) Aggregate Productivity

(b) Vacancies

(c) Labor Market Tightness ($\theta = v/S$)

(d) Observable Tightness (v/u)

(e) Search Effort, Employed

(f) Job-to-Job Transition Rate

(g) E-to-U Transition Rate

(h) U-to-E Transition Rate

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

(i.e., $\gamma = 1$), and (3) a model with exogenous job search. We recalibrate the parameters in the alternative specifications to match the same moments from Table 8 with the exception of the elasticity of search effort to wages. Quadratic search costs imply an elasticity of -0.21, which is below its empirical counterpart of -0.36.[46]

Panel (b) in Figure 5 shows that the response of vacancies varies considerably across specifications. Vacancies drop by 40% in response to the 4% drop in aggregate productivity in our baseline specification with $\gamma = 3.6$. This is perfectly in line with Shimer (2005), who shows that the standard deviation of the cyclical variation in vacancies is 10 times that of aggregate productivity. In contrast, the response of vacancies is muted in economies with exogenous search effort and $\gamma = 1$. Panel (c) shows that labor market tightness decreases on impact by 13% in the economy with $\gamma = 3.6$, which is substantial and much larger than in the other two economies. Note that labor market tightness is defined as vacancies per number of effective job seekers and does not have a direct empirical counterpart. Panel (d) shows a large drop in the the vacancy-to-unemployment ratio, v/u, which is the traditional measure of labor market tightness. It falls by around 54%—14 times the drop in productivity—in the case where $\gamma = 3.6$. The decline is comparable to Shimer (2005), who reports that the standard deviation of the cyclical variation in v/u is 19 times that of aggregate productivity.

Endogenous and highly elastic job search effort is key to the success of the model. As Panel (e) of Figure 5 shows, employed workers' search effort drops sharply as a result of the negative productivity shock with $\gamma = 3.6$. This is because the negative productivity shock and the reduction in labor market tightness both cause a decline in the marginal returns to search. The sharp decline in workers' search effort causes a further reduction in firms' incentive to post vacancies. As in Eeckhout and Lindenlaub (2019), the feedback between employed workers' search effort and firms' vacancy creation incentive amplifies the economy's response to a negative productivity shock and generates empirically plausible declines in vacancies. Panel (f) of Figure 5 shows that elastic search effort also considerably amplifies the decline in job-to-job transitions. The strength of amplification depends on the value of γ because workers' responsiveness to changes in the returns to search depends on how elastic their search effort is.

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

The model also generates large responses of the flows between unemployment and employment. Panel (g) of Figure 5 shows that the separation rate from employment to unemployment doubles at the onset of the negative shock as a consequence of the rise in $R_u(x)$, the reservation productivity. Panel (h) shows that the job-finding rate (U-to-E) declines by about 60% and this decline is persistent. The sharp but short-lived increase in separations into unemployment and persistent declines in the job-finding rate are important features of labor market flows in the US.[47] Our model captures these empirical regularities both qualitatively and quantitatively.[48] As a result, unemployment's response to the negative productivity shock is asymmetric, with the unemployment rate rising fast from 6.8% to 10.6% but declining only slowly as shown in D1 in Online Appendix D.[49] Again, the cases with exogenous search or $\gamma = 1$ generate a smaller response in the job-finding rate than the case with $\gamma = 3.6$.

As aggregate productivity gradually returns to its pre-recession value, employed search effort and job-to-job transition rate gradually return to their previous levels. Interestingly, vacancies and labor market tightness overshoot their pre-recession level, which is due to shifts in the unemployment rate and in the distribution of workers across the job ladder. As the economy recovers, more unemployed workers find jobs, but predominantly at the bottom of the ladder. This shifts the distribution of job seekers towards low-productivity jobs where workers exert high search effort. From the perspective of the firm, workers who are unemployed or employed but at the bottom of the productivity distribution yield the highest expected profits. We summarize the joint dynamics of labor market tightness and unemployment in Figure D2 of Online Appendix D by plotting the Beveridge curve using both the model-based market tightness, $\theta = \frac{v}{S}$, and observable tightness, $\frac{v}{u}$. As in Eeckhout and Lindenlaub (2019), we find a circular movement in the (u, θ)-space in Panel (a) of Figure D2. Interestingly, the relationship becomes more clearly negative when we plot the dynamics in the (u, $\frac{v}{u}$)-space.

The key takeaway is that a job ladder model with highly elastic search effort—as implied by our empirical evidence—considerably amplifies business cycle fluctuations in key labor market indicators. Highly elastic search effort also suggests that workers reallocate to better jobs more

[47] See, for example, Elsby, Hobijn and Şahin, 2015.

[48] The Figure D1 also shows the effects of the productivity shock on the search effort of the unemployed and reservation productivity.

[49] The 56 percent increase in the unemployment rate is also consistent with Shimer (2005), who shows that the standard deviation of the cyclical variation in the unemployment rate is 10 times that of aggregate productivity.

quickly than what quadratic search costs or models that abstract from endogenous search effort would imply. While our model does very well in terms of matching the amplification and volatility in response to this negative shock, we note that it does so with only mixed success in matching propagation. Interestingly, we find that our model's implications for amplification are not driven by a high elasticity of job search when unemployed. We still find substantial amplification even when we set $\gamma = 1$ for the unemployed, but leave $\gamma = 3.6$ for the employed (see Online Appendix D). The reason is that search effort among the employed drops sharply, particularly for those at the bottom of the ladder, which reduces firms' incentives to post vacancies.

5 Concluding Remarks

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

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

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

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

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