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What Drives Job Search? Evidence from Google Search Data

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Abstract

The large-scale unemployment caused by the Great Recession has necessitated unprecedented increases in the duration of unemployment insurance (UI). While it is clear that the weekly payments are beneficial to recipients, workers receiving benefits have less incentive to engage in job search and accept job offers. We construct a job search activity index based on Google data which provides the first high-frequency, state-specific measure of job search activity. We demonstrate the validity of our measure by benchmarking it against the American Time Use Survey and the comScore Web-User Panel, and also by showing that it varies with hypothesized drivers of search activity. We test for search activity responses to policy shifts and changes in the distribution of unemployment benefit duration. We find that search activity is greater when a claimant's UI benefits near exhaustion. Furthermore, search activity responses to the passage of bills that increase unemployment benefits duration are negative but short-lived in most specifications. Using daily data, we estimate that an increase by 1% of the population of unemployed receiving additional benefits results in a decrease in aggregate search activity of 1.7% lasting only one week.

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1 Introduction

Online job search is an increasingly important component of overall job search activity in the United States, with over 83% of job seekers using the Internet for job search in 2008. Freely available data on online job search provides researchers with a high frequency measure of aggregate job search activity. We demonstrate that fluctuations in internet searches for jobs over time and across states track closely to demonstrated drivers of search activity (eg. unemployment rates, days of the week, and holidays) and other measures of job search. We develop a job search index using publicly available Google Search data and estimate the response of job search activities to changes in unemployment benefit policy, utilizing the high frequency variation in online search behavior around the time of the policy change. The policy changes we consider are the recent (2008-2010) unemployment insurance (UI) extensions and expansions on aggregate job search activity. On average, the extensions and expansions of UI decreased job search by 1.7% for every percentage point of the unemployed directly affected by the policy change, with the effect lasting only one week. We undertake a quantitative exercise that suggests that UI policy changes did not affect the unemployment rate significantly during the recession.

Economic theory predicts that job search activity varies with the marginal return of search, UI policies, and liquidity needs; job search activity is also important in determining steady state unemployment levels. However, the models of job search activity are difficult to estimate due to the difficulty of measuring aggregate job search activity. Our new measure of job search activity allows us to develop novel tests of job search theories. Furthermore, the almost immediate availability of Google search data can allow researchers to examine the effects of policies on behavior in real time. Our results demonstrate the utility of Google job search as an instant feedback tool for policy makers.

Our proposed measure of job search activity has a number of advantages over previously used measures of job search, such as those obtained from the American Time-Use Survey (ATUS). Firstly, the ATUS's small sample size creates a situation in which state-month level data may contain fewer than 5 unemployed respondents, making them unsuitable for fine state-level or time-series analysis. For example, most theories of job search predict that local labor market conditions have a strong effect on the magnitude of the search activity response. However, the small samples in the ATUS make it difficult to account for local labor market conditions. Using online search data sidesteps the problem that many encounter when using survey data, where inaccurate recall and the nature of surveyed responses can create biased results.

Another advantage of our measure is that it is available immediately at a daily level. We compile a daily state-level panel spanning 6 years to precisely measure the impact of announcements regarding unemployment benefits on the level of search activity, an exercise unsuited for coarser monthly data. Using variation in state-level unemployment and UI benefit structure, we test for a differential effort response based on differing labor market conditions. Overall, we find evidence for somewhat higher levels of search at the beginning and end of a UI spell. As predicted by theory, changes in search activity are more responsive to changes in policy and labor market conditions when search activity is at a relatively lower level. We also find evidence for declines in search activity following expansions of UI programs during the Great Recession, but that these declines are relatively small and short-lived.

2 Previous Literature

2.1 Empirical Studies

Krueger and Mueller (2010), study how job search behavior of individuals varies across states and at different points during an unemployment spell using American Time Use Survey data. They find elasticities of job search with respect to the level of unemployment benefits on the order of -1.6 to -2.2. They also find increases in job search activities prior to benefit exhaustion, while those ineligible for unemployment benefits see no such increase.

In a different contribution, Krueger and Mueller (2011) administer a survey to UI recipients in New Jersey which asks questions about job search activity and reservation wages. Importantly, as a reference for our study, they find that effort decreases over the duration of unemployment and that reservation wages remain approximately constant throughout the unemployment spell. They look at the correlation between job search activity and job finding rate and find that an extra 20 hours per week make an individual 20% more likely to exit. However, their identification strategy for the effects of the 2009 expansion of Emergency Unemployment Compensation (EUC) cannot separate time trends from the policy change. They find that after the policy change, there is on average 12 minutes less job search per day.

Kuhn and Skuterud (2004) discuss the prevalence of online search as a component of job search activity. They note that, as of 1998, approximately 15% of unemployed jobseekers used the internet to search for jobs, exceeding the amount of job search done through private employment agencies, contacting friends, or utilizing unions. Furthermore, they found that over half of respondents who had internet access from home searched online for jobs. Stevenson (2008) finds that, while a majority of online job searchers are currently employed, over the past 10 years unemployed job searchers have come to use the internet much more extensively. Furthermore, as the penetration of internet access increases, the unemployed devote a greater fraction of their job search time to online search and the proportion of job seekers directly contacting potential employers increases. In mid-2002, 22% of job seekers found their jobs online, a number that has surely increased consistently through the decade. We corroborate these results later in the paper using more recent National Longitutinal Survey of Youth data.

Given the rapid increase in both access to the internet (as of 2010, approximately 80% of Americans had internet access from home) and the increase in the number and size of job search related sites, it is safe to assume that online job search currently represents an important component of overall job search. Furthermore, we believe that online search behavior is an interesting behavior to explain, not only as a proxy for overall job search, but also in and of itself. The increased availability of internet job search services and the decreased use of physical classified jobs ads has made online job search more prevalent over the past decade (Kroft and Pope (2010)). Therefore, online search is becoming a larger part of the aggregate job search activity.

Holzer (1986) finds that job searchers are relatively efficient in the allocation of their search effort, spending more time in job search activities which are more 'productive' in terms of finding a job. This finding highlights the importance of controlling for local labor market conditions, as searchers respond to changing marginal returns to job search.

In addition, data from Google Insights for Search has been used in several other papers. Choi and Varian (2009a and 2009b) and D'Amuri and Marcucci (2011) have demonstrated the utility of Google search data in forecasting several categories of sales and initial unemployment claims. Da, Gao and Engelberg (2011) use Google search data as a proxy for investors' attention to stocks, showing that it predicts stock price movement.

2.2 Job Search Activity and Optimal Policy

An enhanced ability to measure job search activity also offers insight into the moral hazard aspect of extending or increasing unemployment benefits. Raj Chetty (2008) examines the implications of increases in unemployment benefits on duration of unemployment. He separates the impact into a positive 'liquidity' effect and a negative 'moral hazard' effect. Using the Survey of Income and Program Participation, he finds that 60% of the increase in unemployment duration resulting from an increase in UI benefits can be attributed to the 'liquidity' effect. Thus, an observed increase in unemployment duration following an increase in benefits need not be a net welfare loss. If we observe large decreases in job search activity following such an increase, we might surmise that effort is more responsive to unemployment benefits than is the reservation wage.

Mortensen (1977) is the canonical model of job search with expiring UI duration. He shows that, holding the match rate constant, job search activity increases as UI benefits come closer to expiring. Most studies of optimal UI policy focus on the level rather than the duration of benefits, despite the fact that, in practice, duration is the dimension of UI most affected by policy. Kroft and Notowidigdo (2010) estimate that the elasticity of unemployment duration with respect to the benefit level is -1.10 when unemployment is low, but is only -.32 when unemployment is high. They use the above difference to calibrate the optimal replacement rate in a Baily-Chetty sufficient statistic framework. They show that the optimal replacement rate should be higher when there is higher unemployment.

Similarly, Landais, Michaillat, Saez (2010) analyze optimal UI policy over the business cycle. They develop a general equilibrium model where search activity imposes a negative externality on other job searchers. Their model implies that job search activity has little effect on aggregate unemployment in recessions due to job rationing. They demonstrate that the welfare relevant elasticity in the sufficient statistic framework is the macro elasticity of unemployment with respect to benefits. They show that in a calibrated DSGE model, UI should be more generous in recessions.

