UNEMPLOYMENT INSURANCE:

Disincentive Effects on Job Search in the Great Recession

Senior economics paper by

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Abstract

Unemployment insurance (UI) benefits were extended during the Great Recession from 26 weeks to up to 99 weeks. In the years following, various studies have leveraged this unprecedented expansion of UI benefits in order to quantify the disincentive effects of UI on job search. Most studies indirectly examined the disincentive effects by using proxy measures such as unemployment duration or unemployment rate and have reached a wide range of conclusions from little to great measurable disincentive effect. In this paper, I take an alternative approach, using time-use data to directly quantify job search effort. I explore the effects of various specifications of the returns to search, macroeconomic conditions, and demographic characteristics on job search effort, at both the extensive and intensive margins of job search. Several results emerge. First, UI eligibility alone does not meaningfully impact job search effort. Second, raising unemployment benefit levels disincentivizes job search such that a 10% increase in the weekly maximum benefit amount is associated with a 5% decrease in daily job search time. Third, surprisingly, increasing UI duration does not significantly disincentivize, and may even incentivize job search effort. Finally, job search effort is procyclical, where a one percentage point increase in unemployment rate is associated with a 12% decrease in daily job search time. Taken together, these results imply that UI benefit extensions play an important counter-recessionary role and that fears of its disincentive effects are largely overblown.

I. Introduction

Unemployment insurance (UI) is a social welfare program that provides weekly payments up to a certain number of weeks to those who are unemployed through no fault of their own. As with most social welfare programs, its role is somewhat controversial. Proponents argue that UI plays an important part in the social welfare safety net; for example, Chetty (2008) identified the role UI played in smoothing consumption across liquidity-constrained individuals. Detractors, however, point to the moral hazard cost of UI, where individuals whose unemployment is subsidized by UI face reduced incentives to search for work (Chetty 2008). Quantifying this disincentive effect of UI has been of great interest to public economists and has been studied extensively over the past several decades. In this section, I'll begin with an overview of the unemployment insurance program, then briefly outline some of the important UI research that has emerged in the past decade before describing my own contributions to the literature.

1.1 Unemployment insurance

In brief, unemployment insurance is a joint federal-state program funded by state payroll taxes and individually administered by each state; as such, UI policy—including UI eligibility, UI benefit levels and UI benefit durations—varies from state to state. In general, during non-recessionary periods, most states allot 26 weeks of UI benefits (Rothstein 2011). Benefit levels are usually set at some replacement wage percentage up to a maximum cap for weekly benefit amounts (maximum weekly benefit amount, or maximum WBA). In some states, this maximum WBA is indexed to average wages in the state (Meyer 1989). In addition, certain requirements must be met in order to qualify for UI. First, the individual must be unemployed through no fault of their own; job quitters, new labor market entrants and labor market re-entrants cannot receive

UI benefits while job losers and the temporarily unemployed can (Daly, et al. 2011). Second, unemployed individuals must be actively searching for work to be eligible for UI benefits, though the requirements and verification procedures for “actively searching” vary from state to state (“Meeting Eligibility Requirements”). Third, should the unemployed individual receive a job offer, he or she must accept the job (“Meeting Eligibility Requirements”).

While unemployed individuals can generally claim UI for up to 26 weeks, several circumstances can prolong the UI benefit duration available (Rothstein 2011). For one, most states have adopted “triggers” under the federal Extended Benefits (EB) program that automatically extend UI duration by up to 20 weeks under deteriorating state labor market conditions (Rothstein 2011). Furthermore, during the Great Recession, Congress intervened three separate times to further extend unemployment insurance benefits through the Emergency Unemployment Compensation (EUC) program (Rothstein 2011). Thus, in addition to the regular 26 weeks of UI benefits and the 20 weeks of benefits under the EB program, some individuals in certain cases qualified for up to 99 weeks of UI benefits (Rothstein 2011). A UI benefits extension of this magnitude was unprecedented at the time and led to criticisms that UI benefits had become too generous.

In part due to these criticisms, Congress failed to continue the UI benefit extensions when the issue was last debated at the beginning of 2014. A chorus of Republican politicians criticized the generosity of UI benefits and charged that “the extended benefits are a disincentive for people to find jobs,” illustrating policymaker concerns about the magnitude of the disincentive effect of unemployment insurance (Barrett 2014). Quantifying the magnitude of the UI disincentive effect thus becomes important, as it directly drives UI policymaking.

1.2 Prior research

Most economic studies in the past decade have sought to indirectly quantify the disincentive effects of UI benefits by observing their impact on unemployment. Through a variety of different methods, these studies primarily leveraged the unprecedented extension of UI benefit durations during the Great Recession as the source of variation to determine if the increase in UI benefit duration raised the unemployment rate, and if so, by how much (Daly, et al. 2011; Farber & Valletta 2013; Fujita 2011; Rothstein 2011). The range of the estimated unemployment rate increase due to UI benefit extensions differed greatly: on the low end, Rothstein (2011) found that the extensions only increased the unemployment rate by 0.1 to 0.5 percentage points; on the other end of the spectrum, Fujita (2010) found an effect nearly ten times greater, where the benefit extensions raised the unemployment rate by 1.2 percentage points.

The primary drawback of indirectly examining the UI disincentive effect through the unemployment rate is the inherent endogeneity between UI generosity and labor market conditions: UI benefits were only extended during the Great Recession because of rising unemployment, which makes identifying the causal effect of increasing UI generosity on unemployment rate incredibly difficult. Furthermore, as Rothstein (2011) points out, the rise in unemployment rate could actually come from two sources: job search disincentive effects on the unemployed who otherwise would have exited unemployment to find a job; or job search *incentive* effects on the unemployed who otherwise would have exited the labor force and stopped searching. Thus, an observed increase in the unemployment rate can be difficult to link to an increase in job search disincentive effect. Indeed, though both Rothstein and Fujita estimated unemployment exit hazard functions, Rothstein (2011) found that the unemployment rate increased primarily due to reductions in exit into non-employment (job search *incentive* effects) while Fujita (2010) largely found a reduction in exit into employment (job search *disincentive* effects).

Several studies have attempted to circumvent these issues by directly measuring the response of job search effort, as measured by time spent searching for jobs, to UI benefit changes. The theoretical underpinnings of job search effort follow from the basic single-agent search model (Mortensen 1977; Rogerson, Shimer and Wright 2005). According to the model, while unemployed, individuals search for jobs and receive job offers over a period of time at wages given by some wage distribution; these job offers represent the returns to job search. Unemployed individuals also collect unemployment benefits that subsidize their job search time; unemployment benefits thus represent the opportunity cost of job search. From a reservation wage endogenously determined by these returns and costs of job search, the unemployed individual either accepts the job offer and leaves unemployment if the job offer wage is greater than their reservation wage, or declines the job offer and continues searching if the job offer wage is less than their reservation wage. As expected from the moral hazard effect, the model predicts that increases in UI generosity will increase the opportunity cost of job search and thus will decrease search effort intensity (Rogerson, Shimer and Wright 2005). Conversely, other factors such as an increase in the expected job offer wage and an increase in the variance of wage offer distribution increase the returns to job search, which would lead to increased search effort intensity.

Krueger and Mueller (2010) empirically tested this single-agent job search model by examining the effect of UI benefit levels on the amount of time an individual spent on job search. In doing so, they found weakly statistically significant evidence that an increase in UI benefit levels decreased job search time, and that individuals dramatically increased their amount of time spent job searching closer to the expiration of their UI benefits. However, their work only covered 2003-2007 and thus did not examine the variation in UI benefit durations during the Great Recession.

Mukoyama, Patterson and Sahin (2014) also briefly explored the effects of UI benefits on job search time over the business cycle in a broad timeframe that included the Great Recession. Their primary finding was that individual job search time is countercyclical in that individuals tended to search more as labor market conditions deteriorated. Like Krueger and Mueller (2010), they also found that job search effort was decreasing in the weeks of UI benefits remaining with a coefficient of -0.022 (standard error 0.005). That is, for every additional 10 weeks of UI benefits, workers on average would decrease their daily job search time by 0.2 minutes. One critical feature of their work is their specification of the dependent variable: they used an imputed job search time *derived* from time use data rather than direct observations from the time use data. Their imputation method involved a two-step process where they first performed a probit regression on the time use data sample to determine the probability of job search, then performed a linear regression on the time use sample conditional on non-zero job search to determine the intensity of job search for people who do engage in job search. In their imputed formulation, they calculated an expected job search time by multiplying the probability of job search by the intensity of job search conditional on non-zero job search. The primary explanatory variable they used for imputed job search time was the number of job search methods used by the individual job searcher.

The advantage of using imputed job search time is that Mukoyama, Patterson and Sahin (2014) were able to leverage a much larger dataset. They noted that their American Time Use

Survey (ATUS) dataset, which directly observes time use, contained 2500 observations of unemployed individuals per year between 2003-2011. In contrast, their Current Population Survey (CPS) dataset, which only observed the number of job search methods used by the individual, contained 20,000 observations of unemployed individuals per month between 1994-2011, which greatly increased both the number of observations and the time frame observed. However, because their imputation of time use hinged on the number of job search methods used, the imprecision in imputation could very well lead to a biased dependent variable. For example, characteristics not included in their imputation regression equations (e.g., unemployment duration, labor market conditions, access to job search methods, etc.) could influence the heterogeneity of job search intensity within each job search method used, which the imputation of job search time cannot capture. If the omitted characteristics are correlated with the heterogeneity of job search intensity, then their regressions could lead to a biased imputation result.

One thing important to note about the majority of UI literature, including the literature listed here and my own research, is that most studies do not directly measure UI receipt but instead measure UI eligibility. As such, the reported results included in this section and in this paper more broadly quantify the intent-to-treat effect and not the treatment-on-the-treated effect. Indeed, Anderson and Meyer (1997) report that only about 40-50% of UI-eligible individuals actually collect UI benefits. Policymakers should thus interpret the reported results as the effect of UI benefit generosity on all UI-eligible individuals rather than solely an effect on the individuals who collect unemployment benefits.

1.3 My contributions

In this paper, my work fills a gap in the existing literature by directly examining job search time use during the Great Recession. Like Krueger and Mueller (2010) and Mukoyama, Patterson and Sahin (2014), I also use micro-level time use data as a proxy for individual job search effort and examine the effect of changing UI benefit generosity on time spent job searching for UI-eligible individuals. Where Krueger and Mueller (2010) only observe time use from 2003 to 2007 and thus cannot include the effect of UI benefit extensions during the Great Recession, I extend Krueger and Mueller's work by using time use data from 2003 to 2014, which encompasses the Great Recession and includes additional controls for changing UI benefit durations.[1] Where Mukoyama, Patterson and Sahin's work chose to impute job search time for their dependent variable, I complement their work by using the directly observed job search time instead. While the imputed job search time has the advantage of leveraging many more observations from the Current Population Survey data, by directly using the observed job search time in the smaller American Time Use Survey dataset I reduce the potential for bias in the dependent variable. In my regression models, I use a variety of specifications for returns to job search, macroeconomic conditions, and demographic characteristics to determine each of their effects on time spent searching for jobs.

My work yields some surprising results. First, I find that UI eligibility alone is not a significant factor in determining job search effort. Rather, the type of unemployed individual plays a much larger role, where those on temporary layoff (UI-eligible) spend much less time searching than job losers (UI-eligible), job leavers (UI-ineligible) or new labor market entrants

[1] As a confirmation of my methodology, when I use Krueger and Mueller's 2003-2007 time use data set, I am largely able to replicate their results.

(UI-ineligible). Second, I show that increasing generosity of UI benefit amount does appear to disincentivize job search effort in accordance with the single-agent search model and Krueger and Mueller's work. A 10% increase in the UI benefit amount is associated with a 2.0 minute decrease in daily job search effort, which is 5% of the sample mean. Third, I find that the effect of extending UI benefit durations is much more ambiguous, where UI benefit extensions likely have negligible or potentially even positive incentive effects rather than disincentive job search effects. This finding contradicts both Krueger and Mueller's (2010) and Mukoyama, Patterson and Sahin's (2014) works, but would agree with Rothstein's (2011) findings that extending UI durations in the Great Recession did not significantly affect exit to employment and could even have reduced exit to non-employment. Fourth, I find that individual job search effort appears to be procyclical and that job search time decreases with rising unemployment, which disagrees with Mukoyama, Patterson and Sahin's (2014) finding that job search effort is countercyclical at both the aggregate and individual levels. A one percentage point increase in the unemployment rate is associated with a five minute decrease in job search effort, which is about 12% of the sample mean. Taken together, my results imply that the UI benefit extensions during the Great Recession did not play a disincentivizing role for UI-eligible individuals, but instead likely had no effect or could even have incentivized increased job search in a recessionary environment.

The rest of my paper is organized as follows. In Section II, I describe my data sources and cleaning methodology. In Section III, I outline my base regression model and several different robustness checks. Next, in Section IV, I explore several different specifications of macroeconomic conditions. Then, in Section V, I investigate job search effort at the extensive and intensive margins. Finally, in Section VI, I conclude.

II. Data

2.1 American Time Use Survey (ATUS)

My main dataset is the American Time Use Survey (ATUS), which is a survey sponsored by the Bureau of Labor Statistics and conducted by the U.S. Census Bureau on a monthly basis beginning in 2003. Through the roughly 159,000 interviews conducted between 2003 and 2014, the ATUS dataset provides detailed micro-level estimates of the amount of time individual Americans spend on various activities in the course of one "diary day" as well as basic demographic and labor force information about the individual. By aggregating the amount of time each individual survey participant spends on the activities collectively classified as "job search activities," I thus quantify "job search effort."

Over the surveyed years, the ATUS measured activities have undergone minor modifications. As such, several of the activities classified as "job search activities," such as "security procedures related to job search/interviewing" and "travel related to job search and interviewing" were surveyed in some years but not in others. Table 1 presents a list of the different activities surveyed over the years that I classify as job search activities as well as the mean minutes per day spent on each activity by the unemployed population. From this collection of job search activities, I calculate two different measures of "total job search time": while my preferred measurement aggregates all classifiable activities surveyed that year under "total job search time," I also include another measure which only aggregates the job search activities that are available for all years 2003-2014. Both measures of job search time achieve qualitatively similar regression results (see Section 3.2).

