The Impact of Unemployment Insurance on Job Search: Evidence from Google Search Data

By Scott R. Baker and Andrey Fradkin*

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We develop and validate a measure of job search based on Google search data and use it to study the effects of unemployment insurance (UI). We show that individuals on UI search 30% less than the unemployed not on UI and that claimants close to UI exhaustion search twice as much as claimants with over 30 weeks left. We use our estimates to calibrate a model of job finding and find that the decrease in job search due to UI expansions was responsible for an increase in the unemployment rate of less than 0.1% in Texas between 2008 and 2009.

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I. Introduction

The amount of job search exerted by unemployed individuals is a key choice variable in theories of optimal social insurance and business cycles. Existing literature has found that some unemployed individuals respond to an increase in unemployment insurance (UI) generosity by decreasing their job-finding rate. However, the lack of high-frequency and geographically-specified job search data has made it difficult to understand the role of job search (as opposed to reservation wages) in the decreased job-finding rate. We construct and validate a new measure of job search based on Google searches for the term 'jobs' that allows us to identify the effect of UI on job search. We use the Google Job Search Index (GJSI) to show

* Baker: Kellogg School of Management, 2169 Campus Dr, Evanston, IL 60208, s-baker@kellogg.northwestern.edu. Fradkin: National Bureau of Economic Research, 1050 Massachusetts Avenue Cambridge, Massachusetts 02138, afradkin@gmail.com. The first draft of this paper was created on April 17 2011. Note, this paper supersedes a previous version named "What Drives Job Search? Evidence from Google Search Data". Thanks to Caroline Hoxby, Doug Bernheim, Nick Bloom, Hal Varian, David Card, Camille Landais and innumerable seminar participants for their comments and suggestions. Thanks to Jack Bao, David Summers, and Holly Faubion at the Texas Workforce Commission for assistance in obtaining administrative UI data. This research was supported by the Shultz Graduate Student Fellowship in Economic Policy through a grant from the Stanford Institute for Economic Policy Research.

that the effect of UI on job search played a minor role in increasing unemployment rates during the Great Recession.

The first part of this paper validates the GJSI as a proxy for overall job search. We use the ComScore web panel to show that individual searches for 'jobs' are strongly correlated with overall time spent searching for jobs on the internet. We also show that the GJSI can explain a large portion of state-month variation in job search as measured by the American Time Use Survey (ATUS). Furthermore, the index displays the same intra-week and holiday effects as the job search data from ComScore and the ATUS. Lastly, the GJSI moves in the expected direction in response to macroeconomic drivers of job search such as the unemployment rate and labor market tightness.

We then study the relationship between job search and unemployment insurance. We first show that the GJSI falls by 2 percentage points in the month following a UI expansion and that this effect does not persist over time. We then use the GJSI to extract the relative search effort conducted by UI recipients as a function of their remaining UI duration. The main challenge in this exercise is that the GJSI is an aggregate index that is constructed in particular way by Google. We develop a methodology to extract economically meaningful parameters from Google Trends by using non-linear least squares. We combine the GJSI with administrate data on the UI duration of recipients in Texas to estimate our model. We find that individuals on UI search for jobs eight times more than employed individuals and 30% less than the unemployed not on UI. In addition, individuals close to exhausting UI benefits search twice as much as those with over 30 weeks until UI exhaustion.

Our identification comes from combining the precise timing and size of expansions to the UI system with high frequency variation in the composition of the unemployed between 2006 and 2011. Federally mandated expansions to the UI system provide shocks to the potential duration of UI eligibility. Further, due to the differential timing of layoffs and the business cycle among designated market areas (DMA), some DMAs have higher shares of individuals with a given number of weeks of UI left than other DMAs.[1] The variation in the composition of the UI claimants across locations allows us to identify the pattern of job search over unemployment spells and to determine the effects of UI expansions on job search.

The last part of our paper uses our estimates to calibrate a model of job finding using administrative data from Texas. We first estimate a simple model of weekly job-finding as function of the characteristics of the unemployed. We then simulate the job-finding outcomes if unemployment benefits had not been extended. Our simulations show that the decrease in job search due to the UI expansions accounts for less than a 0.1% increase in the unemployment rate between July 2008 and January 2009.

[1]Designated Market Areas are generally defined as geographical areas which can receive the same radio and television signals. Google uses DMA designations to define geographic boundaries in Google Trends. DMAs are generally similar to but not identical to Metropolitan Statistical Areas.

Our study differs from other studies of job finding and job search because it uses Google Search data and administrative UI data. Below, we explain the advantages of our data as opposed to other datasets in the literature. The most commonly used dataset for studying job search is the American Time Use Survey. The ATUS often contains fewer than 5 unemployed respondents per state-month, making it unsuitable for conducting analysis at a disaggregated level. On the other hand, Google search data is an aggregate of thousands of searches and does not suffer as acutely from small-sample bias. Online search data is also free of survey bias such as inaccurate recall and biased answers. Lastly, the immediate availability of Google Trends data makes it possible to diagnose large behavioral response to policy changes in real time (Choi and Varian (2009) and Choi and Varian (2013)).

Another advantage of our approach is that we use administrative UI data from Texas in addition to the state-level Current Population Survey (CPS) data used by Rothstein (2011) and Farber and Valletta (2013) to study UI in the United States. Administrative data is necessary for our exercise because it allows us to precisely measure the composition of the unemployed in a given DMA-week. The CPS, on the other hand, only contains an average of 23 individuals on UI per state-month — making it too small of a sample to adequately study local distributions of UI recipients. Furthermore, the CPS does not ask about the number of weeks left of UI or even if an individual is receiving UI. Therefore, studies using the CPS can only infer the UI status of recipients with significant measurement error. Lastly, our identification strategy relies on the precise weekly timing of UI extensions but the CPS is only conducted at a monthly level. The Bureau of Labor Statistics (BLS) is another source of data on the composition of the unemployed at a state level. However, while it covers the entirety of the unemployed population across the United States, it does not give data by the time to expiration for a given UI recipient. Thus, it is impossible to use the BLS data to determine the composition of the unemployed population in a given state in terms of time to benefit expiration.

The rest of this paper is organized as follows: Section 2 describes prior literature on job search and optimal UI design. Section 3 describes and validates the GJSI. Section 4 documents the expansions to the unemployment insurance system in the United States during the Great Recession and Section 5 shows that the expansions decreased aggregate job search. Section 6 describes the administrative UI data from Texas used in our analysis. Section 7 contains the main empirical results regarding the impact of UI on job search activity and Section 8 describes our calibrated model of job finding and the counterfactual unemployment rates in a world without expansions in the UI system.

II. Empirical Evidence on Job Search and Unemployment Insurance

Economists have been interested in understanding the costs and benefits of UI since the inception of the UI system. Prior literature, such as Meyer and Mok.

(2007), Card and Levine (2000), Katz and Meyer (1990), Lalive (2008) , and Meyer (1990), has focused on the effects of benefit levels and duration on hazard rates out of UI. They use a variety of empirical strategies (regression discontinuity, natural experiments, cross-state variation) to find elasticities of unemployment with respect to benefit levels of around 0.5. Card et al. (2007) conducts a review of the literature on the topic of the spike in exit rate from unemployment near the exhaustion of UI benefits. Their study finds that how 'exit' is measured can dramatically change the estimated effects: the spike in exit rates does not always corresponding to a spike in re-employment rates. Because none of these studies observe job search effort, they cannot tell whether a change in job-finding rates effect comes from search effort or reservation wages.

There have been several studies that use survey data about job search in order to study the response of job search to UI benefits. For example, Krueger and Mueller (2010) use the ATUS to study how the job search behavior of individuals varies across states and at different points in an unemployment spell. They show that job search activity increases prior to benefit exhaustion and that job search activity is responsive to the level of UI benefits. Given the difference in UI generosity, they assert that these elasticities can potentially explain most of the gap in job search time between the U.S. and Europe.