It is worth stressing that none of the above papers derive optimal UI durations or estimate empirical estimates of elasticities of unemployment duration with respect to UI duration. Our paper contributes by providing a credible estimate of the elasticity of search effort with respect to UI durations. Further, we quantify the effect the changes in search effort could have on job finding probability.

3 Data

3.1 Google Search Data

Our measures of job search activity are constructed from indices of search activity obtained from Google Insights for Search. Google Insights allows us to obtain a regional time series of the relative amount of search activity for specific search terms on Google.com.[1] The numerical values we obtain are normalized and scaled measures of this search activity. Specifically, for a given time period, the values represent the number of searches on Google.com for the specified search term relative to the total number of searches on Google.com. Furthermore, the values are normalized such that the highest value for the entire time period is set equal to 100. Thus, the range of values is always between 0 and 100, where higher values represent higher fractions of total searches on Google.com were for the indicated search term.[2] An example of the results from a Google Insights search can be seen in Figure 1.

We use Google Insights in two ways. Firstly, we use data at a state-month level. Monthly search data allows for comparison to CPS and ATUS monthly data. Secondly, we take non-overlapping three month samples of data at a state-day level (Google limits daily data extraction to three month periods). We aggregate the three month periods into a panel of daily data from 2005-2010. Each sample has a different scaling so our empirical specifications include only logged measures of our index, as well as appropriate sample fixed effects, in order to remove the scaling effect. Daily data allows us to measure the immediate effects of shocks to the UI system caused by passage of new legislation or by meeting thresholds in existing legislation. For both methods, we choose the search term 'jobs' as our term of interest.

A natural concern with our Google measure of job search is the representativeness of online job search in terms of overall job search activity. We obtain one measure of how widespread online job search is using the National Longitudinal Survey of Youth (NLSY). The NLSY includes a question that asks respondents about the usage of the internet for job search from 2001 to 2008. In 2003, 53 percent of job seekers used the internet whereas 83 percent did in 2008. The most internet intensive activities are resume submissions, placing ads, and contacting schools' career centers. Rates of internet usage in job search increased with education but did not vary systematically by census region. Furthermore, there are many job related queries that are encompassed in the 'jobs' query. For example, people may search for jobs at a specific company or region. For such queries, Google is one of

[1] http://www.google.com/insights/search

the most effective ways of finding the appropriate job posting.[3] Another concern may be the applicability of the search term 'jobs'. We performed extensive tests and found this term to be highly correlated with a multitude of plausibly job search related terms, such as 'state jobs', 'how to find a job', or 'tech jobs'. The query, 'jobs', also has very high volume compared to related terms and is thus less prone to measurement error.

3.2 CPS

We use the Current Population Survey (CPS) to measure the number and characteristics of the unemployed. The CPS is conducted monthly on a sample of approximately 60,000 households, creating a representative national sample of the civilian, non-institutional population. Each month, the survey asks each member of each household aged 16 or older various questions regarding their work and activities during the week containing the 12th day of the month. Each household is surveyed for four successive months, then not interviewed for eight months, then returned to the sample for the four following months. Individuals are classified as unemployed if they meet the following criteria:

1. Not employed during the reference week
2. Available for work during that time
3. Made specific effort to find employment during the four-week period ending with that reference week.

We use state-month level CPS data from January 2005 to December 2010. Our sample aggregates 10,744,854 individual observations over the 72 months in our sample. We extract the number of unemployed respondents and the characteristics of the unemployed population (age distribution, educational attainment, income). Utilizing CPS data regarding the length of unemployment spells for unemployed respondents, as well as state and national level data on weeks of eligibility for Unemployment Insurance benefits, we calculate the weeks of eligibility remaining for all unemployed individuals.

[2]For example, the query 'Walmart Jobs' exhibits similar intra-year trends as our standard measure.
[3]See Table 11 in the Appendix for a partial list of alternate terms tested

We also break our analysis into subsamples of unemployed individuals based on a proxy for eligibility for UI benefits. We utilize the CPS question on 'Reason for Unemployment' to determine this classification. The most common reason for ineligibility for UI benefits was based on your category of unemployment as opposed to reasons relating to earnings or previous work duration. Those who quit their jobs voluntarily, or are new entrants into the labor force, are generally not eligible for UI benefits. Leveraging this fact to create a CPS proxy for eligibility, an individual is considered 'eligible' if his given reason for unemployment was: 'Job Loser', 'Layoff', or 'Temp Job Ended'. An individual is considered ineligible for benefits if his given reason for unemployment was: 'Job Leaver', 'Re-entrant', or 'New Entrant'.

4 Validity of Search Activity Measure

4.1 ATUS

We use the American Time Use Survey (ATUS) to check the consistency of our measure of search activity. The ATUS data is a survey, taken throughout the year, of approximately 13,000 people. Each year since 2003, the ATUS selects a sample of households from the population of households which have completed their final interview for the CPS. A single person is randomly selected from each household and interviewed by telephone about his activities during the previous day. Weekend days are oversampled by approximately a 2.5 to 1 margin such that 50% of the interviews are conducting in regards to a weekday and 50% in regards to a weekend day. Households are called for up to 8 times in order to obtain an interview with a member of the household, ensuring a relatively high response rate.

We use the ATUS data and Kreuger and Mueller's (2010) methodology in order to compare our Google measure of job search activity to their ATUS measure. ATUS job search activity is calculated using the amount of time that individuals spend in job search related activities.[4] Table 1 gives summary statistics regarding this dataset. Our individual job search value is the sum of all of the categories of job search for each respondent.

From these individual-level values, we take the state averages of job search time per capita for each month. To compare it with our measure, we examine the correlation between the monthly ATUS measure by state and our monthly state measure of job search activity. The correlation is approximately .51, and is robust to inclusion or exclusion of job-related travel time, removing the oversampling of weekend days, or using alternate Google search terms to measure job search activity. Furthermore, as a placebo test, we find insignificant correlation to non-job search related terms such as 'weather' or 'sports'. The Google measure is slightly more correlated with the ATUS job search indicator (the number of individuals engaged in any amount of job search, per capita) than with the ATUS job search time variable. However, the increased correlation may be due to the fact that the ATUS job search indicator has less measurement error than the job search time variable.

Although the two data sets are clearly related, they do exhibit differences. Differences between the two measures of job search can arise for two reasons. First, Google search and the ATUS could be measuring different underlying behavior due to biases in survey answers or due to the fundamental difference between time spent on online job search and all job search. Second, sampling creates variation in estimates and different subgroups are sampled by the two measures.

4.2 ComScore

One possible issue with using Google search data as a proxy for job search effort is that the ratio of Google search to time spent may not be constant across regions or demographics. Furthermore, Google job search activity may be a different type of behavior from online job search in general. We address these issues by using the comScore Web Behavior Database,

[4]We assembled all ATUS data from 2003-2009 (though Krueger and Meuller used only through 2007), and restricted our comparison to people of ages 20-65. We examine comparisons including and excluding 'Travel Related to Work', which includes job search related travel but also many other types of job-related travel. Krueger and Muller included this category in their analysis. ATUS categories encompassing job search activities are: 'Job Search Activities', 'Job Interviewing', 'Waiting Associated with Job Search or Interview', 'Security Procedures Related to Job Search/Interviewing', 'Job Search and Interviewing, other'.

a panel of 100,000 consenting internet users across the United States who were tracked for the year 2007. ComScore tracks users at the domain level and includes household level demographic variables, domain names, referral domain names, and the amount of time spent on a website.[5] We determine whether a person is searching for a job by summing the time spent on websites that contain job relevant terms.[6]

Another worry about Google search is that the ratio of Google search activity to true online job search activity is not constant across regions or time periods. Table 2 shows the coefficient of the regression of total time spent on online job search on amount of Google searches for job related topics observed in comScore. Three regressions are run, the regression without controls, the regression with state fixed effects and the regression with date fixed effects. In all three cases the estimated partial correlation between Google search and total time spent searching is very close. The effect of each Google search for a job in the comScore data is approximately 7.5 minutes spent on job sites. Note, for the state fixed effects specification, the estimate is significantly different from the other two estimates. However, the estimated coefficient only changes by 6 seconds, an economically insignificant amount.