One caveat to using time use data to quantify job search is that among the entire sample of unemployed individuals, 82% of respondents reported zero minutes of job search the day they were surveyed (see Figure A). For individuals who did engage in job search, the time search distribution in the unemployed individuals sample and the UI-eligible sample are similar (see Figure B). As can be observed, while the majority of individuals who engaged in job search had searched between 1 and 120 minutes on their diary day, 26 individuals in both samples reported spending more than eight hours on job search on their diary day, which represents 0.4% of the unemployed individuals sample and 0.8% of the UI-eligible sample. Although such a small outlier subset is unlikely to bias the results, I do include a robustness check that shows when I topcode any job search reported above the eight-hour threshold to eight hours, I still achieve qualitatively similar results (see Section 3.2).

2.2 Current Population Survey (CPS)

While the ATUS does include some demographic and labor force information, the dataset alone has several drawbacks: it only includes state-level geographic information, it does not include prior employment history, and it does not measure unemployment duration or UI eligibility. Instead, this information is inferred from the survey participants' responses in the Current Population Survey (CPS), which all ATUS respondents participate in and which does include most of this information. The CPS, also jointly administered by the U.S. Census Bureau and the Bureau of Labor Statistics, is a comprehensive monthly survey conducted on households in various forms since the early 1940s. The CPS collects information ranging from demographic and labor force information to earnings and education data. In a sixteen month period, the CPS surveys households for eight non-consecutive months: selected households are surveyed for the first four months, are *not* surveyed for the following eight months, and are surveyed again for the last four months. Thus, the CPS can provide both longitudinal data, as the same households are surveyed across different months, as well as panel data, for the cross-sectional data available each month. Following the final CPS interview, a subset of households are selected to participate in the ATUS. An individual over the age of 18 in the household is randomly selected to answer questions about his or her time use over a "diary day" period. The ATUS takes place two to five months after the final CPS interview.

Because all survey participants in the ATUS also participated in the final month of the CPS, the ATUS dataset can be linked to their responses in the final CPS, and then to available responses from CPSs of prior months. I use three different CPS datasets: the ATUS-CPS dataset, the IPUMS-CPS dataset, and the CEPR-ORG dataset. Each provides unique advantages, and I outline their uses below.

The ATUS-CPS dataset is an ATUS-version of the responses from the final CPS included as part of the ATUS data. Thus, the ATUS-CPS and ATUS are easiest to link and share a uniform variable coding. In addition, the ATUS-CPS includes two questions that the ATUS does not—reason for unemployment and length of unemployment spell—from which I infer unemployment insurance eligibility and unemployment duration. The primary drawback of the ATUS-CPS is that it does not include information from first seven CPS months before the final CPS. It also does not contain all the variables of the CPS (e.g., metropolitan area information).

For CPS data from months prior to the final CPS month, I use the IPUMS-CPS dataset, from the Integrated Public Use Microdata Series. This dataset facilitated the longitudinal linking of CPS data across different months, as it includes a unique person ID that identifies the same household and persons within the household across surveyed months. It also uniformly codes many variables that have undergone slight adjustments over the years. As a standalone dataset, I use the IPUMS-CPS data to calculate an imputed unemployment duration since unemployment duration is not directly measured in the ATUS data (see Section 2.3).

When linked to ATUS data, I use the IPUMS-CPS to infer labor force attachment: following Mukoyama, Patterson and Sahin (2014), I use labor force status in the seventeenth month prior to the ATUS (which is either the first, second, third, or fourth CPS month, depending on the length of the two to five month gap between the last CPS and the ATUS) as a proxy for an individual's labor force "stickiness."[2] As an aside about the IPUMS-CPS, there is a known flaw in the dataset in that observations for August 2014 do not have an associated person ID and thus cannot be linked; thus, ATUS respondents whose final CPS month was August 2014 were not linked to prior CPS data.

The third CPS dataset, called CEPR-ORG from the Center for Economic Policy Research, solely aggregates the Outgoing Rotation Group (ORG) CPS data. ORG refers to CPS surveys conducted on households in the fourth and eighth month of their CPS survey period. Termed "outgoing" because the households will either leave the survey pool for eight months (if in the fourth month) or leave the survey pool permanently (if in the eighth month), the CPS ORG surveys include additional questions about weekly working hours and earnings. The CEPR-ORG dataset contains a standardized calculation of hourly wages that includes overtime, tips, commissions, and bonuses for both hourly and nonhourly workers.

As a standalone dataset, I use CEPR-ORG to calculate imputed wages and wage distributions since unemployed workers cannot report labor income in the ATUS (see Section 2.5). Because the ATUS only reports the state but not the city of the survey participant, I also link the CEPR-ORG dataset to the ATUS data in order to learn the Metropolitan Statistical Area (MSA) geographic information of the survey participant. I use the CEPR-ORG dataset for this

[2] Individuals with prior statuses of employment are presumed to be more attached than individuals with prior statuses of unemployment, who are in turn presumed to be more attached than individuals with prior statuses of NILF.

purpose because its variable coding matches the most up-to-date coding of the Bureau of Labor Statistics (BLS) and Federal Housing Financing Agency. However, because the MSA variable coding only exists in the CEPR-ORG dataset for 2005 onwards, ATUS observations in 2003 and 2004 could not be linked to their MSA information and thus were not linked to MSA-level data.

One potential note of caution in using CPS data is that not all respondents complete all eight months in the survey. Indeed, the CPS surveys households, so if the respondent moves houses in the middle of the surveying period, then the initial respondents are not tracked but rather the remaining survey months are completed by the new household that moves in. If there is unobserved heterogeneity in the households who move and thus do not complete all eight months of the CPS, then this could result in a biased regression sample. That said, Rothstein (2011) examined the characteristics of households that did not complete the CPS. He did not find any observable heterogeneity, which would suggest that using the linked CPS data does not produce a biased household sample.

2.3 Unemployment duration

The CPS includes a question about the length of unemployment spell while the ATUS dataset does not, so unemployment duration must be inferred from the ATUS-CPS dataset. I use two different methods of calculating unemployment duration. My main method follows from Krueger and Mueller's (2010) methodology, which I call the KM method:

i. *Persons employed or NILF in the last month of the CPS*: I assume that the person became unemployed in the midpoint between their CPS and their ATUS surveys. For example, if there was a two-month gap between their final CPS survey and their ATUS survey, I assume the person has been unemployed for four weeks.

ii. *Persons unemployed in the CPS:* I assume the person had no re-employment spells between their CPS and their ATUS surveys, and I sum their reported unemployment duration in their CPS survey with the gap between CPS and ATUS surveys. For example, if the person reported an unemployment spell of 10 weeks in their CPS survey with a two-month gap between their final CPS survey and their ATUS survey, I assume the person was unemployed for 18 weeks.

The KM method has the advantage of being simple to compute and straightforward to understand. In order to test its validity, I compare the average unemployment durations from the KM method to average unemployment durations observed in the longitudinal CPS data. While the gap between the last CPS and the ATUS ranges from two to five months, the CPS has four two-month gap periods (months 1-3, 2-4, 5-7, and 6-8; recall the eight-month gap between months 4 and 5) and two three-month gap periods (months 1-4, 5-8). Of these two-month and three-month gap periods, I'll refer to the first month of the gap as the "initial CPS-gap month" and the last month of the gap as the "final CPS-gap month." I calculate the average unemployment duration reported in the final CPS-gap month conditional on the employment status in the initial CPS-gap month. The results are reported in the first two columns of Table 2. As shown, the KM method significantly underestimates the unemployment duration for people who reported being employed or NILF in their last CPS month and slightly overestimates unemployment durations for those who report being unemployed in their last CPS month.

Because of the measurement error of the KM method, I also use a second method, which I call the imputed method, to calculate the length of unemployment spell from the longitudinal CPS data of the years 2002-2014 in the IPUMS-CPS dataset. I use the initial CPS-gap month as a proxy for the last month of the CPS survey and the final CPS-gap month as a proxy for the ATUS survey and ran four regressions:

(i) *Persons employed or NILF in the initial CPS-gap month and unemployed in the final CPS-gap month*: I ran a regression with the two-month gap group and a regression with the three-month gap group of the following form:

$$L_{g,i,F} = \delta_0 + \delta_1 E_{i,I} + \delta' X_i + d_t \quad (1)$$

where $L_{g,i,F}$ is the length of unemployment spell reported in the final CPS-gap month for individual i of gap g; $E_{i,I}$ is the labor force status (employed or NILF) for individual i in the initial CPS-gap month, X_i is the set of demographic characteristics for individual i,[3] and d_t is a time dummy for the year.

(ii) *Persons unemployed in the initial CPS-gap month and unemployed in the final CPS-gap month*: I ran a regression with the two-month gap group and a regression with the three-month gap group of the following form:

$$L_{u,g,i} = \gamma_0 + \gamma_1 L_{i,I} + \gamma' X_i + d_t \quad (2)$$

where $L_{u,g,i}$ is the length of unemployment spell reported in the final CPS-gap month for individual i of gap g; $L_{i,I}$ is the length of unemployment spell reported in the initial CPS-gap month, X_i is the set of demographic characteristics, such as sex or education, for individual i, and d_t is a time dummy for the year.

The results of the regressions are reported in Table 3. Then, using the regression results and labor force and demographic data from the ATUS-CPS and ATUS, I calculate an imputed length of unemployment spell for unemployed individuals in the ATUS with a two-month or

[3] Demographic characteristics include age (and its quadratic), education, sex, race, and the interaction of sex and race.

three-month gap between their last CPS and ATUS surveys. For individuals with four-month or five-month gaps, I calculate their imputed three-month gap and then add four or eight weeks, respectively, to their unemployment duration. Finally, I artificially censored the imputed unemployment duration at zero weeks such that there were no negative values for imputed unemployment duration.

The last column of Table 2 includes a comparison of the average imputed unemployment duration with the average observed CPS unemployment duration and the average KM method calculated unemployment duration. Compared to the unemployment duration observed in the CPS, the imputed method overestimates the unemployment duration, likely due to the artificial zero lower bound that I imposed on the imputed results. Regardless of unemployment duration calculation method, the KM method and the imputed method both achieve qualitatively similar regression results (see Section 3.2).

2.4 Unemployment insurance eligibility

Because neither unemployment insurance eligibility nor reason for unemployment is not directly surveyed as part of the ATUS, I follow Krueger and Mueller’s (2010) methodology of inferring UI eligibility from the reason for unemployment reported in the last month CPS. Like Krueger and Mueller, I specify four types of unemployed persons in the ATUS:

(i) *Job loser (UI-eligible)*: A job loser is defined as someone who reported being a job loser/on layoff, having their temporary job end, or having lost their job in some other way in the ATUS-CPS dataset, or as someone was employed in the ATUS-CPS but unemployed in the ATUS. Note that for the former, this implies no re-employment spells between the CPS and ATUS.

(ii) *Temporary layoff (UI-eligible)*: A person on temporary layoff is defined as someone who reported being unemployed on layoff in the ATUS.

(iii) *New or re-entrant (UI-ineligible)*: A new or re-entrant to the labor market is defined as someone who reported being a new or re-entrant in the ATUS-CPS dataset, or someone who reported as NILF in the ATUS-CPS and unemployed in the ATUS.

(iv) *Job leaver (UI-ineligible)*: A job leaver is defined as someone who reported being a job leaver in the ATUS-CPS dataset. Note that job leavers cannot be observed if they became unemployed between the CPS and ATUS because those individuals are all classified as job losers. As Krueger and Mueller (2010) discuss, this is because the pool of unemployed individuals observed in the CPS contains many more job losers than job leavers. Thus, individuals observed to be employed in the ATUS-CPS but unemployed in the ATUS are far more likely to be job losers than job leavers.

Survey respondents were determined to be UI-eligible if they classified as a job loser or on temporary layoff and if their weeks of unemployment duration were less than the weeks of UI available at the time of their unemployment.

2.5 Imputed wage and wage distributions

As part of the single-agent search model, the expected wage and the variance of the wage distribution are important aspects of the returns to job search. However, unemployed individuals cannot report an expected wage. Thus, using the CEPR-ORG dataset and following Krueger and Mueller's (2010) methodology, I calculate an imputed wage and wage distribution from the following regression:

$$log(w_{i,s}) = \theta_0 + \theta' X_i + d_s + d_t + \varepsilon_{is} \quad (3)$$

where $w_{i,s}$ is the hourly wage including overtime, tips, commissions, and bonuses; X_i is the set of demographic characteristics,[4] d_s is a dummy for fixed state effects, d_t is a dummy for fixed year effects, and ε_{is} is the residual term. I calculated the wage distribution by state as the standard deviation of the residual term by year and state. Then, in order to remove time effects potentially endogenous with labor market conditions, I also calculated a variant of the regression without fixed year effects. The regression results are presented in Table 4. Both methods of calculating imputed wage yielded qualitatively similar regression results (see Section 3.2).

2.6 Other datasets

Maximum weekly benefit amounts (WBA) by state and year were taken from the Office of Workforce Security, U.S. Department of Labor website. In several states in certain years, benefit maximums increase with the inclusion of dependents; in those states, the number of dependents was calculated from the reported number of children and marital status (if the spouse qualified as a dependent under state law). In my base specification, the maximum WBA varies by state, year, and individual.[5] Figure C illustrates the average maximum WBA for the UI-eligible sample population by year.

One possible issue with controlling directly for annual maximum WBA is that several states index maximum WBA to average state wages, which then becomes endogenously related to contemporary state labor market conditions. For robustness, I also calculated an average

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[4] As before, demographic characteristics include age (and its quadratic), education, sex, race, and the interaction of sex and race.

[5] Maximum WBA only varies by individuals in the states which allow a higher maximum WBA for persons with dependents; in those states, individuals who report having children or spouses (in states where spouses qualify as dependents) are assigned a maximum WBA that includes the number of dependents reported.

maximum WBA for each state across the years 2002-2014, where the only variation in time came from the variation in the inclusion or exclusion of benefits permitted for dependents for a given year (e.g., Tennessee only began allotting additional maximum benefits for dependents in 2010; thus, benefits for individuals with dependents in Tennessee varies between pre-2010 and post-2010). The average maximum WBA should thus be abstracted from changing state labor market conditions. Even so, both methods of specifying maximum WBA achieve qualitatively similar regression results (see Section 3.2).