In another study, Krueger and Mueller (2011) (hereafter KM) administer a survey to UI recipients in New Jersey which asks questions about job search activity and reservation wages. They find that effort decreases over the duration of unemployment and that stated reservation wages remain approximately constant throughout the unemployment spell. Importantly, KM present the first longitudinal evidence on job search. In contrast to prior, cross-sectional, evidence, KM find that job search actually decreases as individuals near expiration. Their finding may be due to unobserved heterogeneity across UI claimants that jointly determines exit rates and search intensity. Another important finding in KM is that an extra 20 hours of search is correlated with a 20% higher change of exit to unemployment in a given week. Although this correlation is not causal, it is an important benchmark because there are few other measures of the returns to job search in the literature.

KM also estimate the effect of the 2009 expansion of Emergency Unemployment Compensation (EUC) on job search. They find that there are 11 - 20 fewer minutes of job search per day per individual after the policy change. However, their identification strategy cannot separate time trends from the policy change due to the fact that they only observe a single expansion and lack cross-sectional variation in treatment intensity. This is an important shortcoming because job search activity can vary over time due to factors such as labor market conditions (i.e. Schmieder et al. (2012b)), the weather and seasonality. Our data and research strategy allows us to separately identify the effects of UI policy changes from time trends. First, we observe UI policy changes separately from time trends at a national level because states experienced changes in their UI systems at different times. Second, because the Texas UI data has large variation in local labor market conditions and because we observe 6 years of data, we can control for local labor market conditions and seasonal trends in job search.

Other work in the UI literature suggests that UI extensions may have a significant effect on subgroups of the population even if there is no large effect on aggregate job-finding rates. For instance, Farber and Valletta (2013) studies the recent expansions of the UI system and finds small effects on exit rates and unemployment duration. However, most of the impact flows through reductions in labor force exits, meaning that there are large implications for the population of long-run unemployed. Similarly, heterogeneous effects of UI expansions on job search behavior could either amplify or narrow differences in exit-rate probabilities across the distribution of the unemployed.

Data from Google Trends has been used in several other economics papers. Choi and Varian (2009) and D'Amuri and Marcucci (2009) use Google Trends to forecast product sales and initial unemployment claims. Da et al. (2011) use Google search data show that search data predicts stock price movement and Vlastakis and Markellos (2012) show that demand for information about stocks rises in times of high volatility and high returns.

A. Job Search Activity and Optimal Policy

Economists since Baily (1977) have worked to calculate optimal unemployment insurance policies. In what can be seen as one large natural experiment, the potential duration of UI increased from 26 weeks to 99 weeks in some states during the Great Recession, allowing millions of Americans additional weeks of benefit eligibility. Mortensen (1977) develops a stylized model demonstrating that job search activity should increase as UI benefits come closer to expiring. Therefore, we expect job search activity to decrease following the UI expansions we study. Indeed, Rothstein (2011) finds negative but small effects of the UI expansions on exit from UI. There are two mechanisms by which exit from UI can decrease: decreased job search and higher reservation wages. Furthermore, these responses need not be indicative of poorly designed policy. Chetty (2009) shows that an increase of the duration of unemployment in response to UI changes can be positive if it allows job seekers to find a better match — the "liquidity effect".[2]

The key question regarding UI policy during recessions is how the level and potential duration of benefits should change with labor market conditions. Most studies of optimal UI show that UI generosity should increase during recession. For example, Kroft and Notowidigdo (2011) estimate that the elasticity of unemployment duration with respect to the benefit level is -1.10 when unemployment is low, but is only -0.32 when unemployment is high. They use the above difference

[2] Most studies have found large liquidity effects but little effect on match quality (see Chetty and Finkelstein (2013) for a comprehensive overview). The leading explanation for this fact is non-optimizing behavior (i.e. Spinnewijn (2014))

to calibrate the optimal replacement rate in a Baily-Chetty sufficient statistic framework and find that the optimal replacement rate should be higher when there is higher unemployment. Landais et al. (2013) analyze optimal UI policy over the business cycle with 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. Schmieder et al. (2012a) study the effect of thresholds in benefit durations within the German UI system on job finding probability. They derive a formula for optimal UI duration and show that potential duration should increase during a recession.

III. Google Search Data and Validity

The GJSI is constructed from indexes of search activity obtained from Google Trends. Google Trends gives a time series of the relative amount of local search activity for specific search terms on Google.com.[3] The values of Google Trends represent the number of searches on Google.com for the specified search term relative to the total number of searches on Google.com derived from a sample of all Google search data.[4] We re-sample Google Trends during 4 different weeks and take the average value for each period to reduce sampling bias. Google Trends is normalized so that the highest value for the entire time period and term is set equal to 100. Its range of values is always between 0 and 100, where higher values correspond to total searches on Google.com for a given search term. An example of the results from a Google Trends search can be seen in Figure 1.

The exact volume of searches for 'jobs', or any other term, on Google is kept confidential. However, several tools available as of 2013 offer clues into the raw numbers underlying Google Trends. For example, Google's Adwords tool states that there were 68 million monthly searches for 'jobs' in the United States in the year proceeding April 2013. That amounts to approximately 6 searches per unemployed individual per month in the United States. According to the Adwords traffic estimator, an alternative measure of search volume, the top placed ad for 'jobs' in Texas in April 2013 would generate 25,714 impressions per day or 771,000 impressions per month. That amounts to approximately one search per month per unemployed individual in Texas. If one serves the ad to not just the Google main site but to affiliates in Google's network then the total potential impressions per day is 3.3 million per day. It is unclear whether the impressions numbers that

[3] http://www.google.com/trends/

[4] A potential concern, discussed in detail by Stephens-Davidowitz (2013), is that Google imposes thresholds for reporting search data below which a 0 is displayed in Google Trends. For instance, too few searches were done for the search term 'econometrics' in July 2006 in Texas. Therefore, Google Trends displays a 0 rather than a low number, producing large swings in the time series data. However, for the search term, 'jobs', even at a weekly-DMA level in Texas, there are no zeros reported by Google Trends after 2005. Our results are robust to excluding the first year of data.

Google provides assume that the top ad is seen by all searchers. Nonetheless, the search numbers from Adwords suggest that there is a substantial volume of searches for the term 'jobs' and variants of the term.

We use three samples of from Google Trends: a national daily index to study day-of-week effects, a state-month panel to look at responses to UI policy across states, and a DMA-week panel for our main empirical exercise focusing on Texas. For each series, we choose the search term 'jobs' (excluding search about Steve Jobs and Apple) as our term of interest. The term, 'jobs', captures a large variety of job search activities online. Many job related queries are included in the more general 'jobs' index; for example, people may search for jobs at a specific company ('Walmart jobs') or region ('Dallas jobs'). For such queries, Google is one of the most effective ways of finding the appropriate job posting. Searches for 'jobs' have a greater than 0.7 correlation with other job search related terms, such as 'state jobs', 'how to find a job', and 'tech jobs'.[5]

We also use Google Correlate to determine which search terms that do not contain the text 'jobs' and are most correlated with Google searches for 'jobs'.[6] The most correlated results contain occupation specific searches ('security officer', 'assistant', 'technician'), job search specific terms ('applying for', 'job board', 'how do I get a job') and social safety net searches ('file for unemployment in Florida', 'social security disability'). These results suggest that the search term 'jobs' both picks up a large portion of jobs-related search activity and is highly correlated with other, more specific and detailed, search terms. Importantly, 'jobs', has the highest volume and is least prone to sampling bias of all the terms discussed above.

A. *Importance of Online Job Search*

While the GJSI is a direct measure of only online search activity, online job search has been a rapidly expanding segment of internet use over the past decade and, we argue, is a good indicator of overall job search in the modern economy. Sites like CareerBuilder.com, Monster.com, and Indeed.com receive tens of millions of unique visitors per month. To investigate whether those visitors are representative we turn to the National Longitudinal Survey of Youth (NLSY). In 2003, 53% of NLSY job seekers used the internet whereas 83% did in 2008.[7] Similarly, in the 2011 The Internet and Computer Use supplement of the Current Population Survey (CPS), over 75% of individuals who were searching for work in the past 4 weeks had used the internet to do so. According to Kuhn and Mansour (2014) the most internet intensive activities are resume submissions, placing ads, and contacting schools' career centers. Further, rates of internet usage in job search increased with education but did not vary systematically by census region. Even as far back as 1998, more unemployed job seekers used the internet

[5]See Appendix Table 2 for a partial list of alternate terms tested.