4.3 Macroeconomic Drivers of Job Search

As our Google Job Search Index is not a direct measure of time spent on job search, we want to make sure that it is a consistent proxy of true job search activity.

Table 3 displays results of regressions designed to provide information on the strength of our measure of job search. We find that our measure of job search is strongly correlated with a variety of different macroeconomic variables which traditionally drive job search activity. While these results are not causal, they all appear to move in the 'expected' direction.

Column 1 reports the results of a regression of the change in our measure, month to month, on the change in unemployment rate, as well as month and year fixed effects. We

[5] ComScore tries to address issues of selection into this dataset, but we cannot assess how successfully.

[6] The domain names we search for are those containing 'job','career', 'hiring' and 'work' in addition to the biggest job search sites: monster.com, careerbuilder.com, indeed.com, and linkedin.com. We remove any websites containing 'job' or other terms but are unrelated to job search.

find a strongly positive result, as an increased rate of unemployment should boost the number of more active job seekers. The magnitude corresponds to an increase in online job search activity of .7% when a state undergoes a 1% increase in unemployment rate. In Column 2, we add the number of initial unemployment benefit claims per capita to our regression. While this lowers the effect of a rise in unemployment rate, we still obtain positive effects for both, as is expected, with a nearly 3% increase in predicted job search activity when the number of initial claimants rises by 1 percentage point of the population.

In Column 3, we add the number of final claims in the following month to our regression, finding positive effects for all three variables. We expect that job search this month will be positively correlated with the number of final claims in the next month, as those who search more in this month are more likely to be exiting unemployment benefits in the following month. We find large effects for this variable, with an increase in job search of nearly 5% correlated with a rise in next month's final claimants of 1 percentage point of the population. Column 4 adds the change in tightness (given by the number of vacancies divided by the monthly unemployment rate), to the regression. As labor market tightness increases, we would expect people to increase their job search activity as their marginal return to one more minute of job search has increased (although there do exist models where the direction of this comparative static is ambiguous). Indeed, we still find positive effects of all variables.

4.4 Day of Week and Holiday Effects

Furthermore, it is to be expected that job search would follow strong day, month, and year trends. We expect search to fall on weekends and holidays because of social commitments. We expect search to increase around graduation time in the late spring and to increase over the sample due to higher aggregate unemployment. We find that overall search activity increased dramatically during the recession as unemployment rose and more people start searching for jobs. Job search as measured by our Google search index increases in January after a holiday lull, and also increases at the end of the spring as expected.

We examine the American Time Use Survey, comScore data, and our Google measure in order to determine whether there are significant 'day of the week' effects and 'holiday' effects, as we would expect. Table 4 shows results from regressing indicators for holidays and days of week on job search for each of these three measures. Columns 3 and 4 display results from the American Time Use Survey. We find large drops in search time on holidays, using an indicator equal to one for any holiday as designated by the ATUS, and on weekends, with search peaking during the beginning and middle of the week. Friday exhibits a lower level of search than other weekdays, but higher than weekend days.[7] The comScore measure used is the total time spent on job search sites in a state on a particular day. Columns 5 and 6 display results from the comScore regression. Unlike the ATUS, the most time spent on search is on Tuesdays, gradually dropping off towards the end of the week. There is approximately 40 percent less time spent searching on holidays and 64 percent less on weekends.

Columns 1 and 2 display the results for the Google search index. Google job search shows a strikingly similar intraweek pattern of search behavior to comScore. Google job search activity peaks on Tuesdays and gradually declines afterwards. The ratios of weekend to holiday search are approximately the same for all 3 measures. Furthermore, the intraweek pattern is very similar for Google job search and overall online job search time. We interpret these results as evidence that Google search for 'jobs' is a good proxy for job search online. However, we cannot say whether the differing intraweek pattern between our Google measure and the ATUS measure is due to differences in the type of job search done offline or due to the sampling and design of the ATUS.

[7] ATUS holidays are New Year's Day, Easter, Memorial Day, the Fourth of July, Labor Day, Thanksgiving Day, and Christmas Day

5 Models of Effort Response to Policy

Consider a simple search activity model of a local labor market similar to Chetty (2009). The utility of an unemployed person is given by:

$$u_T(A_0) = u(A_0 - A_1 + b_T) - f(e) + \beta * (\pi(e,\tau) * [V(A_1, w)] + (1 - \pi(e,\tau)) * U_{T-1}(A_1))$$

In the above equation, T denotes time until expiration of benefits, A_0 and A_1 denote assets in consecutive periods and b_T are unemployment benefits. The probability of finding a job is determined by the choice of effort, e, and market tightness τ. The cost of effort, $f(e)$, is assumed to be strictly increasing and convex. Lastly, the continuation value is $V(w)$ for employment. For now, we assume that the wage is constant and that employment is an absorbing state.

The endogenous variable that we seek to explain in the paper is effort, e. Below, we consider some comparative statics for the response of effort with respect to variables of interest. Consider a standard matching function where the match probability is independent of the previous stock of vacancies:

$$\pi(e,\tau) = e * \gamma * \tau^{1-\alpha}$$

$$FOC : f'(e) = \beta * \pi' * (V(A, w) - U_{A,T-1})$$

The response of effort to changes in variables of interest is as follows. Consider an increase in unemployment benefits through an increase in the duration of benefits. Ignoring general equilibrium effects, an increase in unemployment benefits increases the value of being of unemployed in the next period. $\frac{de}{dV_{T-1}} = -\beta * \gamma * \frac{\tau^{1-\alpha}}{f''(e)} < 0$. Therefore, an increase in unemployment benefits causes a decrease in effort. Note that, the decrease in effort is more pronounced when tightness is higher. When the match probability is high, effort is more responsive to changes in UI policy. Furthermore, the higher previous effort is, the less responsive current effort is to changes in the continuation value. Similarly, a decline in the future assets of the household increases search activity by an amount proportional to the match probability: $\frac{de}{dA_1} = \beta * \pi' * (V'(A, w) - U'_{A,T-1}/f''(e) < 0$.

A crucial assumption in the above model is that the match rate is the same between newly unemployed, prior unemployed, new vacancies and old vacancies. However, that may not be the case, as Coles and Smith (1998) show in a model of job search without search frictions. If the probability of match changes systematically over the duration of unemployment, the dynamics of effort response could be nontrivial. If workers sample all vacancies in the first period, their future match rate is determined solely by the flow of new vacancies. Andrews, Bradley, Stott and Upward (2007) use comprehensive data from a job matching market to show that, indeed, the probability of match varies over the duration of unemployment. They show that the stock of new vacancies increases the exit rate from unemployment for job-seekers who are not recently unemployed. In our work, we look at the determinants of search activity over the duration of unemployment but we cannot directly distinguish between explanations of moral hazard versus explanations of lower exit rates caused by longer duration.

The above discussion focuses on the decision of an individual. In reality, our search measure is an aggregate of the decisions of different state populations. Changes in state search activity across states during the recession can be driven differential responses by heterogeneous populations. The aggregate variables that we bring to the data are: unemployment duration, unemployment, and market tightness. It is important to note that these variables are, in general, endogenous and can also affect the decisions of employed job searchers. Our measure of search activity is a weighted sum of the search activity of employed and unemployed. Therefore, in the empirical portion of the paper, we look at policy changes which directly affect only unemployed job seekers.

6 Empirical Strategy and Results

6.1 Unemployment Benefit Extensions

We test for the effect of federal changes to unemployment benefit policy on job search activity using daily search data from Google Insights. In addition, we use responses to changes in benefit durations which occurred due to hitting threshold levels of state unemployment, as governed by federal policy. There are four major modifications to federal unemployment insurance law in our empirical specifications[8]

1. June 30th, 2008 - The Emergency Unemployment Compensation (EUC) program is created, giving an additional 13 weeks of benefits to the unemployed.

2. November 21st, 2008 - The EUC is expanded by 7 weeks for all unemployed and by 13 weeks for those residing in states with greater than 6% unemployment.

3. November 6th, 2009 - The EUC is expanded by 13 weeks for unemployed residents of states with greater than 6% unemployment and an additional 13 weeks for states with unemployment rates greater than 8.5%.