UI duration was taken from Farber, Rothstein, and Valletta (2015) which provided the total number of UI weeks available at the time of unemployment. Figure D illustrates the average number of UI weeks available for the UI-eligible sample population by year and month. As can be observed, the number of UI weeks available in 2003 began slightly higher than the 26-week norm at the tail end of the Dotcom bust, returned to the 26-week norm from 2004 until mid-2008, then began to increase up to the 99-week maximum at the height of the Great Recession. Only in the last several months of the sample in 2014 did the number of UI weeks available return to the 26-week norm.

For the other data, the Bureau of Labor Statistics provided monthly seasonally adjusted unemployment rates at the state level and monthly seasonally unadjusted unemployment rates at the metropolitan statistical area (MSA) level. The Federal Housing Finance Agency provided seasonally unadjusted quarterly housing price indices at the state levels and MSA levels.

III. UI Effect on Job Search

3.1 Base regression model

In order to estimate the effect of unemployment insurance benefits—both duration and level—on job search effort, I use micro-level ATUS data with three main sets of explanatory variables: returns to search, macroeconomic conditions, and demographic characteristics. Returns to search follows from the single-agent search model and includes UI generosity, where increasingly generous UI benefits increases the opportunity costs of job search and thus decreases the returns to search. I also include variables specifying macroeconomic conditions in order to distinguish the effects of deteriorating labor market conditions from the effects of UI benefit extensions on job search effort. Finally, I include a set of various demographic controls such as age, sex, and race. The base specification for my regression model thus looks like the following:

$$T_{i,s,t} = \varphi'^{R_{i,s,t}} + \varphi''^{Z_{s,t}} + \varphi'''^{X_i} + d_t + \varphi_0 + \mu_{i,s,t} \tag{4}$$

where $T_{i,s,t}$ is the search time for individual *i* in state *s* in the year and month *t*, $R_{i,s,t}$ is the returns to search, $Z_{s,t}$ is an indicator of macroeconomic conditions, X_i is the set of demographic characteristics for individual i,[6] and d_t is a year-month time dummy variable. In my base regression, $Z_{s,t}$ is simply a linear control for the state unemployment rate. As part of the demographic characteristics, I include prior labor market participation as a proxy for labor market attachment, similar to the way Mukoyama, Patterson and Sahin (2014) specified labor market attachment. Thus, individuals who indicated they were NILF seventeen months before the ATUS survey are presumed to be less attached to the labor force than individuals who

[6] Demographic characteristics include age (and its quadratic), education, sex, race, the presence of a partner, and the presence of children. They also include the interaction of sex with race, partner, and children. Finally, as the text notes, they include labor market attachment.

reported being employed or unemployed seventeen months prior. Standard errors are clustered by state.

Furthermore, I specify returns to search in the following manner:

$$R_{i,s,t} = \varphi_1 \widehat{log}(w_{i,s,t}) + \varphi_2 std(resid\ w)_{s,t} + \varphi_3 \log(WBA_{ist}) + \varphi_4 D_i + \varphi_5 n_{i,s,t} + d_U \quad (5)$$

where $\widehat{log}(w_{i,s,t})$ is the imputed wage as given in Eq. 3 and $std(resid\ w)_{s,t}$ is the standard deviation of the wage residual by state from the regression in Eq. 3. In the single-agent search model, increases in the imputed wage and the standard deviation of the wage distribution increase the returns to search and thus incentivize job search effort. Both are estimated from the CEPR-CPS dataset, and in my base specification, I include fixed year effects in the estimation of the imputed wage and the standard deviation of the wage distribution. $\log(WBA_{ist})$ is the natural log of the weekly maximum benefit amount. While only a subset of the sample will have high enough prior wages to be affected by the maximum benefit cap, the maximum WBA serves as a proxy measure for the generosity of UI benefit levels in a given state. The maximum WBA varies for UI-eligible individual *i* in states that increase the benefit cap for individuals with dependents. UI-ineligible individuals are assigned a maximum WBA of zero. In my base specification, the maximum weekly benefit also varies for each state by year. D_i is a linear control for the duration of unemployment for individual i. $n_{i,s,t}$ is the weeks of UI benefits left for individual *i* in the year-month *t*; $n_{i,s,t}$ is zero for individuals ineligible for UI benefits. d_U is a dummy for the type of unemployed worker (on temporary layoff, job leaver, new or re-entrant), which, along with the number of UI weeks remaining (e.g., if unemployment duration exceeds the total UI weeks available), is the primary determinant of UI eligibility.

Means of all the regression variables for both the unemployed and UI-eligible samples are presented in Table 5. Base regression results are presented in Table 6 for the unemployed and

UI-eligible only samples. The regression results suggest that, in general, unemployment insurance did not play a statistically significant role in determining daily job search time.

First, unemployment eligibility did not appear to significantly influence job search time (Table 6, "All Unemployed"). Instead, the type of unemployed person appears to be much more significant, as both job losers (the base group) and individuals on temporary layoff qualify for unemployment insurance, but workers on temporary layoff searched significantly less than job losers do. Indeed, the magnitude of the coefficient would suggest that individuals on temporary layoff search between 38 and 40 minutes per day less than the job losers (base group), who on average search 51 minutes per day. That both categories of workers are eligible for UI, but workers on temporary layoff search 75-80% less than job losers suggests that UI-eligibility is not the dominant driver of job search effort. Additionally, that job leavers are not eligible for UI yet do not appear to search differently from UI-eligible job losers only further disputes the connection between UI-eligibility and job search effort.

Second, contrary to what both Krueger and Mueller (2010) as well as Mukoyama, Patterson and Sahin (2014) have found, I did not observe a statistically significant effect where dwindling time on unemployment insurance led to greater job search effort (Table 6). If anything, the positive (though statistically insignificant) coefficient would imply the opposite. This connection will be explored further in Sections IV and V.

Third, the only aspect of unemployment insurance that appeared to influence job search time was the maximum WBA, which was statistically significant for the UI-eligible population at the 10% level (Table 6, UI-Eligible). The negative coefficient implies that increasing generosity of UI levels decreases job search effort, which confirms Krueger and Mueller's (2010) observation of the same effect. Furthermore, the negative coefficient -20.92 suggests that a 10%

increase in the weekly maximum benefit amount would result in a decrease of 2.0 minutes of job search per day, which is approximately 5% of the sample mean of 42 minutes of job search per day. For comparison, the average amount of maximum WBA for the UI-eligible sample increased from $364.14 in 2003 to $440.43 in 2014, which is approximately a 20% increase (see Figure B).

Other findings include a weakly statistically significant positive correlation between job search time and imputed wage as well as a strongly negative correlation between job search time and individuals who are only tangentially attached to the labor force (Table 6). The former finding follows from the single-agent search model, where the increase in expected wage raises the returns to job search. The latter finding also makes intuitive sense in that individuals with a history of being out of the labor force, and thus are less attached to the labor force, are less incentivized to actively participate in job search. In sum, the base regression results largely agree with the theory.

3.2 Robustness checks

I also explored slight variations in my specifications for robustness. First, as explained in Section 2.1, activity times for certain job search activities were not available for all years. I explore the effect of only using the job search activities surveyed for all years as the dependent variable (Table 7, Columns III-1). Next, I use a topcoded specification of job search time, where outlier individuals who report searching more than eight hours on their diary are instead coded as searching for eight hours (Table 7, Columns III-2). Then, because the imputed wage, the standard deviation of wage residual by state, and the maximum WBA across time could be endogenously correlated with prevailing macroeconomic effects across time, I remove the time variation from these variables by removing fixed year effects from the imputed wage and standard deviation of wage residual by state regressions and by averaging the weekly maximum benefit amounts across the years 2002-2014 (Table 7, Columns III-3). Additionally, because of the potential for measurement error in unemployment duration described in Section 2.3, I then use the imputed unemployment duration method as described in Section 2.3 to impute the unemployment duration. The imputed unemployment duration was then used to determine the imputed UI weeks left for the UI-eligible (Table 7, Columns III-4). Finally, I divide the unemployed population into three groups—those in the first third, in the second third, and the last third of their total UI weeks—and interact the grouping variable with the total UI weeks available to see if people search longer at the tail end of their UI availability, and if so, if this changes with the length of UI available (Table 7, Columns III-5).

The results of the different specifications are presented in Table 7, where the first two columns ("Base") are identical to the base regression results reported in Table 6 and have been included for comparison purposes. As evidenced, the results of the robustness checks largely follow the results from the base specification. Again, UI did not appear to play a significant role in determining job search time: UI-eligible workers on temporary layoff still searched significantly less than UI-eligible job losers, and individuals did not appear to search harder closer to UI expiration. For the UI-eligible population, maximum weekly benefit amounts remained statistically significant at the 10% level and negatively correlated with job search time.

One interesting observation is the statistically significant negative coefficient for state unemployment rate in the UI-eligible population across all specifications. This would imply that job search effort is actually procyclical, contrary to what Mukoyama, Patterson and Sahin (2014) had found. I explore this curious result further in the next section, where I specifically examine the role of macroeconomic conditions on job search.

IV. Macroeconomic Specifications

4.1 Macroeconomic specifications model

Oftentimes the most difficult aspect of studying unemployment insurance is an inherent endogeneity issue: UI becomes more generous during recessions, so it becomes difficult to isolate the causal effect of the UI change from the causal effect of the prevailing macroeconomic conditions. Up to this point, I have glossed over this issue; in my base specification, I use state-level variation in UI benefit extensions to get around national-level economic trends, and any remaining state-level macroeconomic variation I attempt to capture by directly controlling for the state unemployment rate. Of course, a linear control for the state unemployment rate is imperfect; positive correlation of the state unemployment rate with total UI duration will result in biased estimated coefficients. As such, because the endogeneity issue is such a confounding aspect of UI research, I also explore several different specifications of macroeconomic conditions.

Beginning with my base specification in Eq. 4, I use a series of different controls for my $Z_{s,t}$ macroeconomic term. I first use a cubic specification for the state unemployment rate (Table 8, Columns IV-1), which follows from Rothstein (2011) where he remarks that this is his preferred specification for labor market conditions. Next, rather than using the state unemployment rate, I use a linear control for the MSA unemployment rate (Table 8, Columns IV-2). Because UI benefit durations and amounts are determined at the state level while MSAs (which can cross state boundaries, as they are determined in part by work commuting distances) better reflects local economic conditions, using MSA-level data reduces the endogenous correlation between UI benefit durations and labor market conditions. The primary drawback of using MSA-level data is the reduction in sample size: roughly 25% of the unemployed individuals in the ATUS did not live in a metropolitan area, and MSA data was not available for ATUS participants prior to 2005.

In my next specification, I return to a linear control for state unemployment rate but include a control for state housing prices in order to distinguish the potential effects of a wealth shock versus a labor market shock (Table 8, Columns IV-3). As Chetty (2008) indicates and Mukoyama, Patterson and Sahin (2014) appears to corroborate, liquidity constraints from an adverse wealth shock could play an important role in UI and job search effort. Although neither the ATUS nor CPS include individual measures of wealth, I instead use local housing prices as a proxy for wealth. Finally, I use MSA-level data for both unemployment rate and wealth to better abstract these effects from state-level UI effects (Table 8, Columns IV-4). The results are presented in Table 8, where again the first two columns ("Base") are the base regression results reported in Table 6 and have been included for ease of comparison.

4.2 Macroeconomic-related results

Surprisingly, many of my results for the macroeconomic variation regressions appear to contradict the existing literature. First, as noted in Section 3.2, job search time appears to be negatively correlated with unemployment rate regardless of specification method. This suggests that individual job search time is procyclical, and the effect is even more pronounced when using MSA-level unemployment rate (Table 8, Columns IV-2 and IV-4, UI-Eligible). Indeed, I find that an increase in the unemployment rate by one percentage point is related to a decrease in job search time by about 5 minutes, which is approximately 12% of the sample mean of 42 minutes. My finding that job search effort is procyclical is at odds with the conclusion that Mukoyama, Patterson and Sahin (2014) reached in their research.

That said, my finding that individual job search time is negatively correlated with rising unemployment rate makes intuitive sense for several reasons. First, under recessionary conditions, workers get discouraged by dismal labor market conditions that reduce the value of their job search. Second, when people on an individual level spend less time searching for jobs, this likely leads to a lower individual probability of finding a job, which could result in a higher unemployment rate in the aggregate. Finally, under expansionary conditions, the availability of more job openings increases the number of opportunities that individuals have to apply and interview for jobs, which would then be reflected in an increase in job search time.

I also did not find an indication that a wealth effect, in either the state housing prices (Table 8, Columns IV-3) or MSA housing prices (Table 8, Columns IV-4), was an important determinants of job search effort, again contradicting the conclusion that Mukoyama, Patterson and Sahin (2014) reached. This is likely due to insufficient statistical power arising from my reduced sample size. Indeed, though it was statistically insignificant, I did similarly find negative coefficients for the wealth effect on job search time.

4.3 UI-related results

Other surprising UI-related results arise from the MSA-level regressions (Table 8, Columns IV-2 and IV-4, UI-Eligible). First, the number of UI weeks remaining becomes statistically significant and *positively* correlated with the job search time. This implies that in a cross-sectional comparison, extending unemployment benefits actually *increases* job search time: for two otherwise identical individuals with the same unemployment duration, the individual living in a state with extended unemployment benefits would tend to search harder than the individual with a shorter UI benefit duration. The statistically significant coefficient of 1.02 for the regression that only includes MSA-level unemployment (Table 8, Columns IV-2, UI-Eligible) implies that every ten weeks of UI benefit extensions incentivizes an additional 10.2 minutes of search. The statistically significant coefficient of 0.88 for the regression that includes both MSA-level unemployment and housing prices (Table 8, Columns IV-4, UI-Eligible) implies that every ten weeks of UI benefit extensions incentivizes an additional 8.8 minutes of search.