[6]According to Google: 'Google Correlate is a tool on Google Trends which enables you to find queries with a similar pattern to a target data series.'

than used private employment agencies, friends, or unions to find a job (Kuhn and Skuterud (2004)). Furthermore, online job search is often successful. Even as early as 2002, 22% of job seekers found their jobs online (Stevenson (2009)). Finally, 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, as documented in Kroft and Pope (2011). Therefore, we conclude that online job search is sufficiently representative and makes up a large component of overall job search.

One concern with the GJSI is that Google searches could be a different type of activity from online job search in general. We use data on individual browsing from ComScore to compare Google searches to other job search related browsing.[8] We determine whether a person is searching for a job by summing the time spent on websites that contain job relevant terms.[9]

With this data, we construct a proxy for our GJSI. We can observe both the number of visits to Google.com overall as well as if a visitor to a job search related site was referred there by Google. We calculate the ratio of visits to job search sites originating from Google as a fraction of total site visits to Google.com. This is analogous to our GJSI, which is based on the number of Google searches related to the term 'jobs' as a fraction of total Google.com searches. Table 1 displays the results of a regression of time spent on job search sites on the proxy for GJSI. We find that a 1% increase in the 'synthetic GJSI' is correlated with an approximately 1% increase in overall time spent on online job search. Furthermore, the fraction of visits to Google that result in a visit to a job search site explains over 50% of the total variability in the amount of job search per capita at a state-month level. These results suggest that our measure of job search is a good proxy for overall online job search effort.

B. Correlation of GJSI and The American Time User Survey

We use Krueger and Mueller (2010) methodology for measuring job search using the ATUS in order to compare our Google measure of job search activity to their ATUS measure of job search.[10] ATUS job search activity is calculated

[7] The NLSY only asked a question about internet use for job search from 2003 - 2008.

[8] The ComScore Web Behavior Database is 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.

[9] For example, we include all domain names containing 'job', 'career', 'hiring', and 'work' in addition to the biggest job search sites (eg. monster.com, careerbuilder.com, indeed.com, and linkedin.com). We remove any websites containing 'job' or other terms but are unrelated to job search.

[10] The ATUS is a survey of approximately 13,000 people taken throughout the year. 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 high response rate.

using the amount of time that individuals spend in job search related activities.[11] The monthly correlation between the national measured averages of job search per capita from the ATUS and the GJSI is approximately 0.56. This correlation is robust to inclusion or exclusion of job-related travel time, removing the over-sampling of weekend days, or using alternate Google search terms to measure job search activity.

We also consider the state averages of job search time per capita for each month. Table 2 shows results of regressions of the GJSI on job search as measured by the ATUS. There is a significant relationship between the Google and ATUS measure across all specifications. Columns 1-3 display the relationship between the GJSI and average ATUS job search activity without any other controls. The 83% decrease in sample size and increase in R^2 between columns 1 and 2 demonstrates the drawback of the small samples in the ATUS, where most state-month observations have no reported job search activity. This makes any meaningful estimation difficult at a geographically disaggregated or high-frequency level. We find that increases in the GJSI tend to be associated with an observation being more likely to have any job search reported as well as with higher levels of average job search time, conditional on non-zero job search time.

Column 7 displays a placebo regression wherein we substitute the term 'jobs' with the term 'weather', finding no relationship between this index and search time. Although the ATUS and GJSI are clearly related, they are not identical. Differences can arise because of biases in survey answers or because online job search differs from offline job search. Further, the two measures might sample different populations or the Google data might capture some searches that are unrelated to searching for jobs but which involve the word 'jobs'.

C. Day of Week and Holiday Effects

Job search should follow day, month, and year trends, with predictable declines in search on weekends and holidays due to social commitments and general societal norms.[12] It should also increase in the late spring because graduating students are looking for jobs and other students are looking for summer jobs. Indeed, the GJSI increases in January after a holiday lull and also increases at the end of the spring as expected. As a test of the validity of the GJSI, we compare relative job search effort for different days of the week using the American Time Use Survey, the ComScore Web Panel, and the GJSI. Figure 2 displays the day-of-week fixed effects for all three measures graphically (full regression results in Table 3). The day of week effects move in tandem for all three measures of job search. For

[11] We assembled all ATUS data from 2003-2009 (though Krueger and Mueller 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'.

example, there are large drops in search on Fridays and weekends across all three measures. Furthermore, the ratios of weekend to holiday search are approximately the same for all 3 measures. We interpret these results as evidence that Google search for 'jobs' is a good proxy for overall job search.

D. Macroeconomic Drivers of Job Search

If the GJSI is a valid proxy, we would expect that it also follows macroeconomic drivers of job search activity. Table 4 displays the results of regressions of the GJSI on labor market conditions at a state-month level. While these results are not causal, they all appear to move in the 'expected' direction and have a high degree of predictive power. All columns use logged GJSI as the dependent variable and all variables have been standardized such that the standard deviation is equal to 1. In columns 1-3, show the results of a regression with the state unemployment rate as the independent variable with varying fixed effects. There is a positive correlation between the unemployment rate and the GJSI, with an increase in the unemployment rate of one standard deviation being associated with an increase in the GJSI of approximately 0.65-0.8 standard deviations.

In Column 4, we add the number of initial unemployment benefit claims per capita to our regression. The coefficient on new claims is positive and significant, consistent with higher levels of job search for newly unemployed individuals. Columns 5 and 6 also include the number of final claims for UI per capita. We expect that current job search will be positively correlated with the number of final claims in the following month for two reasons. First, because those who search more in the current month are more likely to find a job and exit the UI system in the next month. Second, recipients whose benefits will be expiring in the following month will most likely search at a higher rate in the current month. Indeed, we find the expected signs for all measures of labor market conditions, though the point estimate becomes insignificantly positive with the inclusion of both state and month fixed effects.

IV. Unemployment Insurance and EUC

Individuals eligible for unemployment insurance in Texas can typically draw on benefits for up to 26 weeks at a maximum weekly benefit amount of $426 (as of 2013; amount undergoes annual adjustments for inflation). To receive UI benefits, an individual needs to have earned a sufficient amount of wages in their base year (the first four of the past 5 completed quarters prior to their first UI claim) and have worked in at least 2 of the quarters in their base year.[13] Further, UI recipients need to have been laid off for economic reasons, fired without work-related misconduct, or quit for a valid reason. Once on UI, job-seekers must be

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

able to work, be available to work, be registered with Texas Workforce Solutions, and search for full-time work unless exempted.

During times of high unemployment, individuals have access to additional weeks of UI through the federally-funded Extended Benefits (EB) program. EB consists of two tiers, comprising 13 and 7 additional weeks, and is made available at a state-level when a state passes certain thresholds of unemployment. For the first level (13 weeks), a state becomes eligible when the three month moving average of its unemployment rate hits 5%. The second level (7 additional weeks beyond the initial 13 weeks) is available when the three month moving average hits 8.0%.

The federal government created The Emergency Unemployment Compensation to extend the potential duration of UI several times due to the severity of the Great Recession. This program was significantly modified as follows:

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 an additional 13 weeks for those residing in states with greater than 6% unemployment.
3. November 6th, 2009 - The EUC is expanded by 1 week for all unemployed, 13 additional weeks for unemployed residents of states with greater than 6% unemployment, and an additional 6 weeks for states with unemployment rates greater than 8.5%.

The combination of the EUC and EB programs had the effect of increasing the maximum weeks of unemployment insurance from 26 to 99 weeks in many states, including Texas. This was an unprecedented expansion, representing a fourfold increase in unemployment insurance benefit duration. EUC was also characterized by legislative instability, with short term extensions of eligibility repeatedly passed by Congress to extend the program from 2009 through 2012. After the November 6th, 2009 extension, EUC was changed multiple times to extend the period for which individuals were eligible for these expanded benefits (see Appendix Table 1 for details).