4. July 22nd, 2010 - The EUC program is extended by 6 months, preserving the extended benefits for many unemployed.

A sample trajectory of maximum weeks of UI for Oklahoma is displayed in Figure 3. With indicators for the date of each policy change and the period following the policy change, we are able to measure the impact of each extension or expansion. If there exists considerable moral hazard in these programs, with those claiming unemployment not actively seeking work, we would expect to see a fall in job search activity following the extension or expansion of benefits. However, there may be other trends operating on search activity. For identification, we rely on the fact that the states with the most people impacted by the policy

[8] Also included as shocks are dates in which unemployment thresholds for the pre-existing federal Extended Benefits program are met in each state. Extended Benefits are available to workers who have exhausted their regular program and EUC08 unemployment insurance benefits and during periods of high unemployment. The basic Extended Benefits program provides up to 13 additional weeks of benefits when a State is experiencing high unemployment (over 6%). Some States have also enacted a voluntary program to pay up to 7 additional weeks (20 weeks maximum) of Extended Benefits during periods of extremely high unemployment (over 8%).

change should have the highest response in terms of change in job search activity. Note that, for some states, the policy change occurred after the legislation is passed because the policy is activated by a threshold unemployment rate. If the spike in exits from unemployment benefits in the last weeks of availability seen in Meyer (1990) is due to relatively high search activity around the time of benefit expiration, we would expect to find a fall in search activity.[9] However, if the spike in exits is due primarily to a fall in the reservation wage, we may observe little change in the amount of job search activity.

We measure the size of the affected population by using Department of Labor (DOL) data on the amount of unemployed in each 'Tier' of unemployment. Policy changes effectively granted extra weeks of eligibility for states. After a policy change, there is usually an observable spike in the unemployed population starting in a specific week. We use this increase for the month following the change as a proxy for the affected population. This is our best measurement of the population that was about to run out of benefits (within a month) but was able to receive them because of the policy change. Our measure is imperfect for several reasons.

First, some people are eligible for fewer weeks than the maximum and we may not capture these in our measurement. Second, we observe the data only at the monthly level, so we do not know the number of unique individuals affected by the change. We approximate this by dividing by the amount of weeks within the month that the policy was in effect. Third, we do not know how much our measure is biased by people actually finding jobs differentially in different states. We expect that in states where the chance of finding a job is highest, the effort response should be highest. This would bias our results towards 0. Last, the data is imperfectly recorded. We observe clear inconsistencies in the reporting of some states. Inconsistencies were confired through conversation with the DOL. We address data recording issues by rerunning the regression on the subsample of states which, as the DOL asserts, submitted correct data.

Our estimation strategy is a difference in differences. We look at differences in the log of search activity before and after a policy changes and then across states where different numbers of unemployed were affected. The estimating equation is:

$$JobSearchActivity_{st} = \beta_0 + \beta PolicyChangeWeekX_{st} + \gamma * Affected_{s,Policy} * \\ PolicyChange_{st} + \tau_1 InitialUnemploymentClaimants_{st} + \\ \tau_2 ContUnemploymentClaimants_{st} + fe_{season,s} + week_t + dayofweek_t + holiday_t + u_{st}$$

Here, $JobSearchActivity_{st}$ is the logged measure of job search activity (Daily). $fe_{season,s}$ = 1 if an observation is from a given season and state. Fixed effects are also included for each week in the sample, days of week, and holidays. 's' is a state and 't' is a day. $PolicyChangeWeekX_{st}$ is an indicator for various periods (week 1, week 2 and/or week 3) after the policy change day. $Affected_{s,Policy} * PolicyChange_{st}$ is an interaction of $PolicyChange_{st}$ with our measure of the affected population for that state and policy change. $InitialUnemploymentClaimants_{st}$ and $ContUnemploymentClaimants_{st}$ are measured at the weekly level by the DOL.

6.2 Effects of Legislation

In the Daily Panel all of the regressions are run in log levels. On the left hand side is a daily measure of search activity. The regressions presented cover 2005-2010.[10] Years with no concurrent changes act as controls and allow us to estimate day of the week, holiday and week fixed effects. Further, fixed effects for each state and season combination are included to correct for the rescaling induced by the three-month sampling. With these season-state indicators and a logged measure of search activity, the varying linear scaling factors are simply removed as additive fixed effects.

Our first specification pools all of the national policy changes observed in our dataset. The results in Table 5, Column 1, show that a one percentage point increase of the affected population results in a 1.7% decrease in search activity. There is no statistically significant

[9]Months affected by Hurricane Katrina in Louisiana and Mississippi were removed. Results are unaffected by the inclusion of these observations

effect for subsequent weeks. Column 2 limits the subsample to those states for which the DOL is more confident of the data. The point estimate increases to 3.3% for the first week and the subsequent weeks remain insignficant.

We then split up each policy change and look at them separately. Table 6 displays the percent change in search effort for each policy change we observe. Although not all increases in the maximum number of weeks are significant, they are all the expected sign, negative. The largest estimated effect corresponds to the EUC Expansion in November, 2009 (Column 3). Not surprisingly, the 2009 expansion adds the most weeks (26) of eligibility of any policy in our sample.

6.3 Benefit Exhaustion and Eligibility

Two factors affecting the level of job search are eligibility for UI and time until benefits exhaustion. We use the CPS to classify unemployed individuals as eligible or ineligible for UI benefits and determine the weeks of benefits remaining. We then use these data to examine how time until exhaustion of benefits affects the amount of aggregate job search in a state, and if this varies if we restrict our sample to those whom we think are eligible for UI benefits.

We utilize shifts in the composition of the unemployed, with respect to time until benefit exhaustion, in order to identify changes in job search activity. With this measure, we hope to observe how job search activity changes as a claimant draws nearer to the exhaustion of his benefits. We measure the composition of the unemployed through unemployment duration bins. Our vector of independent variables consists of a set of bins of the number of residents per capita who have a certain range of weeks remaining in benefits. For example, one observation may be that in July of 2008 in Arizona, .6% of the population has between 0 and 10 weeks of unemployment benefits remaining, .4% had between 11 and 20 weeks of benefits remaining, and so on.

This particular compositional measure is plausibly exogenous across states on a month to month basis, controlling for time trends and relevant macroeconomic characteristics. In addition, much of the variation in this measure is derived from UI policy changes, which drastically alter the composition of the unemployed in terms of weeks of benefits remaining. With this measure, we are able to assess how job search activity varies as a claimant moves from being newly unemployed to being near the exhaustion of benefits.

Our monthly specification examines shifts in the composition of the unemployed in terms of weeks of benefits remaining:

$$\Delta JobSearchActivity_{stm} =$$
$$\beta_0 + \beta_1 WeeksLeft10_{stm} + \beta_2 WeeksLeft20_{stm} + ... + \beta_y mYear - Month_{ym} + \beta_s State_s + u_{sym}$$

In this specification, $\Delta JobSearchActivity_{stm}$ is the change in logged measure of job search activity. We also include Year-Month and state fixed effects, $Year - Month_y m$ and $State_s$, respectively. Our set of independent variables, such as $WeeksLeftXX$, represent the number of unemployed per capita with less than XX weeks of benefits remaining.

We also break our analysis into subsamples of unemployed individuals based on a proxy for eligibility for UI benefits, as was previously described. We then conduct our analysis using only each of these subsamples; that is, setting $WeeksLeft10$ equal to only the number of eligible (ineligible) unemployed per capita with less than 10 weeks of benefits remaining (or those who would have had less than 10 weeks of benefits had they been eligible).

6.4 Effects of Benefit Exhaustion and Eligibility

Table 7 displays results from our analysis of how time to benefit exhaustion and eligibility for UI benefits affect job search. Column 1 reports results looking at the duration structure of unemployment for the total population of unemployed. We find generally insignificant results and no strong pattern. Columns 2 and 3 present results from splitting our sample into those who we assert are ‘eligible’ or ‘ineligible’ for UI benefits.