Furthermore, the positive, statistically significant coefficient for the number of UI weeks remaining can be examined in conjunction with the positive, statistically significant coefficient on unemployment duration to determine the search effort of a single individual over his or her unemployment spell. Indeed, for a single individual, each additional week of unemployment duration is one less week of UI available. The cumulative effect of an additional week of unemployment is thus the coefficient on the unemployment duration minus the coefficient on the number of UI weeks available. The regression that only includes MSA-level unemployment rate (Table 8, Columns IV-2, UI-Eligible) suggests that each additional week of unemployment results in 0.15 minutes less of job search. This comes from the 0.87 minutes increase from the coefficient on unemployment duration minus the 1.02 minutes decrease from the coefficient on the number of UI weeks remaining. The regression that includes both MSA-level unemployment rate and housing prices (Table 8, Columns IV-4, UI-Eligible) implies that each additional week of unemployment results in 0.17 minutes less of job search. This comes from the 0.71 minutes increase from the coefficient on unemployment duration minus the 0.88 minutes decrease from the coefficient on the number of UI weeks remaining. Results of the same sign and similar magnitude, though not statistically significant, hold for the other specifications (see Robustness Checks, Table 7; Macroeconomic Specifications, Table 8). Together, the regressions suggest that there is practically negligible change, or even a decrease in job search intensity as the UI-eligible individual progresses through the unemployment spell.

Both of these implications—that UI benefit extensions incentivize job search effort in the cross-section, and that the UI-eligible unemployed person tends to search less as his or her unemployment duration progresses in the individual—contradict Krueger and Mueller's (2010) and Mukoyama, Patterson and Sahin's (2014) results. The latter finding is somewhat easier to explain. At the beginning of unemployment, the individual likely has an accumulated a stock of available resources from his or her social capital, such as former coworkers or family members, who provide notice of job opportunities. Job search is thus more intense at the beginning of unemployment while the individual collects UI and leverages the resources available. As time passes and social capital depreciates, the stock of job opportunities dwindle and the individual must rely more on the flow of job opportunities, so the job search intensity correspondingly decreases through the course of the unemployment spell. Furthermore, it is possible that if individuals exhaust one or two job search methods early in their unemployment spell, they may search less intensely even while using more search methods later in their unemployment spell. If this is the case, their imputed job search time as calculated by Mukoyama, Patterson and Sahin (2014) from the number of job search methods used may overestimate job search effort later in the unemployment duration spell, which would lead them to the opposite conclusion I reached.

That UI benefit extensions appear to incentivize job search effort is more difficult to explain. One potential explanation for the counterintuitive effect I observe could be the result of unobserved heterogeneity in the sampled population, where individuals who inherently search harder for jobs have shorter unemployment spells and use less UI, and the individuals who inherently search less remain unemployed to the end of their UI duration. Yet this heterogeneity effect should have also been captured in the unemployment duration, where it would imply that people with longer unemployment durations tend to search less. Rather, controlling for the number of weeks of UI remaining, the positive and statistically significant coefficient on the unemployment duration instead implies that individuals search harder the longer they are unemployed.

It is also possible that the true source of variation in UI weeks remaining was due to deteriorating labor market conditions (i.e., the endogeneity where policymakers extend UI benefit durations in response to deteriorating labor market conditions), the full effect of which was not captured in the MSA-level unemployment rate and thus became reflected in the countercyclical nature of UI benefits. But this explanation is also improbable: one, the MSA-level unemployment rate is likely a better reflection of local labor market conditions than the state unemployment rate, which would reduce their endogenous correlation; and two, job search time is negatively correlated with unemployment rate but positively correlated with weeks of UI remaining, so the positive correlation in unemployment rate and UI duration cannot simultaneously explain both effects.

A third possibility is that some unobserved state fixed effect is the true source of variation that explains job search effort. For example, if states with longer unemployment benefit durations also tend to provide more job search assistance or be comprised of industries that require more job search time, then the coefficient on the weeks of UI remaining would be biased upward. If this is the case, then UI benefit extensions likely had a negligible disincentive effect such that even unobservable state characteristics played a larger role in influencing job search behavior.

A fourth possibility is one that Rothstein (2011) suggests: that UI benefit extensions during the Great Recession actually played a larger role in incentivizing discouraged workers to search for jobs than disincentivizing unemployed workers from searching as intensely.

Controlling for unemployment duration, the worker with more weeks of UI remaining is more likely to choose to continue searching for jobs while the worker with fewer weeks of UI remaining is more likely to become discouraged and stop searching, eventually leading to an exit into non-employment. This possibility will be explored further in the next section when examining the extensive margins of job search.

Finally, the coefficient on the maximum WBA remained negative but was no longer statistically significant using MSA-level unemployment rate (Table 8, Columns IV-2 and IV-4). This was likely due to the reduction in sample size and thus reduction of statistical power. Indeed, the size of the negative coefficient was in line with other estimates of the coefficient for maximum WBA but the standard error had increased by 33-45%.

V. Margins of Job Search

One potential troubling aspect of the job search data is the significant number of unemployed people who do not engage in daily job search. As noted in Section 2.1 and observed in Figure A, only approximately 18% of unemployed persons in the observed sample participated in job search. Even removing weekend diary days from the sample, only about 26% of observed unemployed individuals spent any time at all searching for jobs. Due to the heavy clustering about zero in the dependent variable, in this section I explore the distinction between the *extensive margin* of job search, which probes why people engage in job search to begin with, and the *intensive margin* of job search, which explores the intensity of job search conditional on any job search at all.

5.1 Extensive margin of job search

In order to explore the extensive margin of job search, I use a probit model that follows from my base specification in Eq. 4. The only differences are that I use a binary job search variable as the dependent variable rather than the numeric time spent on job search variable, and that I use year time dummies instead of year-month dummies since several year-month time dummies exactly predicted binary job search. The results of the probit regression are presented in Table 9, where the first set of columns ("Base") are identical to the base regression results reported in Table 6 and the second set of columns ("Probit") are the average marginal effects of each variable from the probit regression. In addition to the probit average marginal effects, for ease of interpretation I also separately graphed the probability of job search for several variables, including the weeks of UI remaining, unemployment duration, weekly maximum benefit level, and state unemployment rate, over a range of their values while holding all other variables in the regression at their mean (Figs. E-H).

As before, many of the previously observed factors, including imputed wage, temporary layoff status, and tangential labor force attachment continue to play a statistically significant role at the extensive margin,(Table 9, "Probit"). Similar to the MSA-level regressions for the UI-eligible (see Section 4.3), again both weeks of UI remaining and unemployment duration are statistically significant and positively correlated with job search probability (Table 9, "Probit," UI-Eligible). Although the average effect for a one unit change (one week) for both variables is only an incremental 0.22%, the effect over the period of weeks of UI remaining or unemployment duration is large (see Figures E and F).

As with the MSA-level regressions in Section 4.3, the results for weeks of UI remaining and unemployment duration can be interpreted either through cross-section or for a single individual. In the cross-sectional interpretation, holding unemployment duration constant, the UI-eligible individual with more weeks of UI remaining is more likely to engage in job search than a UI-eligible individual living in a state with fewer weeks of UI available. This would corroborate Rothstein's (2011) findings that UI benefit extensions could play an incentive effect at the extensive margin by encouraging UI-eligible unemployed workers to continue searching, and that this incentive effect diminishes for workers closer to the expiration of their UI benefits. This is also altogether not implausible, as UI benefit receipt is contingent upon continued job search.

If UI benefit extensions do indeed have job search *incentive* effects, this would have crucial implications for UI policy. On the one hand, fears of detrimental moral hazard effect from longer UI benefit durations—including the aforementioned Republican lawmakers who charged that the extended benefits discouraged people from finding jobs—seem to be largely exaggerated. Neither the MSA-level regressions of Section 4.3 nor the extensive margin results suggest that moral hazard has a significant effect regarding UI benefit extensions. On the other hand, encouraging unemployed workers to continue searching for jobs would raise the unemployment rate and thus the number of people collecting UI benefits, which would increase the expected cost of the overall UI program. Policymakers must therefore weigh the societal benefits of motivating discouraged workers to continue searching for jobs with the financial cost of paying for more people on UI.

Returning to the probit regressions, the coefficients on unemployment duration and weeks of UI benefits remaining can also be interpreted for the single individual. As with the MSA-level regressions in Section 4.3, an individual progressing through the course of his or her unemployment spell experiences the cumulative effect of an additional week of unemployment duration and one less week of UI remaining; here, the average marginal effects of unemployment duration and weeks of UI remaining are both 0.22%, which cancel each other out. This implies that a single individual is equally likely to engage in job search throughout the course of unemployment, which again contradicts previous findings that individuals begin their job search toward the end of their UI benefit period (Krueger and Mueller 2010).

Unlike UI benefit duration available, UI benefit amounts appear to have a statistically significant disincentivizing effect on job search, where increasing the maximum weekly benefit amount by 10% results in a 1.1% reduction in job search probability (Table 9, "Probit," UI-Eligible; see Figure G). The moral hazard effect of UI is thus more reflected in the dollar amount that individuals can collect rather than the temporal duration that individuals can collect benefits for. Finally, again individual job search behavior was found to be procyclical, where a one percentage point increase in the state unemployment rate decreased the job search probability by 3% (Table 9, "Probit," UI-Eligible; see Figure H). Again, this finding contradicts the countercyclical job search behavior observed by Mukoyama, Patterson and Sahin (2014), likely due to the same reasons outlined in Section 4.2.

5.2 Intensive margin of job search

Next, I explore the intensive margin of job search, where I leverage my same base specification but only include the observations with job search times greater than zero. The results are presented in Table 10, where the first two columns ("Base") are the base regression results reported in Table 6 and have been included for ease of comparison.

Perhaps most interestingly, the different classes of unemployed workers no longer represented statistically significant different states (Table 10, Columns V-2, Unemployed); likely, once the individual on temporary layoff began the job search effort, he or she searched similarly to the job losers and job leavers. Furthermore, in examining the regression results for the UI-eligible population, the coefficient for weeks of UI remaining stayed positive and statistically significant while the coefficient for unemployment duration, though still positive, was no longer statistically significant (Table 10, Columns V-2, UI-Eligible). This is possibly due to the reduction in statistical power, as the sample size for the intensive margin is less than a fifth the sample size of the base regression and the standard error nearly tripled in size. The result continues to suggest that, in the cross-section controlling for unemployment duration, UI benefit duration still appears to have a negligible or even incentivizing effect. Turning to UI benefit amounts, the coefficient on the maximum WBA for the UI-eligible sample is still negative but no longer statistically significant (Table 10, Columns V-2, UI-Eligible). This could again suggest that the sample size was too small, as the standard error again more than tripled in size. It could also imply that the maximum WBA plays a larger role at the extensive margin, where it is strongly statistically significant, than the intensive margin, where it is statistically insignificant.

VI. Discussion & Conclusion

I began with a base regression model to estimate how returns to search (including UI eligibility, UI benefit duration and UI benefit amount), macroeconomic conditions, and demographic characteristics affected job search time. I then made a series of minor adjustments to my specifications to check for robustness. Then, I varied my controls for macroeconomic conditions in an attempt to reduce endogeneity issues, which has always been a difficult endeavor in UI research. Finally, I separately examine job search effort at the extensive and intensive margins.

In general, I found that UI eligibility did not play a significant role in determining job search effort. Instead, the specific class of unemployed individual played a larger role. As observed, while both job losers and temporarily unemployed individuals were eligible for UI, temporarily unemployed individuals searched for significantly less time than job losers. Furthermore, neither job leavers nor new entrants qualify for UI, yet they did not search statistically differently from job losers.

The moral hazard effect of UI was most directly observed in UI benefit amounts, which did appear to disincentivize job search for UI-eligible individuals. Across almost all specifications, increasing maximum weekly benefit amount was negatively correlated with job search time. In general, the magnitude of this effect is estimated such that a 10% increase in maximum WBA would, on average, approximately decrease job search time by 2.0 minutes, which is approximately 5% of the sample mean.

The effect of extending UI duration is much more ambiguous. In certain specifications, such as MSA-level unemployment or at the extensive margin, increasing the number of UI weeks remaining was positively correlated with job search time. In the cross-section, this would imply that extending UI benefit durations has an *incentive* rather than disincentive effect. The likeliest explanation is that the UI benefit extensions play a role at the extensive margin by incentivizing otherwise discouraged workers to continue searching for jobs. This would corroborate Rothstein's (2011) findings that unemployment benefit extensions during the Great Recession had very little disincentive effects on unemployment exit into employment but played a larger role in preventing unemployment exit into non-employment.

The effect of the number of UI weeks remaining can also be examined in conjunction with the effect of unemployment duration to study job search effort on the individual level through the course of the unemployment spell. The statistically significant positive coefficients on the number of UI weeks remaining and the unemployment duration (with a slightly larger magnitude on the number of UI weeks remaining) imply that job search effort decreases slightly as the individual progresses through the unemployment spell. This result again would contradict some of the prior literature (Krueger and Mueller 2010; MPS 2014). An explanation for the observed effect is the change in the availability of job search opportunities. Towards the beginning of the unemployment duration, a readily available stock of job opportunities from accumulated social capital likely incentivizes more intense job search. When the stock of opportunities are exhausted and the individual must instead turn to the flow of job opportunities, the decline in opportunities available leads to a decrease in job search intensity.

Finally, individual job search effort appeared to be procyclical for UI-eligible individuals, contradicting Mukoyama, Patterson and Sahin's (2014) determination that job search effort is countercyclical. Procyclical job search was observed across a variety of specification methods, including MSA-level unemployment rates and probit regressions at the extensive margin. On average, the magnitude of the effect is such that a one percentage point increase in the unemployment rate would imply an approximate five minute decrease in the amount of time spent job searching. Several possible reasons, including a discouraged worker effect, an inverse relationship between individual job search intensity and aggregate unemployment, or the inverse relationship between job opportunities and unemployment rate could all explain the procyclicality of job search effort.

From the sum of these results, several policy implications follow. First, the fears about UI benefit extensions during the Great Recession greatly disincentivizing job search are overblown. At worst, the benefit extensions had no statistically significant impact on job search effort, and at best the benefit extensions actually incentivized more individual job search. Second, because increasing UI benefit amounts results in a measurable disincentive effect while extending UI duration does not, the generosity of unemployment benefits should preferably be increased along the time axis during recessions to best help unemployed individuals. Third, because job search effort is procyclical, if UI benefit extensions do indeed encourage job search effort then UI benefits could play an important counter-recessionary role by in both incentivizing discouraged workers to search again as well as smoothing consumption for liquidity-constrained individuals. Together, these results can hopefully better inform the UI policy response in future economic downturns.