Our primary specification uses the legislative changes to the unemployment insurance system as locally exogenous shifters of the number of weeks of unemployment benefits an individual is eligible for. We use both benefit duration shifts that occur due to the changes in the EUC program as well as those due to hitting certain state-level unemployment thresholds. This latter category includes both thresholds set by the new Emergency Unemployment Compensation as well as the previously enacted Extended Benefits program.

An important consideration for our analysis is the extent to which individuals can anticipate the legislative changes to UI policy. We think that these policies were relatively unexpected by individuals on UI for several reasons. First, expansions and extensions were often politically contentious and it was uncertain whether they would be passed or in what exact form. In the UI extension bills in 2009-2011, some bills were even passed retroactively, with individuals losing benefits for a short time before regaining them. In addition, many of the expansions came at predetermined thresholds of unemployment rates by state. Such expan-

[13]This amount is generally equal to 37 times the UI weekly benefit amount

sions would be unpredictable at a high-frequency level because it is hard to predict short-run unemployment rate changes. Finally, we also do not see evidence of increased news coverage in the weeks leading up to expansions in unemployment benefits. Figure 3 displays counts from newspapers in Texas of articles about the EUC or EB system for the 15 days before and 15 days following each expansion or extension. The increase in coverage only begins 2 days before the policy change. This gives us confidence that individuals were not exposed to much information about changes to UI benefits until the time immediately preceding those changes. However, to the extent to which some individuals did anticipate the imminent expansion in UI benefits (e.g. the perceived probability of expansion went from somewhere above 0% to 100% instead of from 0% to 100%), our estimates would most likely represent lower bounds on the true effects on search.

V. The Aggregate Effects of UI Expansions on the GJSI

In this section we investigate whether UI expansions affected the overall level of job search. We use cross-state variation in the timing of UI policy changes to identify the effect of those changes on job search. Different states crossed the EUC and EB thresholds at different times. The time at which each threshold was crossed should be independent of factors impacting state level job search conditional on labor market conditions in the state and time trends. We use this variation to estimate the equation below:

$$\log GJSI_{st} =$$
$$\alpha_0 + \alpha_i * L(i).Expansion_{st} + \beta * X_{st} + \gamma_t Year - Month_t + \gamma_s State_i + \epsilon_{st}$$

$L(i).Expansion_{st}$ is an indicator variable that equals one when the most recent expansion of UI in state 's', happened 'i' months ago, during time 't'. X_{st} are covariates representing local labor market conditions (unemployment and employment rates), and γ_t and γ_s are year-month and state fixed effects, respectively.

Figure 8 displays the coefficients for the temporal effect of expansions and their 95% confidence intervals for the above specification. These coefficients are detailed in Table 7, column 2. There is a statistically significant initial drop of about 2.5% in the GJSI in the month of a UI expansions. Over the following months, this magnitude approaches 0 and the coefficient becomes statistically indistinguishable from 0. The result above is robust to excluding local labor market conditions and to varying the amount of lagged indicators included in the regression. Including state time trends does not change this pattern. These results show that UI expansions had at least a small and temporary effect aggregate job search activity.

Columns 3 and 4 in Table 7 display results from the analogous regression using only within-Texas variation. We find similar effects, with declines in job search soon after UI expansions that fade in magnitude and significance as time passes.

The aggregate effect of the expansions can potentially mask large effects of UI on job search effort for specific sub-populations. For example, individuals with few weeks of UI left might greatly adjust their search effort whereas those with many weeks might not react to the expansion. In this next section we study these effects using data on the composition of UI in terms of weeks left.

VI. Texas UI Data

Our administrative UI data is from the Texas Workforce Commission. The data spans 2006-2011 and includes every recipient of UI in Texas during that time period. In total, over 2 million individuals received UI over 2.7 million unemployment spells during this period. Administrative data offers a number of advantages over alternate data sources and a few disadvantages. The primary benefit of the data is its accuracy and granularity. The UI system is complicated by features such as waiting periods, part-time work allowances, and variable claim amounts. Therefore, simply calculating the number of weeks of UI benefits remaining by using the maximum weeks of eligibility minus an individuals' 'weeks since becoming unemployed' (as is typically done in papers using survey data) often gives starkly incorrect results. Our calculations of potential weeks left adjusts for these complications. Moreover, because we observe the whole UI population, we can calculate the distribution of individuals currently receiving UI with regards to the number of remaining eligible weeks. We are also able to match each individual to DMAs, whereas other data sources are often restricted to state or Census region level analysis.

The main downside of focusing on Texas is that it might not be representative of the US and that we lose some variation in the timing of the UI expansions. While the timing of the expansions differed across states according to the unemployment rates, it did not differ within state. We discuss how to identify effects of interest even with this limitation in the next section.

Figure 4 shows that the total number of UI recipients in Texas over time rose from a baseline of around 100,000 during 2007 to over 400,000 during 2009 and 2010 and remains at elevated levels through the end of 2012, with over 300,000 claimants. The data covers a number of demographic and economic characteristics for individual UI recipients. We observe an individual's age, gender, and zip code of residence. We use the zip code to assign individuals to DMAs which are then matched to the GJSI. Furthermore, we observe a recipient's tier of benefits, received retroactive payments, weekly eligible benefit amount, and weekly amount received. The latter two variables can differ if a claimant works part time. Part-time work can offset some share of UI benefits and lengthen a claimants' UI spell. We combine the data on benefits received with details of the UI legislation in effect each week to we calculate the remaining weeks of eligibility for each recipient.

Following Rothstein (2011), we study the effects of the potential UI duration under two different assumptions: "current policy" and "current law". Under the "current policy" assumption, UI recipients expect UI expansions to be extended indefinitely (such that the current policy lasts indefinitely). Under the "current law" assumption, UI recipients expect UI expansions to expire according to current law with no additional laws passed. A sample trajectory of maximum number of weeks eligible for all new UI recipients under the two assumptions is displayed in Figure 5. For "current policy", we see a simple stepwise function that increases with each new piece of legislation passed or Extended Benefits threshold met and then plateaus at 93 weeks in late 2009. For "current law", the legislated expiration date of EUC can often cut short an individuals' benefits.

Figure 6 shows the average expected remaining duration of UI benefits under each assumption. The difference in expected maximum eligibility time between the two assumptions is over 40 weeks during parts of 2009 and 2010. This gap in expected weeks left is driven by the fact that the EUC program was often extended for only a few months at a time, so any new users would only be able to take advantage of a fraction of the headline number of weeks available before EUC expired. The large jump in early 2011 reflects the extension of the EUC program from March 2011 until December 2012.

Although the policy changes are complicated, there exists a substantial population of sophisticated UI recipients who understand the nuances of the cutoff dates for the EUC program. For example, one popular forum about unemployment and unemployment benefits, found at www.city-data.com, has a large number of posts regarding the UI and EUC programs in general, often in great detail. Questions are often answered within hours and are eventually read millions of times. Furthermore, some forum participants have answered several thousand questions about unemployment benefits. Visitors are clearly aware of the cutoff dates they face and likely respond to those dates rather than headline numbers reported by some media outlets.

Another important aspect of UI is that individuals do not use it in the straightforward manner that many policymakers and researchers assume. The 'standard' use of UI is thought of as an individual losing a steady job, having zero income, applying for UI benefits, receiving standard weekly benefit checks, undertaking job search while receiving UI, and finally finding and starting a new job. There are large deviations from this timeline in the administrative data. Some individuals have no observed income for a number of quarters before applying for UI. Other UI recipients work part-time (seen in Figure 7 during their entire UI spell. Part-time workers have extended UI spells and often go without UI for several weeks until they are granted large lump-sum retroactive payments. There are also many individuals who exit UI early but do not receive income in the subsequent quarters. Departures from "standard" use play a large role in shaping the duration, potential duration, and income during a UI spell but are missed by the majority of current UI research.