For those who are eligible for unemployment benefits, we find little effect of the duration structure on unemployment, except when individuals reach their final 10 weeks of unemployment. During these final 10 weeks, we see an increase in search of 1.5% for every 1% of the population in this category. Among the ineligible, we find no such pattern, and a number of week bins where we find that more ineligible unemployed produces lower aggregate job search activity. This finding is due to the fact that eligible unemployed are a distinct group from ineligible unemployed and they search at a higher rate. As we control for changes in overall unemployment levels, an increase in the amount of ineligible unemployed with no change in the overall level of unemployment is equivalent to a decrease in the number of eligible unemployed, and a corresponding drop in the overall level of job search.

7 Quantitative Significance

We have estimated the effect of expansions and extension of UI benefits on job search activity. In order to evaluate effects on policy-relevant outcomes, we need to convert the resulting change in job search activity into a job finding probability; that is, find the elasticity of job finding with respect to job search. The ideal exercise would examine a national panel of individual level data on job search as well as job finding in order to quantify effects of increased search effort across different local labor markets. In the absence of this matched individual level panel, we combine our estaimtes of search effort response to policy with Krueger and Mueller's (2011) estimate for the elasticity of UI exit to job search time in order to provide an estimate of the effects of UI extensions on job finding.

Estimating a regression at the month-state level with the total minutes spent on job search in the ATUS as the dependent variable (controlling for the unemployment rate, state, year and month fixed effects), we find that a 1% increase in job search increases time spent on job search in a week by 2.7 minutes per day (Table 8, Column 1). Suppose that there are 100 people in the population and that 10% are unemployed. In the ATUS, each unemployed person searches an average of 29 minutes per day, while each employed person searches about

.7 minutes. Therefore, there are 313 minutes of total job search in our economy. An expansion of UI benefits affecting 1% of the population (1 person) leads to a 1.7% decrease in aggregate job search (Table 5, Column 1), corresponding to a 14.4 minute per day decrease in aggregate search. Assuming the effect is concentrated solely on the affected person, this represents a 50% decrease in job search for the affected person. Krueger and Mueller (2011) estimate that the effect of an extra 20 hours a week of search is a 3.5% increase in exit probability. Using this estimate and our estimated search decrease of 100.8 minutes per week, we find a decrease in exit probability by .3%. Given that each policy on average affects .33% of the population, on average, 3,070 people do not find jobs because of a policy change we observe. If we use the maximum effect we find, for the November 2009 legislation, the number of searchers that do not find jobs increases by a factor of 10, to 30,700 people. The estimates are economically small and suggest that the immediate effects of UI expansions do not have an economically significant impact on the aggregate unemployment rate.

Now consider a similar exercise but using an alternate conversion of Google search to time spent on online job search using the comScore panel. Controlling for the unemployment rate, season-state, day of week and week fixed effects we find that a 1% increase in job search increases time spent on job search in a day by .35% per day (Table 8, Column 2). Suppose that there are 100 people in the population and that 10% are unemployed. In comScore, each active searcher searches an average of 28 minutes per day and each inactive searcher searches .02 minutes per day. Thus, there are 282 total minutes of online job search in the economy. An expansion of UI benefits affecting 1% of the population leads to a 1.7% decrease in job search, corresponding to a 1.6 minute decrease in aggregate search activity per day. Assuming the effect is concentrated solely on the affected person, this represents a 6.2% decrease in job search for the affected person. Following the same procedure as with the ATUS data, we find that, on average, 334 people do not find jobs because of a policy change we observe. If we use the maximum effect we find, for the November 2009 legislation, the number that do not find jobs increases to approximately 3340 people. The comScore estimates are an order of magnitude smaller than those using the ATUS calibration.

We explain the discrepancy by noting that the comScore regression includes controls that mirror the specification for estimating the causal effect of a policy change. On the other hand, the ATUS partial correlation with the Google search measure was estimated using a monthly estimation because of the lack of more detailed ATUS data. Further, the effect in the ATUS could be bigger the ATUs captures more types of job search (i.e. interviews and phone calls). Lastly, job searchers in comScore may be selected non-randomly into the sample. In any case, both sets of estimates support that the UI benefit extensions enacted from 2008-2010 did not have an economically significant effect on unemployment rates.

8 Conclusion

This paper demonstrates the validity of a novel measure of aggregate job search activity in the economy. Using data from Google Insights, we have constructed a daily index at a state level which we utilize to examine moral hazard due to UI and labor market conditions. We believe that this measure can be usefully applied in directly testing theories regarding job search behavior. One potential application is in macro models of the labor market, where aggregate job search activity is usually inferred from a calibrated elasticity.

Using the panel variation in the unemployment duration of UI claimants, we demonstrate that search activity is higher for those at the onset an unemployment spell and and those when nearing exhaustion of their benefits. We also find that job search responses to the passage of bills that increase unemployment benefits duration are negative but small in most specifications. Using daily data, we estimate that on average an increase by 1% of the population of unemployed directly affected by an increase in maximum weeks of UI results in a 1.7-3.2% decrease in job search activity for 1 week. When the effort response is broken out across each policy, we find that the Nov 2009 expansion of UI for up to an additional 26 weeks in some states had the greatest impact. Although less precisely estimated, an increase in 1% of the population affected by the policy change, results in a 17% decrease in search. Both of the estimated effects lasted for only a week. Our estimates suggest that the immediate impact of policy changes on effort is small.

Our quantitative exercise suggests an economically small effect of 1100 people not finding a job in a week after the policy change. A challenge in the future is to more credibly relate percentage changes in online search activity to real world changes in actual job finding and into time spent searching as measured in minutes. We note that there are several other elasticities of job search with respect to UI which we have not estimated. Other elasticities relate to the dynamic responses of job searchers over their duration of unemployment to increases in maximum weeks. Furthermore, we do not know the extent to which expectations about policy changes shaped pre-policy change search levels.

Our results are applicable to debates regarding the optimal structure of UI. A key input into the Baily-Chetty framework is the elasticity of search activity with respect to benefits which we have estimated in this paper. Furthermore, the modest magnitudes and short duration of the search responses suggest that extensions of UI are not a primary driver of persistent unemployment in the Great Recession.

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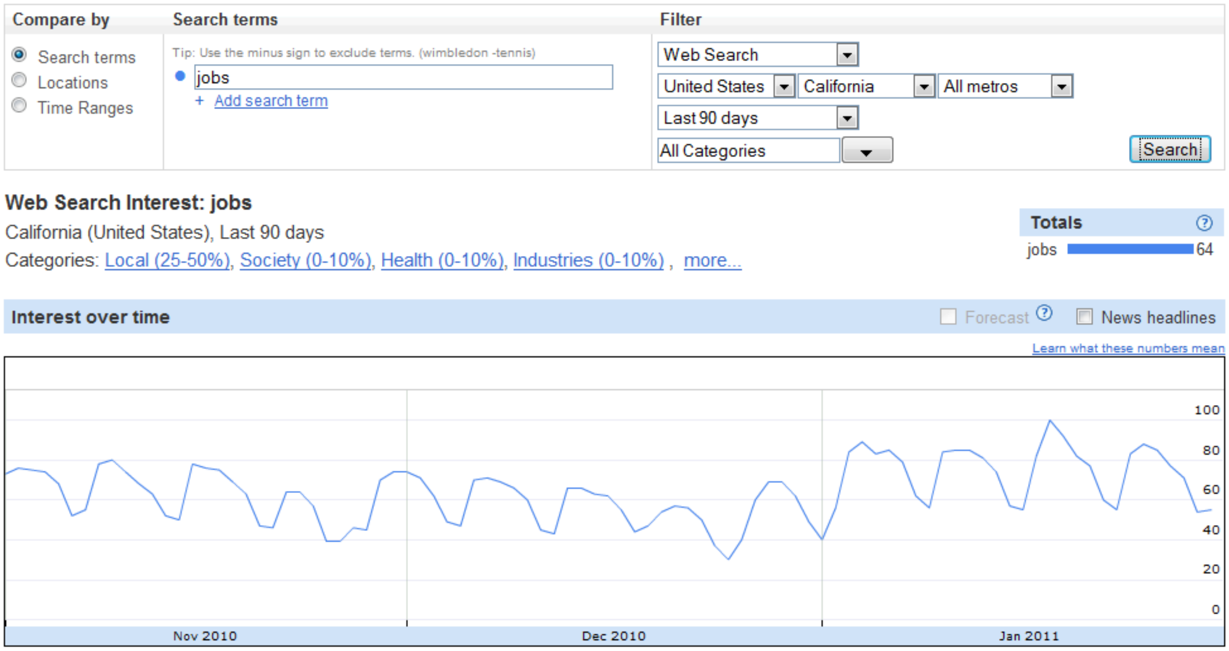