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Appendix: Tables and Figures

Table 1: Average Minutes per Day Spent on Various Job Search Activities

Code	Activity	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
t050401	Job search activities*	13.7	12.3	16.9	26.2	20.2	38.7	33.0	31.8	31.5	34.9	30.5	28.0
t050402	Other job search activities	14.8	4.7	---	---	---	---	---	---	---	---	---	---
t050403	Job interviewing	1.2	1.1	1.2	1.9	2.8	0.9	0.8	0.6	1.0	3.4	2.3	1.0
t050404	Waiting associated with job search or interview	0.3	0.7	0.5	0.1	0.0	2.6	0.1	0.3	0.9	0.2	0.0	0.1
t050405	Security procedures rel. to job search/interviewing	---	---	---	---	0.1	---	---	---	---	---	---	---
t050499	Job search and Interviewing, not otherwise classified	0.8	2.5	1.6	---	0.0	---	0.0	0.4	---	---	---	0.7
t180504	Travel related to job search and interviewing	---	---	4.7	5.3	10.4	5.0	5.4	5.1	3.5	4.5	2.5	3.4
Total		*30.8*	*21.2*	*24.8*	*33.4*	*33.5*	*47.1*	*39.4*	*38.1*	*36.9*	*43.1*	*35.4*	*33.1*
Total for activities that are available all years		*30.0*	*18.7*	*18.5*	*28.2*	*23.0*	*42.2*	*33.9*	*32.7*	*33.4*	*38.5*	*32.8*	*29.1*

**"Active job search activities" for years 2003-2004; combined with "other job search activities" for years 2005-2014*
***The dashes indicate that the particular job search activity was not surveyed that year*
****Universe: unemployed persons between the age of 20 and 65. All averages are weighted with the ATUS statistical weights.*

Table 2: Average Unemployment Duration, Observed in CPS or Calculated from CPS-ATUS

Gap in Observed Months	Initial Employment Status	Avg. Unemp. Dur. Observed in CPS (Weeks)	Avg. KM Unemp. Dur. (Weeks)	Avg. Imputed Unemp. Dur. (Weeks)
2	Employed/NILF	16.25	4.00	18.92
	Unemployed	33.95	41.76	39.33
	All	*23.59*	*19.89*	*27.65*
3	Employed/NILF	16.36	6.00	19.21
	Unemployed	38.37	45.36	41.91
	All	*25.28*	*19.97*	*27.00*
4	Employed/NILF		8.00	21.78
	Unemployed		47.46	44.32
	All		*19.18*	*27.52*
5	Employed/NILF		10.00	27.49
	Unemployed		51.30	48.15
	All		*20.29*	*30.36*
All			***19.85***	***27.19***

The table compares the average unemployment durations that are observed in the CPS data, calculated by the KM method in the ATUS data, and imputed with linear regressions in the ATUS data, conditional on the labor force status observed in the initial gap month (see Section 2.3). Observations between CPS months can observe two- and three-month gap periods, while observations between the final month of the CPS and the ATUS consist of two-, three-, four- or five-month gap periods. The table illustrates how the KM method tends to underestimate the unemployment duration while the imputed method tends to overestimate the unemployment duration.

Table 3: Regression to Determine Unemployment Duration

Variable	Init. Emp./NILF - 2 mo.	Init. Emp./NILF - 3 mo.	Init. Unemp. - 2 mo.	Init. Unemp. - 3 mo.
Initially NILF	16.55 (0.157)***	16.76 (0.208)***		
Initial unemployment duration			0.81 (0.013)***	0.77 (0.019)***
Age	1.00 (0.027)***	0.97 (0.034)***	0.23 (0.031)***	0.38 (0.046)***
Age^2	-0.01 (0)***	-0.01 (0)***	0.00 (0)***	0.00 (0.001)***
Some college	-0.96 (0.168)***	-0.81 (0.209)***	0.15 (0.145)	0.24 (0.213)
College	-0.89 (0.224)***	-0.85 (0.27)***	0.50 (0.168)***	0.96 (0.243)***
Female	-2.29 (0.168)***	-1.85 (0.207)***	-0.25 (0.146)*	-0.75 (0.24)***
Black	5.79 (0.336)***	6.16 (0.427)***	0.86 (0.276)***	0.84 (0.395)**
Hispanic	0.70 (0.261)***	0.50 (0.324)	-0.39 (0.251)	-0.91 (0.374)**
Asian	2.09 (0.567)***	1.63 (0.708)**	0.42 (0.437)	0.69 (0.655)
Native American	2.66 (0.746)***	2.73 (0.925)***	0.36 (0.739)	-0.69 (1.12)
Mixed Race	1.02 (0.694)	0.56 (0.861)	0.59 (0.609)	0.84 (0.86)
Female*Black	0.03 (0.459)	-1.08 (0.581)*	-0.21 (0.388)	0.53 (0.536)
Female*Hispanic	1.48 (0.396)***	1.63 (0.497)***	0.23 (0.385)	0.52 (0.576)
Female*Asian	0.13 (0.813)	0.55 (1.015)	0.31 (0.691)	0.83 (0.977)
Female*Native American	-1.08 (1.083)	-2.56 (1.347)*	-0.33 (1.039)	0.02 (1.53)
Female*Mixed Race	0.57 (0.984)	-0.11 (1.197)	-0.19 (0.826)	-1.49 (1.215)
Constant	-19.47 (0.505)***	-18.06 (0.647)***	2.90 (0.56)***	2.31 (0.871)***
No. Observations:	106018	66663	75191	45469
R-Squared:	0.17	0.17	0.70	0.63

,, and *** denote significance at the 10%, 5%, and 1% levels, respectively.*
Parentheses contain robust standard errors.
For the first two columns, see Eq. 1; for the last two columns, see Eq. 2.
Regression dataset: IPUMS-CPS, 2001-2014, longitudinally linked.

Table 4: Regression to Determine Imputed Wage

Variable	With Year Fixed Effects (Base)	Without Year Fixed Effects
Age	0.06 (.000)***	0.05 (.000)***
Age^2	0.00 (.000)***	0.00 (.000)***
Some college	0.17 (.001)***	0.18 (.001)***
College	0.52 (.001)***	0.53 (.001)***
Female	-0.24 (.001)***	-0.24 (.001)***
Black	-0.22 (.002)***	-0.21 (.002)***
Hispanic	-0.22 (.002)***	-0.21 (.002)***
Asian	-0.11 (.003)***	-0.1 (.003)***
Native American	-0.11 (.006)***	-0.11 (.006)***
Mixed Race	-0.06 (.004)***	-0.06 (.004)***
Female*Black	0.12 (.002)***	0.12 (.002)***
Female*Hispanic	0.06 (.002)***	0.07 (.002)***
Female*Asian	0.04 (.004)***	0.05 (.004)***
Female*Native American	0.03 (.008)***	0.03 (.008)***
Female*Mixed Race	0.03 (.006)***	0.03 (.006)***
Constant	1.52 (.005)***	1.64 (.005)***
Year Fixed Effects	Yes	No
No. Observations:	1908745	1908745
R-Squared:	0.33	0.32

,, and *** denote significance at the 10%, 5%, and 1% levels, respectively.*

Parentheses contain robust standard errors.

See Eq. 3 for the regression equation.

Regression dataset: CEPR-ORG, 2003-2014. Does not include self-employed or self-incorporated individuals, students, or individuals with wages less than $1/hr or greater than $200/hr.

Table 5: Sample Means for Regression Variables

	Variables	Means - Unemployed Sample	Means - UI-Eligible Sample	Regressions Used
Dependent Variable	Time spent job searching (total)	35.66	42.41	Base
	Time spent job searching (available all years)	31.09	37.10	III-1
	Time spent job searching (topcoded)	34.69	41.47	III-2
	Binary search	0.21	0.24	V-1
Returns to Search	Imputed wage (with fixed year effects)	2.69	2.75	Base
	Imputed wage (without fixed year effects)	2.68	2.74	III-3
	Standard deviation of wage residual by state (with fixed year effects)	0.48	0.48	Base
	Standard deviation of wage residual by state (without fixed year effects)	0.48	0.48	III-3
	Temporary layoff	0.12	0.23	All
	Job leaver	0.02	0.00	All
	New entrant	0.40	0.00	All
	Unemployment duration	19.85	13.64	Base
	Imputed unemployment duration	27.19	17.90	III-4
	Time left on UI	39.01	42.52	Base
	Imputed time left on UI	31.03	38.56	III-4
	Max WBA (by year)	5.98	5.99	Base
	Max WBA (averaged)	5.96	5.97	III-3
	UI Weeks Left - Group 1	0.71	0.77	III-5
	UI Weeks Left - Group 2	0.11	0.15	III-5
	UI Weeks Left - Group 3	0.07	0.08	III-5
	(Group 1) * Total weeks available	40.18	43.10	III-5
	(Group 2) * Total weeks available	6.39	8.50	III-5
	(Group 3) * Total weeks available	3.65	4.56	III-5
Macro variables	State unemployment rate (monthly)	7.43	7.38	Base
	MSA unemployment rate (monthly)	7.75	7.70	IV-2, IV-4
	State housing price index (quarterly)	5.19	5.20	IV-3
	MSA housing price index (quarterly)	5.82	5.82	IV-4
Individual Characteristics	LF attachment (unemployed)	0.16	0.12	All
	LF attachment (NILF)	0.19	0.09	All
	LF attachment (no information)	0.29	0.28	All
	Age	37.11	38.72	All
	Age^2	1545.03	1656.06	All
	Some college	0.30	0.29	All
	College	0.17	0.20	All
	Female	0.50	0.44	All
	Partner	0.47	0.53	All
	Children	0.47	0.44	All
	Black	0.22	0.18	All
	Hispanic	0.19	0.18	All
	Asian	0.03	0.02	All
	Native American	0.01	0.01	All
	Mixed Race	0.02	0.02	All
	Female*Partner	0.25	0.23	All
	Female*Child	0.28	0.21	All
	Female*Black	0.11	0.08	All
	Female*Hispanic	0.10	0.07	All
	Female*Asian	0.02	0.01	All
	Female*Native American	0.01	0.00	All
	Female* Mixed Race	0.01	0.01	All
	Weekend	0.29	0.28	All
No. Observations:		5899	3060	

Table 6: Base Regression on Job Search Time

Variable	All Unemployed	UI-Eligible
Imputed wage	61.00 (34.306)*	129.58 (67.068)*
Standard deviation of wage residuals by state	47.07 (126.210)	-21.47 (235.905)
Temporary Layoff	-38.18 (4.686)***	-40.38 (5.390)***
Job Leaver	-1.13 (15.772)	
New Entrant	-12.33 (8.690)	
Unemployment duration	-0.07 (.062)	0.33 (.374)
UI Weeks Left for UI-eligible	0.05 (.100)	0.48 (.333)
Log max WBA	0.07 (1.590)	-20.92 (11.449)*
State Unemployment Rate	-1.76 (1.481)	-5.23 (2.639)*
LF Attachment (Unemployed)	0.42 (6.754)	3.40 (6.856)
LF Attachment (NILF)	-13.23 (3.505)***	-15.55 (5.697)***
LF Attachment (No Info)	2.81 (4.386)	7.54 (5.332)
Age	0.30 (2.307)	-3.03 (4.007)
Age^2	-0.01 (.025)	0.03 (.042)
Some college	-4.00 (8.795)	-12.27 (15.472)
College	-9.25 (20.095)	-39.13 (38.229)
Female	6.92 (11.021)	18.07 (19.133)
Partner	0.77 (7.404)	3.09 (9.181)
Children	-2.67 (7.666)	-2.54 (8.808)
Black	17.30 (8.296)**	27.27 (14.595)*
Hispanic	2.08 (7.239)	16.16 (13.950)
Asian	-14.59 (10.044)	13.25 (23.662)
Native American	29.93 (47.700)	-23.41 (26.419)
Mixed Race	0.75 (16.531)	13.17 (20.024)
Female*Partner	-13.29 (7.190)*	-16.71 (8.946)*
Female*Children	-6.75 (8.209)	-2.74 (9.904)
Female*Black	-7.99 (8.820)	-16.08 (12.803)
Female*Hispanic	3.22 (4.896)	4.32 (8.849)
Female*Asian	16.25 (11.657)	5.62 (25.098)
Female*Native American	-49.93 (48.088)	8.27 (29.093)
Female*Mixed Race	-18.20 (18.932)	-37.84 (27.456)
Weekend	-33.48 (2.436)***	-44.20 (4.022)***
Constant	-167.07 (49.912)***	324.17 (78.944)***
No. Observations:	5899	3060
R-Squared:	0.12	0.19

,, and *** denote significance at the 10%, 5%, and 1% levels, respectively.*
Unemployment type base group is the job losers.
Parentheses contain robust standard errors clustered at the state level.
Regression dataset: ATUS, 2003-2014, ages 20-65