VII. The Effect of Unemployment Insurance on Job Search Intensity

We want to understand the contributions made to the index by different types of searchers and by changes in the UI system. The simplest specification for such an investigation is an OLS model in which the GJSI is predicted by the composition of the unemployed and the state of the UI system. Below is one possible specification, which includes the percentages of the unemployed with given potential durations as well as state and year-month fixed effects.

$$\log JS_{it} =$$
$$\beta_0 + \beta_1 WeeksLeft10_{it} + \beta_2 WeeksLeft20_{it} + ... + \beta_t Year - Month_t + \beta_i State_i + u_{it}$$

The coefficients corresponding to the weeks-left bins are likely to be correlated with relative job search of that unemployed category. However, they are hard to interpret quantitatively because the GJSI is a non-linear transformation of the searches of the unemployed (we present the results of OLS specifications in Appendix A). In order to be precise about the job search decisions of the unemployed, we need to explicitly model the manner in which the GJSI is constructed. We are the first to show how to use Google Trends data to interpret underlying behavioral parameters.

Consider the following illustrative example. Suppose that there are two types of job searchers, the employed and the unemployed. In that case, the observed measure of job search from Google equals:

$$JS = \frac{1}{\mu}\left[\frac{\gamma_{Ut}N_{Ut} + \gamma_{Et}N_{Et}}{\alpha_{Et}N_{Et} + \alpha_{Ut}N_{Ut}}\right] \tag{1}$$

In the above equation, N_{Ut} and N_{Et} refer to the number of unemployed and employed individuals at time t. The coefficients γ represent the total amount of job search by the corresponding type at time t and the coefficients α represent the overall amount of search by those types at time t. Lastly, μ is a query specific scaling factor that sets the maximum value of the series to 100. Our estimation strategy requires 2 behavioral assumptions:

1) $\alpha_{it} = \alpha_t \ \forall i$

2) $\gamma_{it} = \gamma_i \kappa_t \ \forall i$

The first assumption states that all types of individuals do not systematically differ in overall search demand. It is unlikely that this assumption will hold precisely, but we have few strong priors on the direction of the difference in overall search behavior. We might expect that the unemployed might use Google more because they are sitting at home on their computers all day. Alternatively, we might expect the employed to use Google more because they are working at a computer. However, all that is necessary for our identification strategy to produce results with little bias is that any systematic differences in overall search behavior by type are dwarfed by differences in job search activity. We also ran Monte Carlo simulations under alternative assumptions about the α_i's. Our tests found that the bias due to small violations of assumption 1 is unlikely to be large.

The second assumption states that the amount of job search done by different types can be decomposed into a type specific job intensity level and a time specific trend. We stipulate that the ratio of job search between any two types is constant over time. This is a standard implication of optimal job search behavior in many models of job search. Our parameter of interest is the ratio of job search between different types of job seekers.

Given our assumptions we derive the following equation by taking the logarithm of both sides of Equation 1:

$$\log JS = -\log{(\mu N)} + \log{(\frac{\kappa_t}{\alpha_t})} + \log{(\gamma_U N_{Ut} + \gamma_E N_{E2})} \tag{2}$$

We then convert Equation (2) into the following estimation equation where each observation is an DMA-week:

$$\log JS_{dt} = \beta_{0d} + \beta_{1dt} + \beta_{2t} + \log{(\gamma_E N_{Edt} + \gamma_U N_{Udt})} + \epsilon_{dt} \tag{3}$$

β_{0d} is an DMA specific fixed effect, β_{1dt} is a DMA specific time trend (to account for differential trends in internet usage by DMA) and β_{2t} are Texas-wide time fixed effects.[14] We proceed by estimating equation 3 in several specifications which vary the amount of job searcher heterogeneity. The error term in the above equation represents DMA-time specific fluctuations in job search. These errors are caused by unobserved drivers of search such as DMA specific weather changes or Google's sampling error.

We also include an indicator for whether the week was an extension week in order to test for any blanket effects of extensions on job search, separate from their effect on the potential eligibility of the unemployed. For example, UI extensions may raise awareness about the UI system amongst all UI recipients.

One worry about our estimates is that the composition of unemployed at a DMA-week level is endogenous. Our identifying assumption is that DMA specific returns to job search are uncorrelated with high frequency changes in the composition of job seekers in that DMA. Suppose that firms drastically increase recruiting in an DMA at the same time that more people's benefits are about to expire in that DMA. Then our coefficient on the number of individuals who are about to expire will also include some component of a general increase in search effort in that DMA because of higher returns to search. We have no direct evidence on DMA specific recruiting intensity. However, the correlation of census region vacancies[15] and the GJSI is negative, suggesting that the response of va-

[14] Results are qualitatively unchanged when including a quadratic DMA-specific time trend.

cancies to the composition of the unemployed is not first order during this period. Given the abundance of unemployed labor during the recession, it is doubtful that firms would strongly react to small changes in job search effort among the already unemployed given the relatively small proportions of the population that each UI expansion affects.

A related concern with our specification is that we may be picking up job search responses by the spouses of the unemployed. We do not have any data on the joint job search decisions of unemployed spouses but note that many unemployed individuals are young males who are not yet married. Another worry is that the job search activity by the employed might be driving our results due to a correlation of changes in job search behavior between employed and unemployed populations. We think that this is unlikely because, although the unemployed make up less than 10% of the labor force, on average they search 50 times more than the employed, according to the ATUS (seen in Appendix Table 3).

A. Evidence on The Effects of EUC and EB on Job Search from Texas

We now turn to the NLLS results based on Texas administrative data. Table 5 displays estimates from a nonlinear least squares (NLLS) model based on Equation 3 with three types of job seekers: those on UI, those not on UI and the employed (see Appendix Table 4 for OLS version). Columns 1 and 2 display the coefficients corresponding to the γ_i's in Equation 1. The coefficient on the number on UI is approximately 25% smaller than the coefficient on the number of unemployed individuals not on UI. This corroborates empirical results from KM as well as standard models of moral hazard that predict less search among the unemployed who are on UI. Second, the employed search less than one tenth as much as the unemployed. Lastly, there is a drop of search effort of 1.9% in the 4 weeks following a policy change. This effect is conditional on the decrease in search caused by shifting individuals from unemployment to UI. These results suggest that there was a significant effect of UI policy changes on the job search of unemployed individuals during the recession.

We now test whether individuals with different weeks-left of UI search with different intensities. Importantly, we use the 'current law' definition of weeks left (results using 'current-policy' beliefs are in the Appendix). Table 5 columns 3 and 4 display coefficients corresponding to search effort by individuals with 0 to 10, 11 to 20, 21 to 30 and 30 or more weeks left. Individuals with higher numbers of potential weeks search even less. Specifically, those with fewer than 10 weeks remaining search 70% more than those with 10 - 20 weeks remaining and 103% more than those with more than 30 weeks remaining.. Finally, in column 4, the effect of a UI expansion in the past month is small and no longer significant.

[15] Vacancies are measured at a monthly level by the Job Openings and Labor Turnover Survey.

[15] Appendix Figure 1 displays the coefficients from a NLLS regression with weeks-left binned at a 5 week level. The results confirm that there is a higher level of search nearer to UI expiration. However, we lose precision on the coefficients past 15 weeks left.

Therefore, most of the impact of the UI expansions on job search is accounted for by mechanical changes to the composition of the unemployed (i.e. eligibility for UI benefits and number of weeks of benefits remaining).

B. Cross-State Evidence on The Effects of EUC and EB on Job Search

We also estimate the effect of the UI expansions using state-level data from the CPS. Table 6 displays results from a national analysis using data from the CPS to attempt to control for variation in the composition of the unemployed population in a given state. We follow Rothstein (2011) in constructing a panel of individuals on unemployment insurance across states and over time from CPS data, using repeated survey observations and data on job loss reasons to distinguish between lengths of UI spells and eligibility for unemployment insurance, respectively.