Figure 1: Example of Google Insights Search

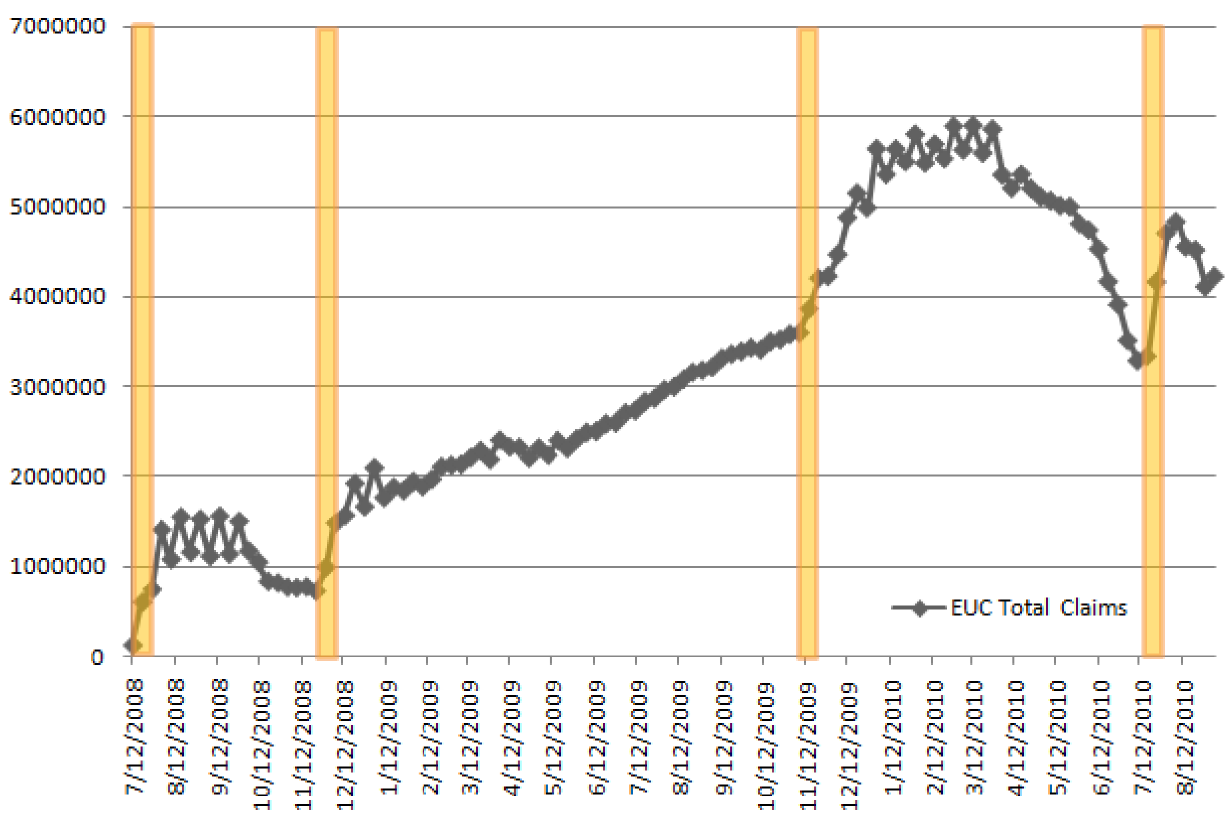

Figure 2: Continued Unemployment Claims

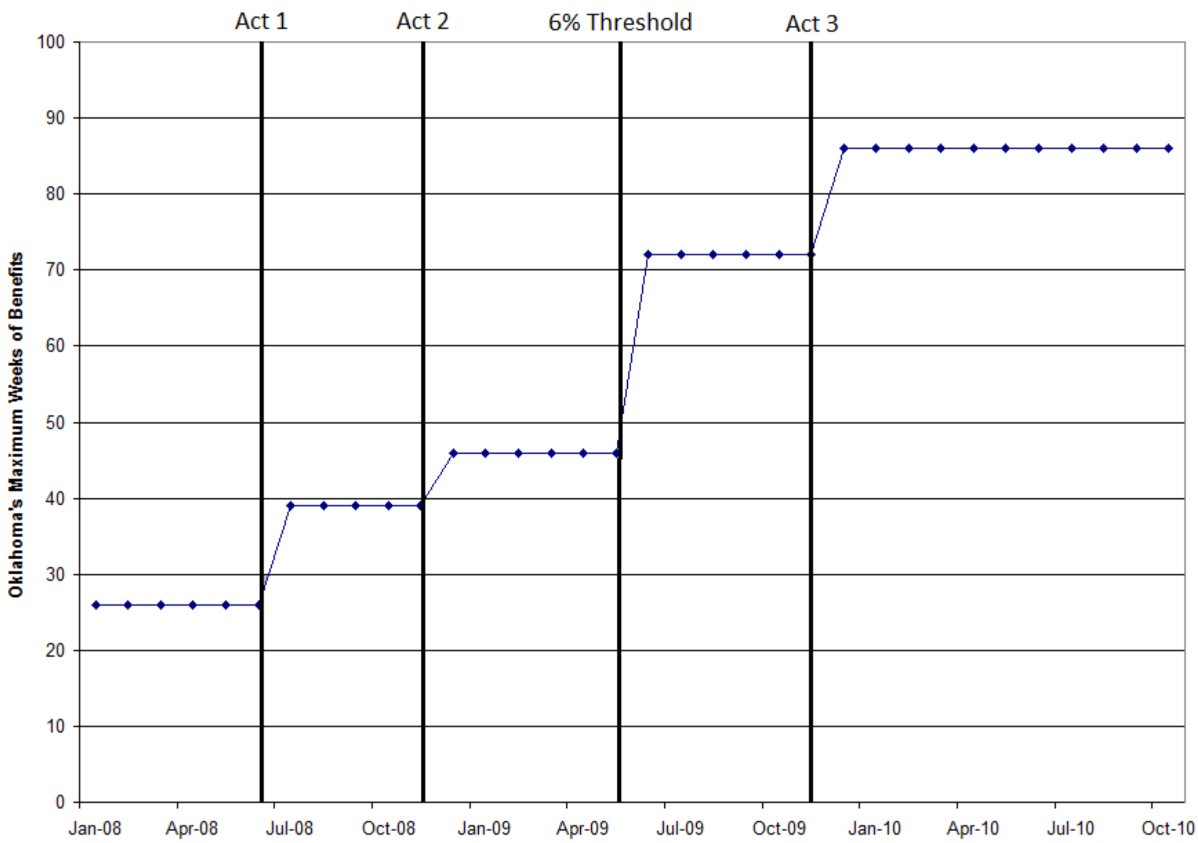

Figure 3: Total Weeks of UI Benefits Available in Oklahoma, 2008-2010

	No. Respondents	% of Total	Avg Job Search (min per day)	Avg Job Search Ex. Travel (min per day)	Participation in Job Search	Avg Job Search of Participants
By Labor Force Status						
Employed	57,914	76.12%	.63	.47	.78%	81.3
Unemployed	3,252	4.27%	29.1	25.3	18.23%	159.7
Not in Labor Force	14,921	19.61%	.8	.6	.82%	98.1
By Holiday						
Holiday	1,328	1.7%	.60	.54	.68%	80.6
Non-Holiday	74,759	98.3%	1.9	1.6	1.33%	128.6
By Weekend						
Weekend	38,431	50.5%	.87	.71	.64%	109.8
Weekday	37,656	49.5%	2.9	2.4	1.8%	134.8

Subsample of ATUS respondents is taken to match the demographic subsample used by Krueger and Mueller. We use all respondents for both weekends and weekdays, while noting that weekends are oversampled to include an equal amount of weekend and weekdays. We drop respondents younger than age 20 or older than 65. We include years 2003-2009, while Krueger and Mueller use only 2003-2007.