Table 7: Robustness Checks of the Base Regression on Job Search Time

Variable	Base (Unemp.)	Base (UI-Elig.)	III-1 (Unemp.)	III-1 (UI-Elig.)	III-2 (Unemp.)	III-2 (UI-Elig.)	III-3 (Unemp.)	III-3 (UI-Elig.)	III-4 (Unemp.)	III-4 (UI-Elig.)	III-5 (Unemp.)	III-5 (UI-Elig.)
Imputed wage	61.00	129.58	57.22	104.56	62.37	133.04	42.41	147.16	63.16	131.25	60.08	130.60
	(34.306)*	(67.068)*	(30.607)*	(58.017)*	(32.676)*	(64.450)**	(36.103)	(62.902)**	(33.115)*	(66.716)*	(34.952)*	(67.446)*
Standard deviation of wage residuals by state	47.07	-21.47	31.31	12.83	42.17	-24.67	128.98	-86.01	44.19	-27.09	45.67	-25.97
	(126.210)	(235.905)	(113.235)	(207.939)	(120.798)	(227.790)	(137.991)	(244.735)	(125.176)	(236.143)	(125.122)	(231.385)
Temporary Layoff	-38.18	-40.38	-31.69	-33.29	-37.59	-39.99	-38.09	-40.49	-37.80	-40.05	-37.15	-40.18
	(4.686)***	(5.390)***	(3.948)***	(4.773)***	(4.572)***	(5.302)***	(4.699)***	(5.439)***	(4.727)***	(5.230)***	(4.678)***	(5.283)***
Job Leaver	-1.13		1.78		2.48		-1.17		-6.69		-6.67	
	(15.772)		(15.584)		(14.716)		(15.714)		(16.423)		(16.442)	
New Entrant	-12.33		-12.36		-9.70		-12.15		-17.48		-17.55	
	(8.690)		(8.146)		(7.774)		(8.741)		(10.910)		(10.027)*	
Unemployment duration	-0.07	0.33	-0.02	0.29	-0.06	0.29	-0.05	0.40	-0.19	0.16	-0.01	0.15
	(.062)	(.374)	(.058)	(.374)	(.059)	(.360)	(.060)	(.372)	(.091)**	(.344)	(.144)	(.476)
UI Weeks Left for UI-eligible	0.05	0.48	0.06	0.38	0.05	0.42	0.05	0.52	0.01	0.31		
	(.100)	(.333)	(.094)	(.330)	(.095)	(.315)	(.099)	(.332)	(.110)	(.268)		
Log max WBA	0.07	-20.92	-0.19	-16.26	0.48	-21.79	0.10	-25.42	-1.02	-20.17	-0.66	-20.82
	(1.590)	(11.449)*	(1.537)	(9.645)*	(1.440)	(11.161)*	(1.591)	(10.866)**	(1.820)	(11.142)*	(1.709)	(11.532)*
State Unemployment Rate	-1.76	-5.23	-1.71	-4.67	-1.70	-5.19	-1.68	-5.26	-1.77	-4.73	-2.76	-5.22
	(1.481)	(2.639)*	(1.402)	(2.480)*	(1.392)	(2.558)**	(1.449)	(2.539)**	(1.546)	(2.302)**	(1.716)	(2.592)*
LF Attachment (Unemployed)	0.42	3.40	-2.81	0.99	0.62	3.97	0.40	3.45	0.78	3.22	0.72	3.02
	(6.754)	(6.856)	(5.278)	(6.677)	(6.421)	(6.934)	(6.773)	(6.831)	(6.627)	(6.871)	(6.717)	(6.970)
LF Attachment (NILF)	-13.23	-15.55	-11.20	-12.02	-13.35	-15.24	-13.31	-15.49	-13.09	-15.69	-13.00	-15.15
	(3.505)***	(5.697)***	(3.378)***	(5.589)**	(3.383)***	(5.611)***	(3.501)***	(5.671)***	(3.541)***	(5.670)***	(3.749)***	(5.787)**
LF Attachment (No Info)	2.81	7.54	2.21	7.01	1.77	6.12	2.76	7.53	2.78	7.40	3.02	7.50
	(4.386)	(5.332)	(4.190)	(5.156)	(3.878)	(4.844)	(4.392)	(5.309)	(4.433)	(5.328)	(4.550)	(5.286)
UI Weeks Left - Group 1											-8.02	13.00
											(12.625)	(21.938)
UI Weeks Left - Group 2											-3.83	21.98
											(13.706)	(26.663)
UI Weeks Left - Group 3											-8.34	
											(22.984)	
(Group 1)*Total UI Weeks Available											0.36	0.45
											(.221)	(.338)
(Group 2)*Total UI Weeks Available											0.35	0.25
											(.210)*	(.429)
(Group 3)*Total UI Weeks Available											0.36	0.37
											(.390)	(.751)
Constant	-167.07	324.17	-149.18	322.97	-169.22	329.61	-190.77	340.95	-158.59	321.53	-162.27	316.68
	(49.912)***	(78.944)***	(44.693)***	(68.539)***	(47.782)***	(77.532)***	(53.839)***	(78.553)***	(51.562)***	(79.353)***	(48.465)***	(81.008)***
All available job search time	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Averaged log wages and WBA	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No
Imputed unemployment	No	No	No	No	No	No	No	No	Yes	Yes	No	No
No. Observations:	5899	3060	5899	3060	5899	3060	5899	3060	5899	3060	5899	3060
R-Squared:	0.12	0.19	0.12	0.18	0.13	0.19	0.12	0.19	0.12	0.19	0.12	0.19

,, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Parentheses contain robust standard errors clustered at the state level. Unemployment type base group is the job losers. Regression dataset: ATUS, 2003-2014, ages 20-65*
III-1 specifies the job search time with only the activities that are available in all years. III-2 topcodes job search time to eight hours. III-3 specifies the imputed wage, standard deviation of wage residuals, and log maximum WBA without fixed years. III-4 specifies the unemployment duration and UI weeks left using the imputed method (see Section 2.3). III-5 specifies the weeks of UI left by dummy groups, where Groups 1, 2, and 3 refer to individuals in their first third, second third, and last third of their total UI duration, and the base group is the UI-ineligible.

Table 8: Variants in Macroeconomic Specifications for the Regressions on Job Search Time

Variable	Base (Unemp.)	Base (UI-Elig.)	IV-1 (Unemp.)	IV-1 (UI-Elig.)	IV-2 (Unemp.)	IV-2 (UI-Elig.)	IV-3 (Unemp.)	IV-3 (UI-Elig.)	IV-4 (Unemp.)	IV-4 (UI-Elig.)
Imputed wage	61.00	129.58	62.37	129.41	11.43	88.73	82.79	182.59	51.23	132.12
	(34.306)*	(67.068)*	(34.343)*	(68.106)*	(48.122)	(110.068)	(32.899)**	(60.207)***	(51.843)	(118.859)
Standard deviation of wage residuals by state	47.07	-21.47	40.11	-28.13	147.89	-77.67	63.50	26.24	147.84	-96.73
	(126.210)	(235.905)	(126.969)	(237.602)	(169.349)	(308.062)	(133.269)	(211.372)	(177.842)	(317.719)
Temporary Layoff	-38.18	-40.38	-38.17	-40.40	-44.26	-50.65	-38.20	-40.46	-47.16	-54.61
	(4.686)***	(5.390)***	(4.654)***	(5.320)***	(6.483)***	(7.630)***	(4.641)***	(5.387)***	(6.489)***	(7.679)***
Job Leaver	-1.13		-0.74		3.80		-1.13		-0.89	
	(15.772)		(15.657)		(20.681)		(15.762)		(21.481)	
New Entrant	-12.33		-12.16		-5.46		-12.38		-8.95	
	(8.690)		(8.606)		(12.905)		(8.702)		(13.669)	
Unemployment duration	-0.07	0.33	-0.08	0.22	0.02	0.87	-0.08	0.35	0.00	0.71
	(.062)	(.374)	(.062)	(.398)	(.096)	(.407)**	(.060)	(.379)	(.101)	(.392)*
UI Weeks Left for UI-eligible	0.05	0.48	0.04	0.35	0.14	1.02	0.05	0.53	0.16	0.88
	(.100)	(.333)	(.099)	(.359)	(.127)	(.354)***	(.100)	(.346)	(.128)	(.343)**
Log max WBA	0.07	-20.92	0.16	-19.01	1.18	-20.52	0.08	-17.04	0.50	-19.29
	(1.590)	(11.449)*	(1.572)	(11.382)	(2.354)	(15.300)	(1.595)	(11.486)	(2.492)	(16.675)
State Unemployment Rate	-1.76	-5.23	-12.02	-36.10			-1.95	-5.83		
	(1.481)	(2.639)*	(14.452)	(20.162)*			(1.537)	(2.641)**		
State Unemployment Rate^2			1.68	4.49						
			(1.928)	(2.675)*						
State Unemployment Rate^3			-0.08	-0.20						
			(.077)	(.105)*						
State Housing Index							-7.70	-21.35		
							(11.201)	(13.502)		
MSA Unemployment Rate					-2.02	-4.80			-2.85	-5.35
					(.998)**	(1.995)**			(1.237)**	(2.014)**
MSA Housing Index									-17.82	-20.34
									(14.584)	(14.206)
LF Attachment (Unemployed)	0.42	3.40	0.36	3.40	-1.75	2.47	0.38	3.44	-4.17	-2.37
	(6.754)	(6.856)	(6.786)	(6.943)	(8.722)	(7.806)	(6.737)	(6.880)	(8.991)	(7.982)
LF Attachment (NILF)	-13.23	-15.55	-13.45	-15.82	-12.50	-11.63	-13.13	-15.40	-13.00	-9.90
	(3.505)***	(5.697)***	(3.610)***	(5.790)***	(4.608)***	(7.293)	(3.520)***	(5.691)***	(4.759)***	(7.043)
LF Attachment (No Info)	2.81	7.54	2.87	7.69	-1.98	8.34	2.80	7.31	-2.10	8.27
	(4.386)	(5.332)	(4.370)	(5.286)	(5.591)	(7.028)	(4.397)	(5.287)	(5.861)	(7.270)
Constant	-167.07	324.17	-146.27	388.58	-119.10	-36.95	-160.97	328.91	-84.85	6.58
	(49.912)***	(78.944)***	(58.096)**	(88.384)***	(59.521)*	(108.480)	(48.689)***	(72.107)***	(65.850)	(120.545)
Cubic controls for state unemployment rate	No	No	Yes	Yes	No	No	No	No	No	No
State housing prices	No	No	No	No	No	No	Yes	Yes	No	No
MSA unemployment rate	No	No	No	No	Yes	Yes	No	No	Yes	Yes
MSA housing prices	No	No	No	No	No	No	No	No	Yes	Yes
No. Observations:	5899	3060	5899	3060	3594	1848	5899	3060	3435	1752
R-Squared:	0.12	0.19	0.12	0.19	0.14	0.23	0.12	0.19	0.14	0.24

,, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Parentheses contain robust standard errors clustered at the state level. Unemployment type base group is the job losers. Regression dataset: ATUS, 2003-2014, ages 20-65*

IV-1 specifies state unemployment rate cubically. IV-2 specifies MSA unemployment rate in place of state unemployment rate. IV-3 uses state-level unemployment and housing index specifications. IV-4 uses MSA-level unemployment and housing index specifications.

Table 9: Average Marginal Effects from Probit Regression on Job Search Probability

Variable	Base (Unemp.)	Base (UI-Elig.)	Probit (Unemp.)	Probit (UI-Elig.)
Imputed wage	61.00 (34.306)*	129.58 (67.068)*	0.52 (.150)***	0.82 (.245)***
Standard deviation of wage residuals by state	47.07 (126.210)	-21.47 (235.905)	-0.50 (.552)	-0.88 (.744)
Temporary Layoff	-38.18 (4.686)***	-40.38 (5.390)***	-0.24 (.026)***	-0.27 (.028)***
Job Leaver	-1.13 (15.772)		0.01 (.042)	
New Entrant	-12.33 (8.690)		-0.04 (.019)**	
Unemployment duration	-0.07 (.062)	0.33 (.374)	0.0000 (.000)	0.0022 (.001)**
UI Weeks Left for UI-eligible	0.05 (.100)	0.48 (.333)	0.0002 (.001)	0.0022 (.001)***
Log max WBA	0.07 (1.590)	-20.92 (11.449)*	-0.04 (.022)*	-0.12 (.037)***
State Unemployment Rate	-1.76 (1.481)	-5.23 (2.639)*	-0.01 (.006)*	-0.03 (.009)***
LF Attachment (Unemployed)	0.42 (6.754)	3.40 (6.856)	0.01 (.026)	0.03 (.038)
LF Attachment (NILF)	-13.23 (3.505)***	-15.55 (5.697)***	-0.08 (.021)***	-0.08 (.043)*
LF Attachment (No Info)	2.81 (4.386)	7.54 (5.332)	-0.01 (.015)	0.02 (.022)
Constant	-167.07 (49.912)***	324.17 (78.944)***		
No. Observations:	5899	3060	5899	3060
R-Squared / Pseudo R-Squared:	0.12	0.19	0.12	0.16

,, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Parentheses contain robust standard errors clustered at the state level. Probit regressions use year time dummies rather than year-month dummies.*
Unemployment type base group is the job losers.
Regression dataset: ATUS, 2003-2014, ages 20-65

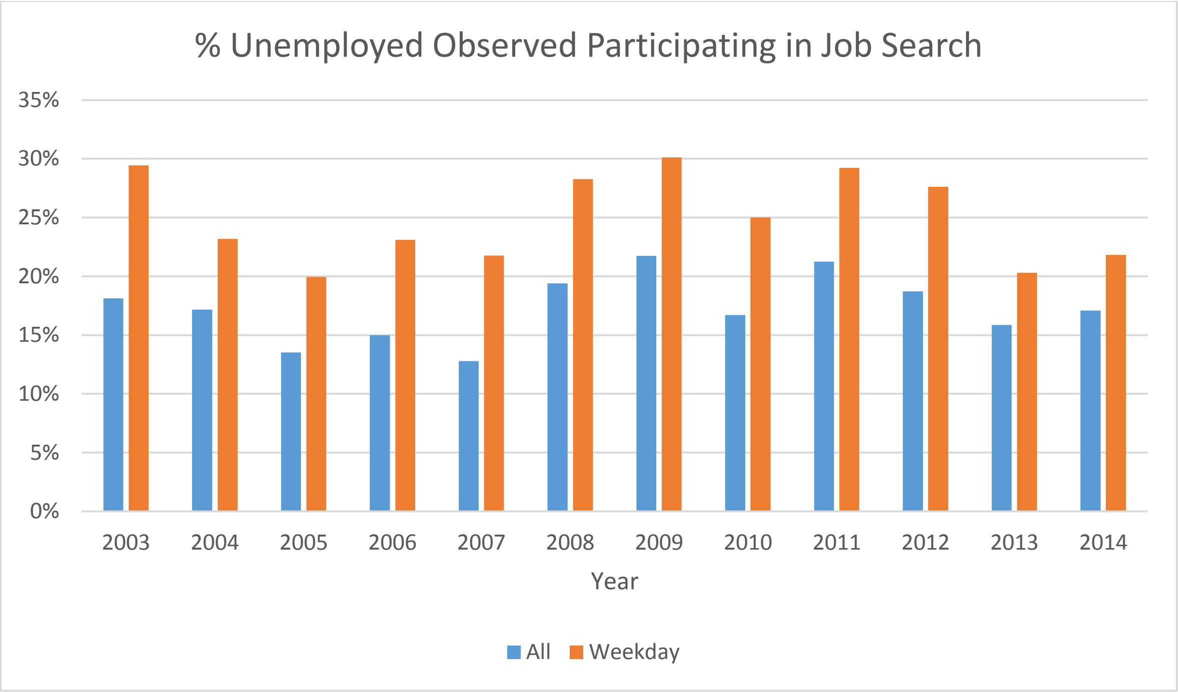
Table 10: Regression on Job Search Effort at the Intensive Margin

Variable	Base (Unemp.)	Base (UI-Elig.)	V-2 (Unemp.)	V-2 (UI-Elig.)
Imputed wage	61.00	129.58	-32.44	149.89
	(34.306)*	(67.068)*	(95.165)	(155.273)
Standard deviation of wage residuals by state	47.07	-21.47	567.55	549.59
	(126.210)	(235.905)	(391.961)	(593.227)
Temporary Layoff	-38.18	-40.38	-4.74	-14.70
	(4.686)***	(5.390)***	(27.933)	(31.310)
Job Leaver	-1.13		-4.52	
	(15.772)		(45.076)	
New Entrant	-12.33		-14.30	
	(8.690)		(29.643)	
Unemployment duration	-0.07	0.33	-0.02	1.65
	(.062)	(.374)	(.288)	(1.031)
UI Weeks Left for UI-eligible	0.05	0.48	-0.07	2.27
	(.100)	(.333)	(.268)	(.925)**
Log max WBA	0.07	-20.92	0.63	-32.11
	(1.590)	(11.449)*	(5.390)	(38.943)
State Unemployment Rate	-1.76	-5.23	-1.22	-8.86
	(1.481)	(2.639)*	(3.473)	(5.103)*
LF Attachment (Unemployed)	0.42	3.40	-18.03	-6.79
	(6.754)	(6.856)	(18.935)	(21.577)
LF Attachment (NILF)	-13.23	-15.55	-34.83	-72.20
	(3.505)***	(5.697)***	(15.352)**	(27.680)**
LF Attachment (No Info)	2.81	7.54	6.18	28.26
	(4.386)	(5.332)	(14.662)	(17.672)
Constant	-167.07	324.17	206.81	107.88
	(49.912)***	(78.944)***	(151.257)	(271.955)
No. Observations:	5899	3060	1086	634
R-Squared:	0.12	0.19	0.26	0.36

,, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Parentheses contain robust standard errors clustered at the state level. Unemployment type base group is the job losers.*

Regression dataset: ATUS, 2003-2014, ages 20-65

Figure A



All participants included here reported non-zero job search times.