This estimating equation is similar to the one in the previous section. Columns 1-3 use OLS, while columns 4-6 display non-linear least squares results. We find negative effects of a UI expansion on job search. However, the magnitude of the coefficient drops as we include variables controlling for composition of the unemployed in the state. Furthermore, a proxy for the amount of individuals with less than 10 weeks left is associated with more job search in specifications 3 and 6. These results confirm that the driver of these declines of search after expansions was the mechanical change in the composition of the unemployed, both in terms of eligibility for unemployment insurance and in terms of the number of weeks of benefits that remained for a given claimant.

We do not replicate the exact specification seen in 5 using state level data because the CPS cannot be used to accurately measure the weeks left of UI for an unemployed individual. The procedure used in Rothstein (2011) to construct weeks left assumes that each UI claimant is eligible for the maximum number of weeks of benefits that UI claimants could potentially have access to. However, a large portion of UI claimants do not have access to the maximum weeks of benefits and not all eligible unemployed claim UI every week. Further, the CPS is a monthly measure whereas we are interested in the precise number of weeks. Lastly, the CPS often contains fewer than 10 individuals in a given state-month observation and over 50% of state-month observations contain fewer than 18 unemployed individuals who seem eligible for UI. For these reasons, we view the results in Table 6 as a robustness check rather than as the main empirical specification in the paper.

VIII. The Response of the Unemployment Rate to Decreases in Job Search Due to UI Extensions

Rothstein (2011) finds that UI extensions raised the unemployment rate by 0.1 to 0.5 percentage points. This increase in unemployment might be caused by several mechanisms, including decreased job search, lower exit of the labor force, higher reservation wages, and more firing by firms. In this section, we place an upper bound on the importance of the decreased job search channel in determining the increase unemployment rates due to UI expansions between July 2008 and January 2009.

Our calibration strategy combines estimates of the job search response to the UI system with job finding probabilities from the Texas administrative data. Consider the cohort of individuals in Texas that was unemployed and eligible for UI at the time that the EUC was passed in July 2008. 26% of this cohort found a permanent job in Texas by January 2009, 18% left UI for an extended period of time without finding a job in Texas and the rest either remained on UI or were temporarily off UI at the end of December 2008.[16] We construct a counterfactual in which these individuals were only eligible for a maximum of 26 weeks of UI, rather than the 46 weeks, during this period. In our model, the effect of additional UI is that it reduces the propensity of individuals to search and thus changes their propensity to find a job and to leave UI.

We assume the following equation for the job finding rate, J_{wt}, for an individual with w weeks of UI benefit eligibility left at week t:

$$J_{wt} = e_w \frac{J_t}{\sum e_w N_{wt}} \tag{4}$$

where e_w is the relative amount of search effort exerted by that individual, R_t is the average job finding rate in period t and N_{wt} is the number of individuals at time t with w weeks left of UI. We calibrate the above equation by setting e_w equal to the appropriate coefficients in column (5) of Table 5. In this specification, individuals with fewer weeks left search more and are more likely to find a job. Individuals in the model also exit UI permanently without a job with a probability, nj_w, that is function of the amount of weeks of UI remaining. Lastly, UI recipients can temporarily exit UI at a rate l and return at a rate r. Note, there is no choice variable in our model. We simply keep track of the flows of individuals into and out of UI according to their transition probabilities as a function of weeks left of UI.

We simulate the outcomes of this cohort under either the actual EUC regime or a counterfactual regime without any extensions. We find that without the 13 week extension in July and 7 week extension in November, an additional 2.7% of the UI eligible cohort in July 2008 would be employed by January 2009. In total, this is relatively small economic effect given a near-doubling of weeks of UI eligibility. These estimates translate to a 0.08% decline in the unemployment rate in a world without the EUC assuming an overall unemployment rate in Texas of 6% and that half of the unemployed are eligible for UI (long-term averages of UI eligibility in Texas are approximately 50% of the unemployed population). The small effect of EUC is due to the fact that policy shifted the relative probability

[16]See Appendix B for details regarding these calculations and the calibration below.

of job finding several weeks into the future but barely changed the overall probability of finding a job during this time. Even those who most benefit from EUC eventually increase search effort as their weeks expire. Furthermore, because UI legislation had an expiration date, few individuals acted as though they would have access to over 80 weeks of UI even though they eventually did, given repeated extensions. Therefore, they searched as if they had fewer weeks left than allowed by the policy at the time.

Equation 4 likely overstates the true effect of job search effort on job finding rate for two reasons. First, there is strong evidence of decreasing returns to scale to job search at both an individual level and market level (see a discussion of job rationing in Landais et al. (2013)). However, we assume constant returns to scale. Second, unobserved individual heterogeneity is likely to be important in determining job finding rates, with more employable individuals having greater returns to job search effort and exiting unemployment earlier.[17] In such a scenario, we would be estimating the returns to job search effort for those individuals who would have exhausted their initial 26 weeks of UI benefits. Therefore, we view our exercise as an upper bound on the possible effects of EUC on employment through the job search channel.

IX. Conclusion

We develop a new measure of job search from Google search data that is high-frequency, geographically precise, and freely available to researchers. We benchmark the GJSI to a number of alternate measures of job search activity and find a high correlation. We then use the GJSI to show that job search decreased following the UI expansions during the recession of 2007 - 2009.

We find that individuals with 0-10 weeks of UI left search over 2 times more than other UI recipient. Furthermore, we show that job search dropped by over 2% in the four weeks after policy changes that extended or expanded UI benefits. Our identification strategy uses high frequency variation in the composition of the unemployed as well as the precise timing of expansions to the UI system.

We find that UI policy expansion and UI benefit exhaustion affect aggregate job search effort. We use our estimates of relative search intensities to calibrate a model of job search and job finding. We use the model to simulate counterfactuals without UI expansions. We find that the unemployment rate in Texas would be only 0.08% lower if there had not been any expansions in weeks of UI eligibility during 2008-2009. These results suggest that expansions in the UI system during the Great Recession did not meaningfully contribute to heightened levels of unemployment due to the direct effect of reduced levels of job search.

[17] We do not model the general equilibrium effects of UI but those may interact with job search effort in complicated ways. For example, a decrease in job search could have resulted in fewer vacancies posted by firms. In turn, this could have lowered J_t. However, because there were so many unemployed individuals relative to vacancies during the recession, we think that this mechanism is second-order.

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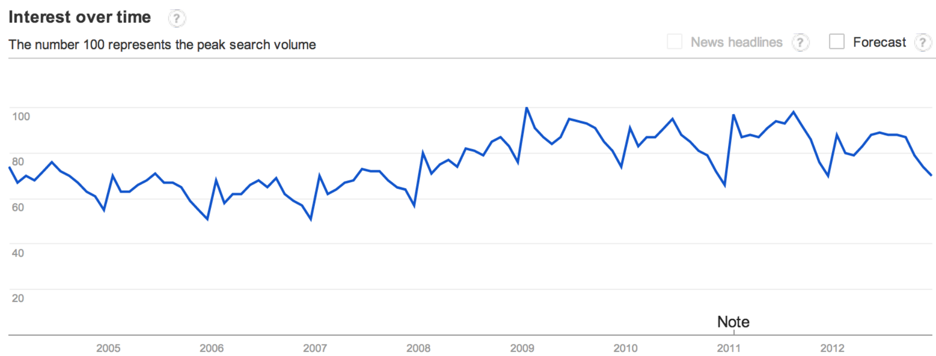
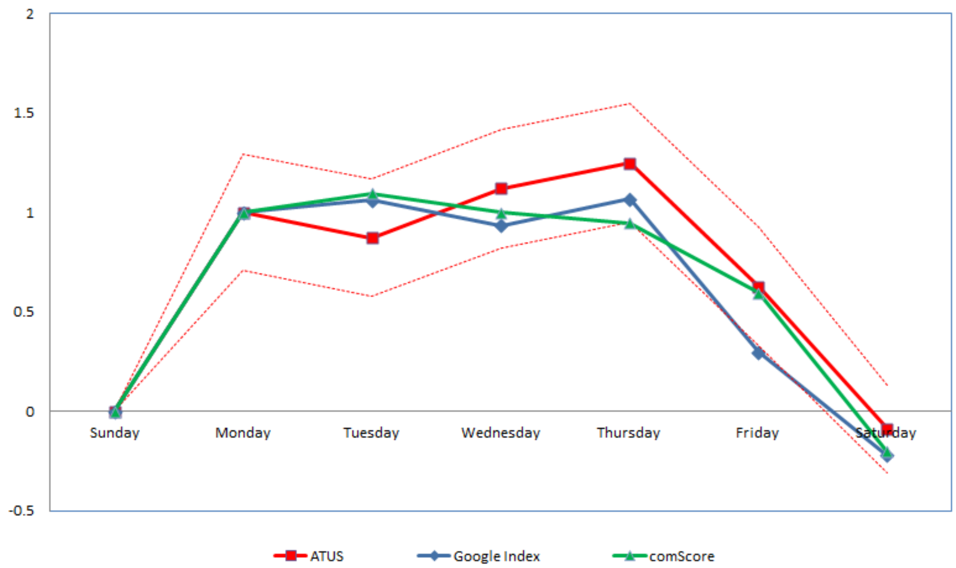
X. Figures