Table 1: ATUS Summary Statistics

	(1)	(2)	(3)
VARIABLES	Total Job Search Time	Total Job Search Time	Total Job Search Time
Google Job Searches	7.511***	7.429***	7.507***
	(0.0109)	(0.0108)	(0.0109)
Constant	0.380***	0.380***	0.380***
	(0.00139)	(0.00137)	(0.00139)
Observations	1.88e+07	1.88e+07	1.88e+07
R-squared	0.025	0.051	0.025
Zip Code FE	NO	YES	NO
Date FE	NO	NO	YES

Robust Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The dependent variable is the total minutes spent by a household on job search for a day. The independent variable is the amount of job sites visited that were referred to by Google search. Specifications are in order without fixed effects, with state fixed effects and with day fixed effects.

Table 2: Correlation of Google Search to Online Job Search Time

	(1)	(2)	(3)	(4)
VARIABLES	Δ Jobs Search	Δ Jobs Search	Δ Jobs Search	Δ Jobs Search
Change in Unemp Rate	1.345***	1.080***	1.285***	
	(0.253)	(0.258)	(0.263)	
Change in Init. Claims Per Cap		3.488***	3.514***	3.495***
		(0.534)	(0.529)	(0.529)
Next Month Final Claims Per Cap			2.913**	2.818**
			(1.146)	(1.158)
Change in Tightness				0.0116***
				(0.00333)
Observations	3395	3395	3293	3293
R-squared	0.754	0.758	0.766	0.766
Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

'Jobs Search' refers to the logged change in our Google Index of job search activity from month to month. Change in unemployment rate is the change in the raw percent unemployment rate. Change in initial claims per capita is the change in the number of initial claimants of unemployment benefits, per capita, by state. 'Next Month Final Claims' is the per capita amount of claimants receiving their final unemployment benefit payment, by state. Change in tightness refers to the change in vacancies divided by the unemployment rate from month to month.

Table 3: Empirical Tests of Google Job Search Measure

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Google Search	Google Search	ATUS Job Search	ATUS Job Search	ComScore Job Search	ComScore Job Search
Holiday	-0.127***	-0.110***	-1.092**	-1.025*	-0.400***	-0.390***
	(0.00471)	(0.00440)	(0.551)	(0.548)	(0.0457)	(0.0452)
Monday	0.226***		1.764***		0.619***	
	(0.00276)		(0.263)		(0.0261)	
Tuesday	0.240***		1.338***		0.678***	
	(0.00288)		(0.265)		(0.0316)	
Wednesday	0.211***		1.975***		0.618***	
	(0.00272)		(0.267)		(0.0288)	
Thursday	0.161***		2.198***		0.585***	
	(0.00257)		(0.268)		(0.0261)	
Friday	0.0670***		1.103***		0.369***	
	(0.00207)		(0.268)		(0.0339)	
Saturday	-0.0500***		-0.157		-0.125***	
	(0.00171)		(0.200)		(0.0212)	
Weekend		-0.171***		-1.754***		-0.637***
		(0.00181)		(0.142)		(0.0265)
Observations	102482	102482	76087	76087	18187	18187
Season-State FE	YES	YES	NO	NO	NO	NO
Week FE	YES	YES	NO	NO	YES	YES
Year-Month FE	NO	NO	YES	YES	NO	NO
State FE	NO	NO	YES	YES	YES	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

'Google Search' refers to the logged value of our Google Search Index. 'ATUS Job Search' refers to the logged number of minutes of time spent on job search for each ATUS respondent. 'comScore Job Search' refers to the logged number of minutes online job search per capita as measured by comScore. Holiday is an indicator equal to one if the ATUS diary day or Google Search Index day was a holiday. Each day represents an indicator equal to 1 if the ATUS diary day was the given day of the week. Weekend is an indicator equal to one if the ATUS diary day was a Saturday or Sunday. All specifications include state and year-month fixed effects.

Table 4: Day of Week and Holiday Effects

	(1)	(2)
VARIABLES	All States	Subsample of States
First Week * Affected	-1.713**	-3.262**
	(0.862)	(1.535)
Second Week * Affected	-0.812	-1.318
	(1.302)	(1.745)
Third Week * Affected	0.662	0.792
	(0.634)	(1.707)
First Week	-0.00519	-0.00132
	(0.00524)	(0.00768)
Second Week	0.00110	-0.00345
	(0.00595)	(0.00796)
Third Week	-0.00398	-0.00621
	(0.00487)	(0.00729)
Observations	102482	60140
R-squared	0.634	0.614
Season-State FE	YES	YES
Day of Week FE	YES	YES
Week FE	YES	YES
Holiday FE	YES	YES

Standard Errors Clustered at the Season-State Level in Parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The dependent variable is the log of search activity at a day/state level. Week variables refer respectively to the first, second and third week after a policy change. Six policy transitions are pooled into the indicator measure: the passage of the four pieces of legislation and the 2 changes possibly triggered after the legislation was enacted. The affected population is determined by the relative increase of UI claimants within a month of the policy change (discussed in the paper). Season-state fixed effects, day of week fixed effects, week fixed effect and holiday fixed effects are included. The second column drops states which the Department of Labor indicated did not carefully report their UI statistics.

Table 5: Google Search Response To Policy Changes

VARIABLES	Legislation 1	Legislation 2	Legislation 3	Legislation 4	First Threshold	Second Threshold
Indicator	-0.0154	-.0293**	0.0129	-0.0205**	-0.00333	0.0120
	(0.0256)	(0.0129)	(0.0149)	(0.00955)	(0.0219)	(0.00830)
Affected * Indicator	-6.435	-1.896	-17.29**	-0.729	-4.929	-4.383*
	(6.740)	(2.410)	(7.120)	(0.592)	(10.09)	(2.616)
Observations	102482	102482	102482	102482	102482	102482
R-squared	0.634	0.634	0.634	0.634	0.634	0.634
Season-State FE	YES	YES	YES	YES	YES	YES
Week and Weekend FE	YES	YES	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES	YES	YES

Standard errors clustered at season-state in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The dependent variable is the log of search activity at a day/state level. Legislation 1 is the initial passage of EUC, Legislation 2 occurred in Nov. 2008, Legislation 3 occurred in Nov. 2009, and Legislation 4 is the extension of the EUC program in July 2010. Six percent and eight percent are measured when states crossed the thresholds for additional weeks as determined by the legislation. The independent variables are interactions of the week after a policy change with the affected population. The affected population is determined by the relative increase of UI claimants within a month of the policy change (discussed in the paper). Season-state fixed effects, day of week fixed effects, week fixed effect and holiday fixed effects are included.

Table 6: Individual Policy Change Effects - 1 Week After

	(1)	(2)	(3)
VARIABLES	All Unemployed	Eligible Unemployed	Ineligible Unemployed
Δ 0-10 Weeks Remaining	0.347	1.485**	-0.398
	(0.438)	(0.699)	(0.599)
Δ 11-20 Weeks Remaining	-0.565	-0.325	-0.517
	(0.362)	(0.499)	(0.502)
Δ 21-30 Weeks Remaining	-0.555**	-0.269	-0.683*
	(0.282)	(0.398)	(0.396)
Δ 31-40 Weeks Remaining	-0.633***	-0.418	-0.902***
	(0.229)	(0.407)	(0.330)
Δ 41-50 Weeks Remaining	-0.267	0.132	-0.415
	(0.279)	(0.382)	(0.404)
Δ 51-60 Weeks Remaining	-0.674*	0.219	-1.486**
	(0.389)	(0.526)	(0.656)
Δ 61-70 Weeks Remaining	-0.0849	0.156	0.0438
	(0.295)	(0.357)	(0.513)
Δ 71-80 Weeks Remaining	-0.170	0.327	-0.422
	(0.302)	(0.380)	(0.502)
Δ 81-90 Weeks Remaining	-0.214	1.185**	-1.636**
	(0.415)	(0.591)	(0.702)
Δ 91-99 Weeks Remaining	-0.451	0.249	-1.175**
	(0.381)	(0.601)	(0.477)
Observations	3395	3395	3395
R-squared	0.842	0.842	0.842
Year-Month FE	YES	YES	YES
State FE	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Independent variable is the logged change in our Google Index of job search activity from month to month. XX Weeks left refers to the percent of the population in a given state which has the listed number of weeks of UI benefit eligibility remaining. Column (1) gives results from a regression including all of the unemployed (as measured by the CPS), while Column (2) restricts the unemployed to those who satisfy a proxy for eligibility for UI benefits. Individual is considered 'eligible' if his reason for unemployment was: 'Job Loser', 'Layoff', or 'Temp Job Ended'. He is considered ineligible if his reason for unemployment was: 'Job Leaver', 'Re-entrant', or 'New Entrant'. Also included as regressors but not shown are differenced unemployment rates, differenced initial claims per capita, and lagged job search activity.