Figure B

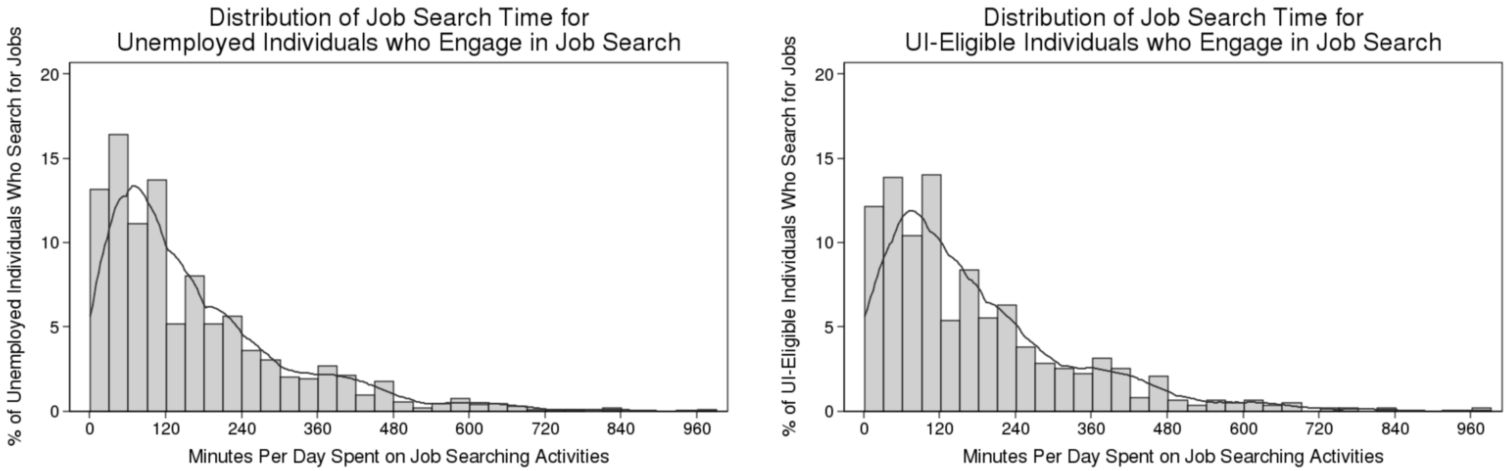
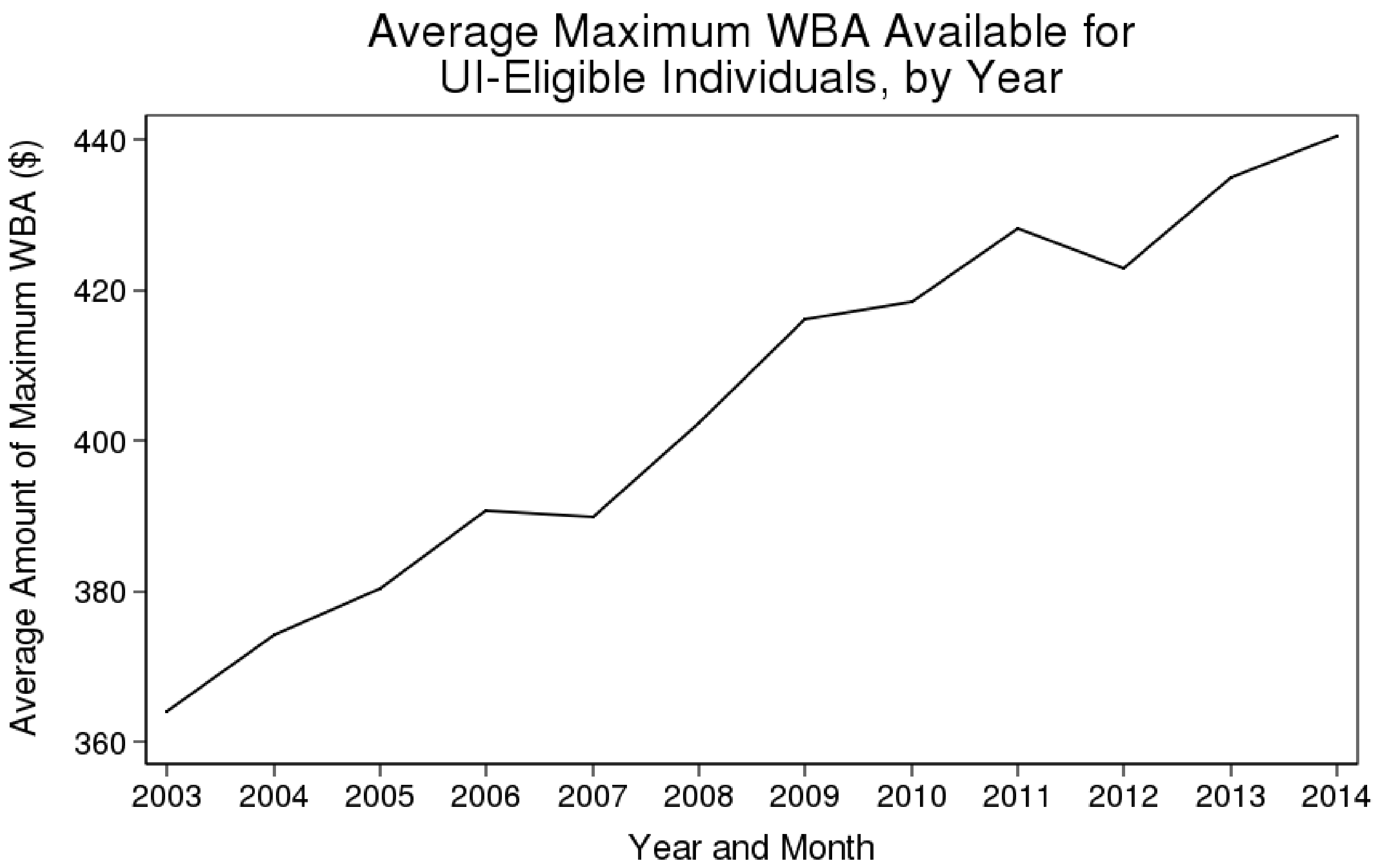
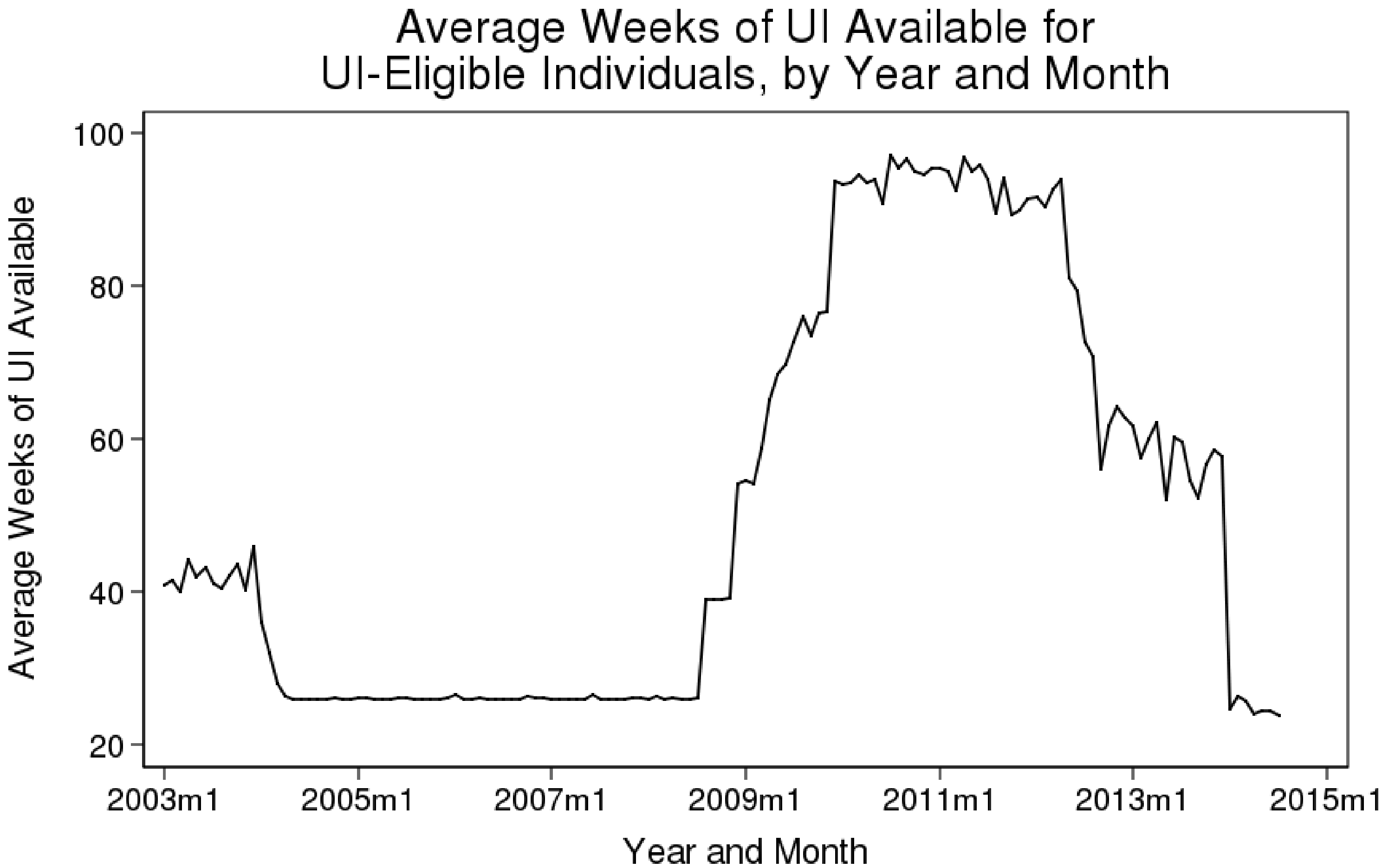

Distribution of Job Search Time for
Unemployed Individuals who Engage in Job Search
% of Unemployed Individuals Who Search for Jobs
0
5
10
15
20
0
120
240
360
480
600
720
840
960
Minutes Per Day Spent on Job Searching Activities
Distribution of Job Search Time for
UI-Eligible Individuals who Engage in Job Search
% of UI-Eligible Individuals Who Search for Jobs
0
5
10
15
20
0
120
240
360
480
600
720
840
960
Minutes Per Day Spent on Job Searching Activities

Figure C



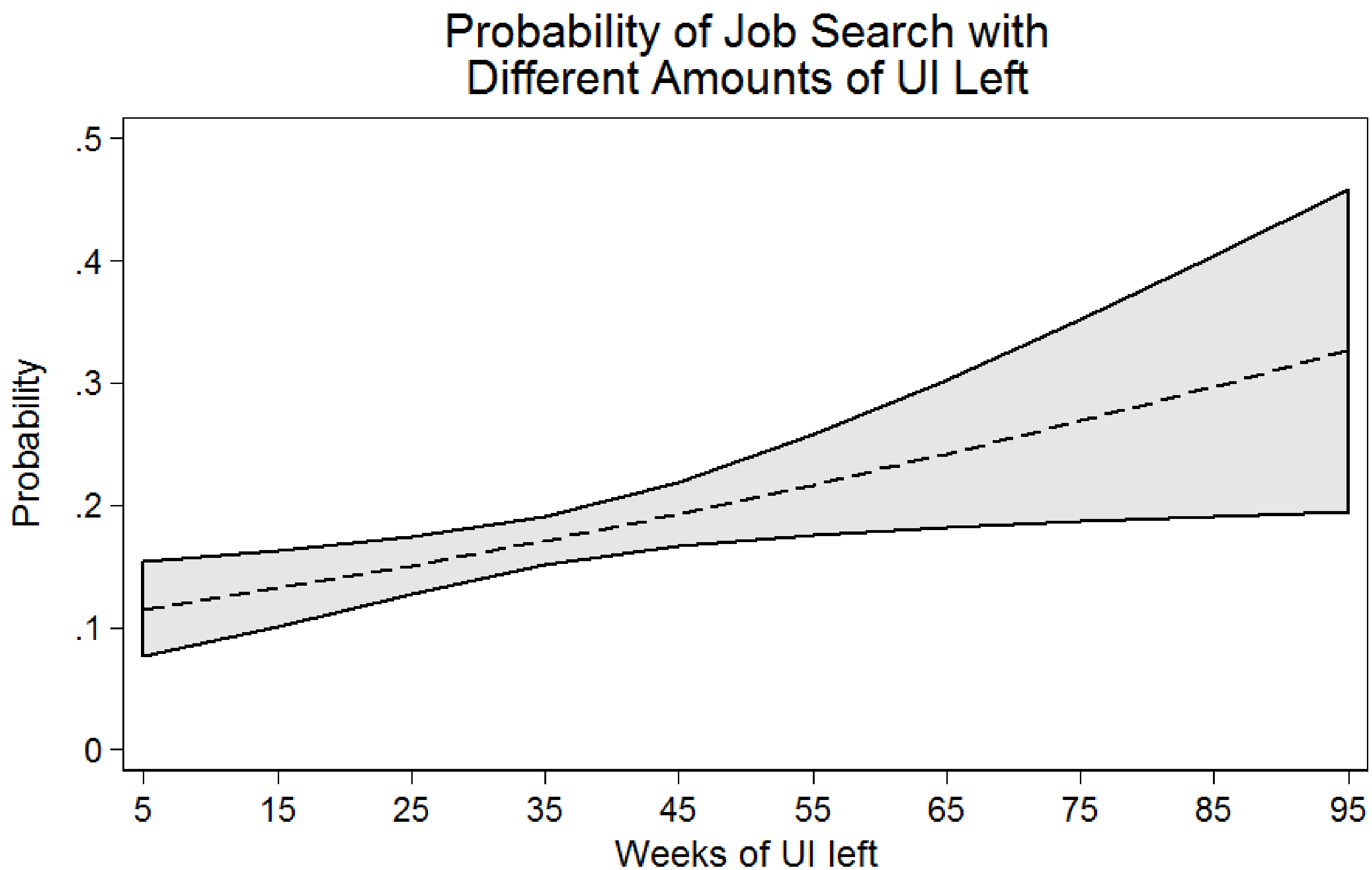
Maximum weekly benefit amounts by year averaged across the UI-eligible sample. Averages are weighted by ATUS statistical weights.