Figure 1. : Google Trends Example Search



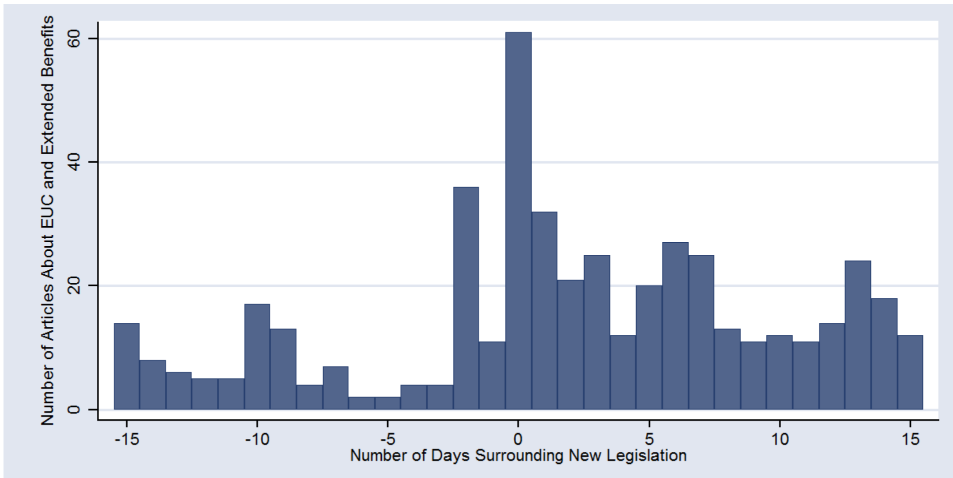
Notes: Figure gives the result of query on Google Trends using the search term 'jobs in the United States from 2004 to 2013. Displayed data are monthly values. Google Trends accessible at http://www.google.com/trends/.

Figure 2. : Day of Week Fixed Effects



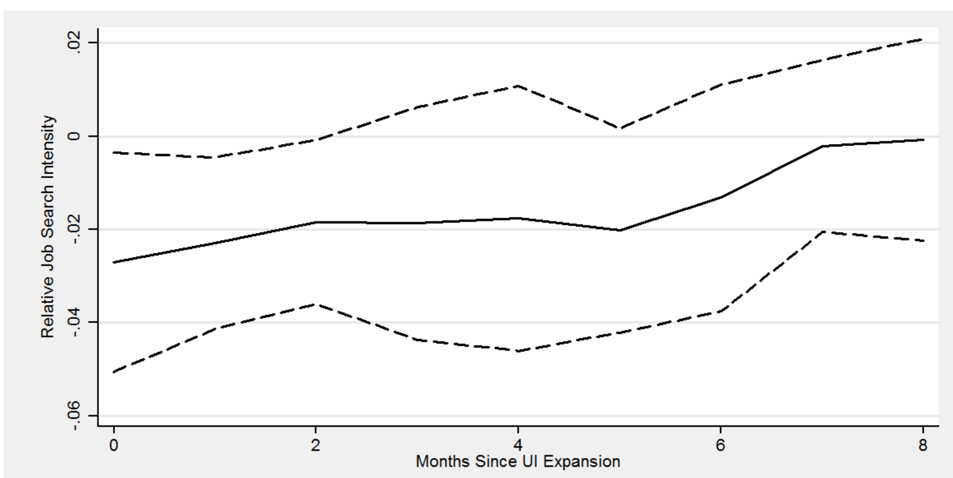
Notes: Figure shows coefficients and standard error bands from three separate regressions. Each regresses a measure of job search on day-of-week dummies and relevant geographic and seasonal fixed effects. ATUS represents coefficients derived from data from the American Time Use Survey from 2003-2010. ComScore represents coefficients derived from data from a sample of the ComScore Web Panel in 2007. Google Index represents coefficients derived from data from the Google Job Search Index from 2004-2013.

Figure 3. : Number of News Articles Regarding EUC



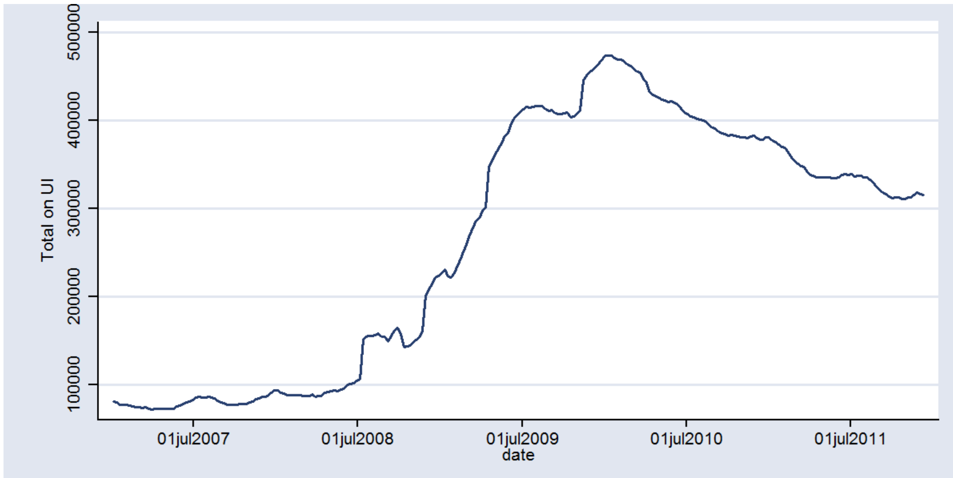
Notes: Columns show the number of articles per day written about the emergency unemployment compensation or extended benefits programs. Searches are run on the Access World News Newsbank archives, which covers more than 1,500 US Newspapers. Search terms include "emergency unemployment compensation" and "extended benefits".

Figure 8. : Impulse of State Level Search in Response to UI Expansions



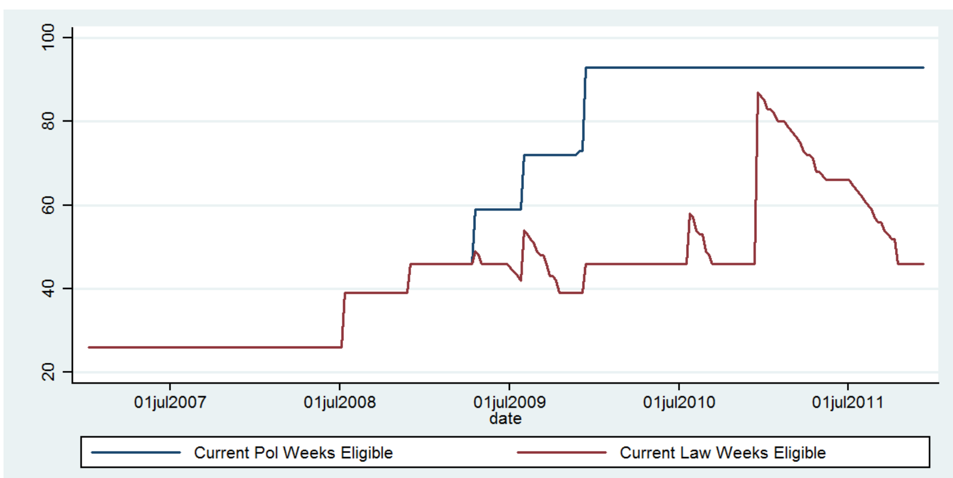
Notes: Each point represents the coefficient on an indicator of the months elapsed since the last UI expansion in the state. Controls for year-month, unemployment rate and employed rate are included. Standard errors are clustered at the state level.