Table 7: Monthly Panel - Eligibility

VARIABLES	ATUS Search Time	Log(ComScore Search Time)
Log Google Job Search	2.671*	0.347***
	(1.426)	(0.0784)
Unemployment Rate	0.159	21.41**
	(0.167)	(8.968)
Observations	2976	18178
Year FE	YES	NO
Month FE	YES	NO
State FE	YES	NO
Season-Sate FE	NO	YES
Day of Week FE	NO	YES
Week FE	NO	YES

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Independent variable is the logged change in our Google Index of job search activity from month to month. XX Weeks left refers to the percent of the population in a given state which has the listed number of weeks of UI benefit eligibility remaining. Column (1) gives results from a regression including all of the unemployed (as measured by the CPS), while Column (2) restricts the unemployed to those who satisfy a proxy for eligibility for UI benefits. Individual is considered 'eligible' if his reason for unemployment was: 'Job Loser', 'Layoff', or 'Temp Job Ended'. He is considered ineligible if his reason for unemployment was: 'Job Leaver', 'Re-entrant', or 'New Entrant'. Also included as regressors but not shown are differenced unemployment rates, differenced initial claims per capita, and lagged job search activity.

Table 8: Monthly Panel - Eligibility

A Appendix

Data on percentage of the population in various tiers or bins of unemployment benefits is taken from monthly CPS data. Self-reported unemployed respondents are tallied and the duration of their unemployment is noted. Total weeks of benefits available are derived from state unemployment benefits laws combined with federal unemployment benefit laws. Weeks of benefit availability are added when a respondent's state crosses the unemployment rate threshold for additional federal benefits, when they become available in 2008 and 2009. Also noted is the presence of a week waiting period for any given state, which delays the onset of benefits by 1 week relative to the onset of unemployment. With respondents' unemployment duration and the total weeks of availability, we construct a measure of the percentage of a state's population which falls into any of a number of bins of weeks left. For example, a resident who has been unemployed for 21 weeks in a state with a waiting period and which offers 26 weeks of benefits would have $26-21+1 = 6$ weeks of benefits remaining, and would fall into the '0-10 Weeks Left' bin as well as the '6-10 Weeks Left' bin. If, in the next week, Congress passed a bill extending benefits by 7 weeks, he would now have $26-22+1+7 = 12$ weeks of benefits remaining and would then fall into the corresponding bins. Controlling for the overall rate of unemployment, these bins measure shifts in the distribution of the unemployed in terms of nearness to benefit exhaustion.

The variables regarding initial and continued unemployment claims are taken from the US Department of Labor, which publishes weekly reports on these numbers for all states. Initial claims numbers represent the number of unemployment benefit claimants, per capita, by state, who are on their first week of benefits. The continued claims numbers represent the number of unemployment benefit claimants, per capita, by state, who are receiving benefits but not for the first week. For the monthly panel, a monthly average for each set of weekly data is utilized.

Table 9: State Unemployment Benefits - 2004

State	Wait Period?	Min Benefit	Max Benefit	Min Duration	Max Duration
Alabama	No	45	210	15	26
Arizona	Yes	40	205	12	26
Arkansas	Yes	63	345	9	26
California	Yes	40	410	14	26
Colorado	Yes	25	398	13	26
Connecticut	No	15	429	26	26
Delaware	No	20	330	24	26
D.C.	Yes	50	309	19	26
Florida	Yes	32	275	9	26
Georgia	No	40	300	9	26
Hawaii	Yes	5	417	26	26
Illinois	Yes	51	326	26	26
Indiana	Yes	50	348	8	26
Kansas	Yes	87	351	10	26
Kentucky	No	39	365	15	26
Louisiana	Yes	10	258	21	26
Maryland	No	25	310	26	26
Massachusetts	Yes	29	508	10	30
Michigan	No	81	362	14	26
Minnesota	Yes	38	478	10	26
Mississippi	Yes	30	210	13	26
Missouri	Yes	40	250	13	26
Nebraska	Yes	36	280	15	26
Nevada	No	16	317	12	26
New Hampshire	No	32	372	26	26
New Jersey	Yes	61	490	15	26
New Mexico	Yes	58	290	19	26
New York	Yes	40	405	26	26
North Carolina	Yes	36	416	13	26
Ohio	Yes	90	323	20	26
Oklahoma	Yes	16	275	22	26
Oregon	Yes	96	410	3	26
Pennsylvania	Yes	35	461	16	26
Rhode Island	Yes	56	441	8	26
South Carolina	Yes	20	278	15	26
Tennessee	Yes	30	275	13	26
Texas	Yes	53	328	9	26
Utah	Yes	24	377	10	26
Virginia	Yes	50	316	12	26
Washington	Yes	109	496	12	30
West Virginia	Yes	24	358	26	26
Wisconsin	No	49	329	12	26

Wait Period refers to the existence of a one week waiting period at the start of an unemployment spell during which a claimant cannot yet receive benefits. Min Benefits and Min Durations refer to minimum levels and lengths of benefits given that one meets the minimum requirements to be eligible for any unemployment benefits.

Table 10: Summary of Major Unemployment Legislation

Bill	Date Passed	Effect	Summary
Supp. Appropriations Act	June 30th, 2008	EUC Created	Extends emergency unemployment compensation for an additional 13 weeks. States with unemployment rates of 6% or higher would be eligible for an additional 13 weeks.
Unemp. Comp. Extension Act	Nov 21th, 2008	EUC Expanded	Provides for seven more weeks of unemployment insurance benefits. States with an unemployment rate above six percent are provided an additional 13 weeks of extended benefits.
Worker, Homeownership, and Bus. Asst. Act	Nov 6th, 2009	EUC Expanded	Extends unemployment insurance benefits by 13 weeks in states that have jobless rates above 8.5 percent.
Unemp. Comp. Extension Act	July 22nd, 2010	EUC Extended	Extends the filing deadline for federal unemployment insurance benefits until November 30, 2010.

Detailed are major pieces of legislation which affected the availability and generosity of federal extended unemployment benefits.

Table 11: Google Search Term Correlations

	Jobs	How to Find	Tech	State	City	Retail	Walmart	Sales	Temp	Local	Online	Monster	Weather
Jobs	1.000												
How to Find	0.804	1.000											
Tech	0.943	0.812	1.000										
State	0.893	0.643	0.839	1.000									
City	0.949	0.816	0.916	0.882	1.000								
Retail	0.910	0.799	0.875	0.797	0.914	1.000							
Walmart	0.762	0.867	0.773	0.578	0.844	0.809	1.000						
Sales	0.840	0.569	0.806	0.868	0.799	0.799	0.506	1.000					
Temp	0.740	0.457	0.671	0.749	0.680	0.662	0.395	0.714	1.000				
Local	0.842	0.729	0.811	0.791	0.930	0.848	0.784	0.737	0.575	1.000			
Online	0.883	0.869	0.871	0.735	0.932	0.885	0.934	0.677	0.525	0.872	1.000		
Monster	0.887	0.524	0.749	0.854	0.819	0.476	0.286	0.749	0.629	0.499	0.664	1.000	
Weather	0.212	0.284	0.231	0.191	0.333	0.242	0.337	0.157	0.056	0.452	0.345	-.0961	1.000
Sports	-0.569	-0.455	-0.527	-0.569	-0.570	-0.468	-0.433	-0.404	-0.580	-0.455	-0.478	-.514	-0.106

Numbers represent correlations of national Google search indexes for the listed search terms from 2004-2011.