Figure D



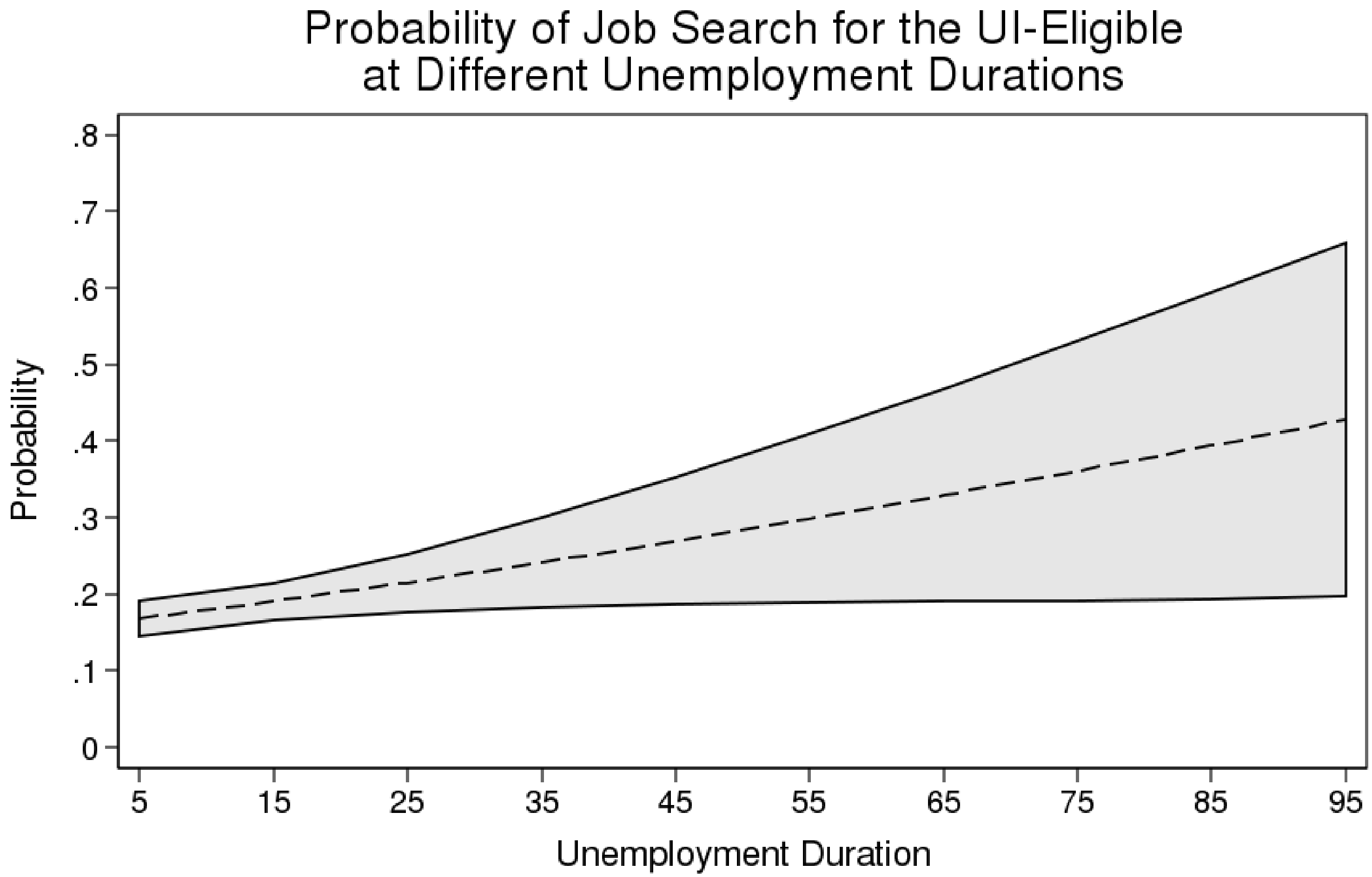
Weeks of UI eligible by year and month averaged across the UI-eligible sample. Averages are weighted by ATUS statistical weights.

Figure E



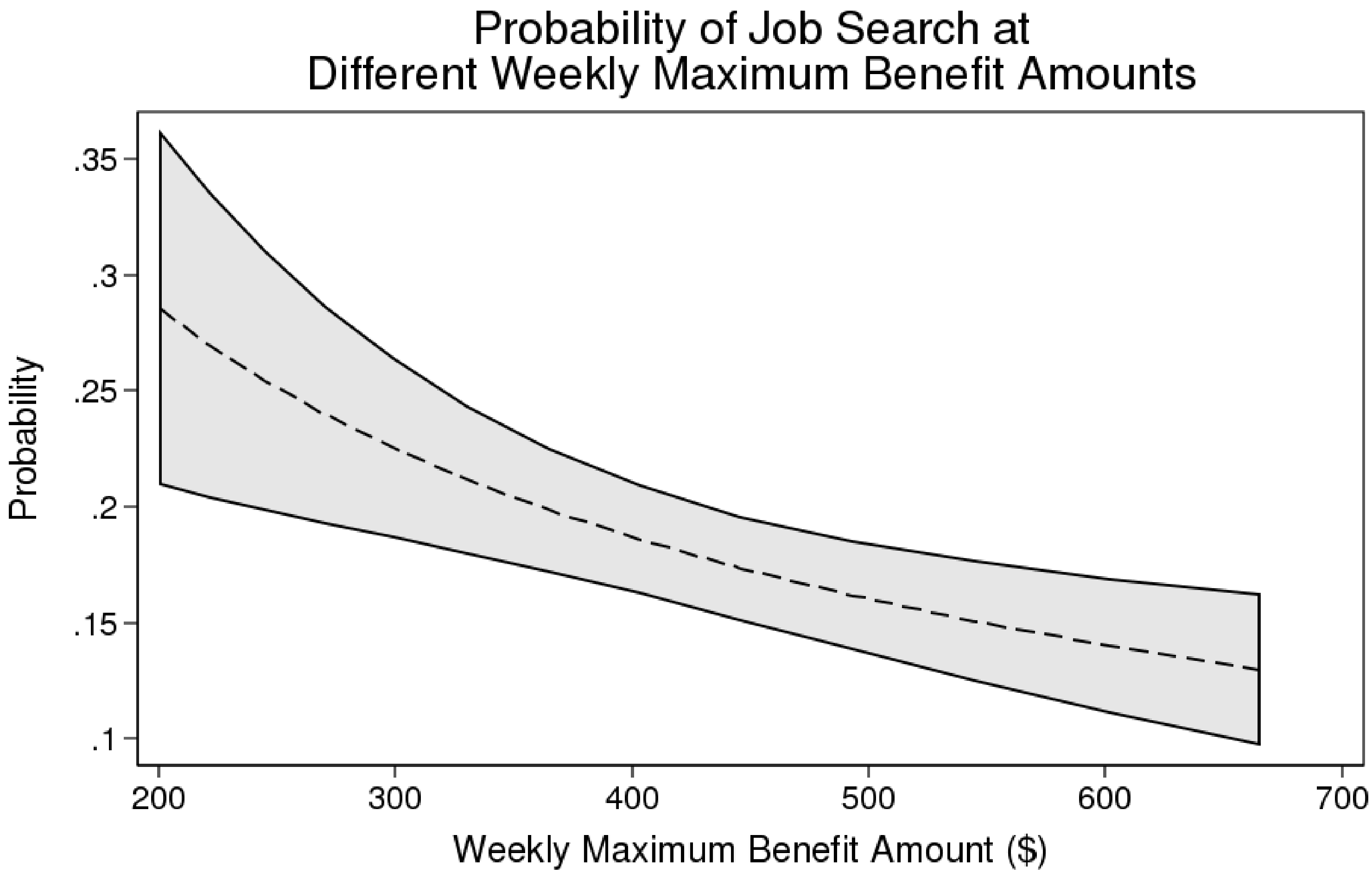
Dashed line: Probability curve over a range of weeks of UI left, holding all other variables (including unemployment duration) at their means
Solid lines: Upper and lower 95% confidence bands

Figure F



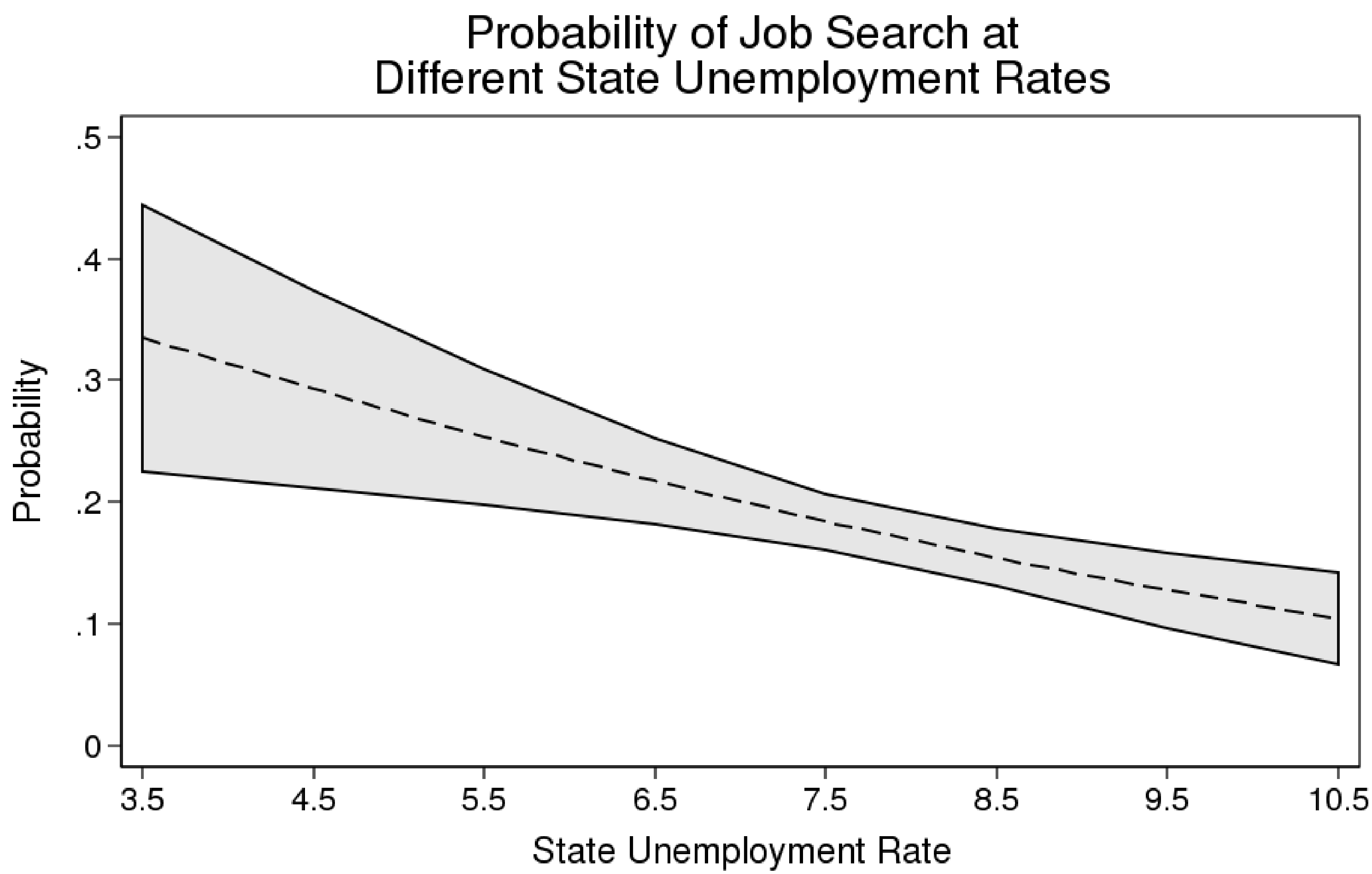
Dashed line: Probability curve over a range of weekly maximum benefit amounts, holding all other variables (including weeks of UI left) at their means
Solid lines: Upper and lower 95% confidence bands

Figure G



Dashed line: Probability curve over a range of weekly maximum benefit amounts, holding all other variables at their means
Solid lines: Upper and lower 95% confidence bands

Figure H



Dashed line: Probability curve over a range of weekly maximum benefit amounts, holding all other variables at their means
Solid lines: Upper and lower 95% confidence bands