Figure 4. : Total Number on UI: Texas



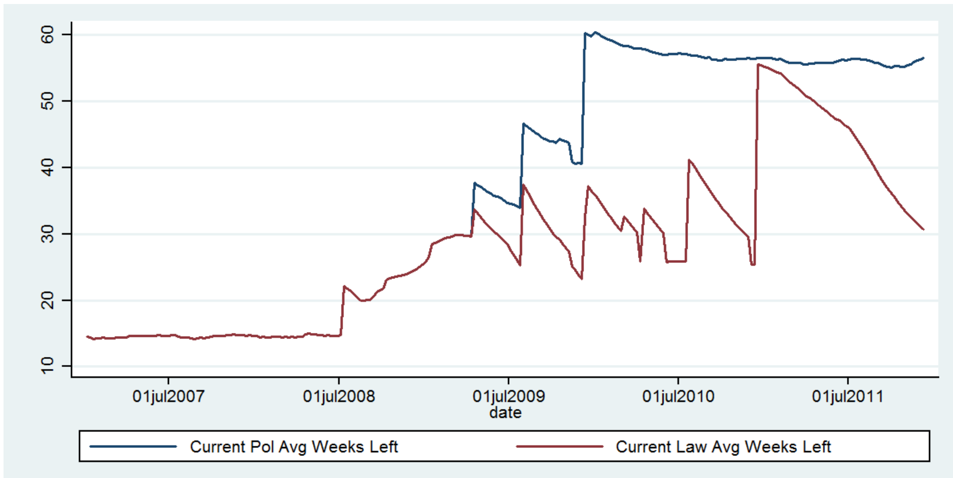
Notes: Graph shows the total number of UI recipients in the state of Texas over time from January 2007 to December 2011. Data obtained from the Texas Workforce Commission.

Figure 5. : Weeks Eligible for New UI Recipients by Type



Notes: Graph shows the number of weeks a newly unemployed UI recipient is eligible for, assuming that the individual is eligible for the maximum number of weeks in a state at a given week. 'Current Pol' refers to an assumption that the current UI policy, as of the listed week, is continued for all time. 'Current Law' refers to an assumption that the current UI law, as of the listed week, will be obeyed, meaning many of the extended benefits will expire in the future. Data covers all UI recipients in Texas.

Figure 6. : Average Weeks Left by Type



Notes: Graph shows the average number of weeks the population of UI recipients are eligible for. 'Current Pol' refers to an assumption that the current UI policy, as of the listed week, is continued for all time. 'Current Law' refers to an assumption that the current UI law, as of the listed week, will be obeyed, meaning many of the extended benefits will expire in the future. Data covers all UI recipients in Texas.

Figure 7. : Part Time Work

Notes: Figure shows fraction of workers who had positive income while also receiving unemployment benefits. Workers who received enough income to offset 100% of UI benefits are excluded. Data take from administrative UI data from Texas from 2005-2011.

XI. Tables

Table 1—: Correlation of Google Search to Online Job Search Time - ComScore Data

VARIABLES	(1) Job Search Per Cap	(2) Log(Job Search Per Cap)	(3) Log(Job Search Per Cap) High Pop	(4) Log(Job Search Per Cap)
Synthetic GJSI	0.254***			
	(0.00879)			
Log(Synthetic GJSI)		1.248***	1.075***	0.807***
		(0.0437)	(0.0449)	(0.0355)
Observations	600	600	516	600
R^2	0.583	0.577	0.527	0.911
State FE	NO	NO	NO	YES
Month FE	NO	NO	NO	YES

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

Synthetic GJSI is an index constructed from the number of visits to Google.com that lead to a job search site over the total number of visits to Google.com across a state-month observation. The dependent variable measures the amount of time users spend on job search related websites, per capita, in a given state-month. Column 3 utilizes only states with a population in excess of 1 million. All numbers taken from 2007 ComScore web panel data. The Synthetic GJSI ratio has a mean of 0.009.

Table 2—: ATUS Search Time Correlation

VARIABLES	(1) Search Time	(2) Search Time-NonZero	(3) Search Indicator	(4) Search Time	(5) Search Time-NonZero	(6) Search Indicator	(7) Search Time
log(Google Job Search)	0.327***	1.890***	0.0413***	3.268***	6.035*	0.261***	
	(0.0284)	(0.208)	(0.00498)	(0.730)	(3.523)	(0.0594)	
log(Google Weather Search)							0.113
							(0.584)
Observations	3,541	589	3,541	3,541	589	3,541	3,541
R^2	0.049	0.285	0.173	0.075	0.619	0.300	0.069
State FE	NO	NO	NO	YES	YES	YES	YES
Month FE	NO	NO	NO	YES	YES	YES	YES

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

Google Job Search is the log of the Google Job Search Index. ATUS Search Time is the average number of minutes per day respondents report that they spent on job search in a given state-month. The ATUS Job Search Indicator gives the average fraction of individuals engaging in any level of job search in a given state-month. Standard errors clustered at a state level. Columns 2 and 5 use the sample of state-month observations with non-zero job search time recorded. Google Weather Search is an index analogous to the GJSI but using the term 'weather'.

Table 3—: Day of Week Fixed Effects for Google, ComScore, and ATUS

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Google JS	Google JS	ATUS JS	ATUS JS	comScore JS	comScore JS
Monday		0.237***		0.0902***		0.111***
		(0.00231)		(0.0134)		(0.00427)
Tuesday		0.251***		0.0689***		0.132***
		(0.00238)		(0.0136)		(0.00430)
Wednesday		0.223***		0.0999***		0.119***
		(0.00233)		(0.0136)		(0.00431)
Thursday		0.169***		0.112***		0.106***
		(0.00232)		(0.0137)		(0.00430)
Friday		0.0709***		0.0560***		0.0623***
		(0.00206)		(0.0137)		(0.00430)
Saturday		-0.0527***		-0.00747		-0.0172***
		(0.00169)		(0.0102)		(0.00429)
Holiday	-0.148***	-0.147***	-0.0497*	-0.0533*	-0.0659***	-0.0664***
	(0.00444)	(0.00397)	(0.0278)	(0.0280)	(0.00629)	(0.00631)
Weekend	-0.217***		-0.0891***		-0.115***	
	(0.00205)		(0.00725)		(0.00256)	
Observations	111,152	111,152	76,087	76,087	18,615	18,615
Year FE	NO	NO	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	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 the GJSI. '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 the GJSI 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. Specifications include differing fixed effects because of the differing nature of each dataset. All include, at a minimum, state and time fixed effects. Google data necessarily utilizes Season-State fixed effects, while we use finer time fixed effects with the ATUS and ComScore data.

Table 4—: Empirical Tests of Google Job Search Measure

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Log(JS)	Log(JS)	Log(JS)	Log(JS)	Log(JS)	Log(JS)
Unemployment Rate	0.669***	0.658***	0.808***	0.602***	0.497***	0.656***
	(0.0349)	(0.0348)	(0.0337)	(0.0373)	(0.0638)	(0.0587)
Init. Claims Per Cap				0.110***	0.0738**	0.168***
				(0.0319)	(0.0372)	(0.0229)
Next Final Claims Per Cap					0.150**	0.0765
					(0.0739)	(0.0544)
Observations	3,444	3,444	3,444	3,444	3,342	3,342
R^2	0.439	0.550	0.706	0.557	0.555	0.721
Month FE	NO	YES	YES	YES	YES	YES
State FE	NO	NO	YES	NO	NO	YES

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

Observations are at a state-month level. 'Jobs Search' refers to the logged monthly state level GJSI. Initial claims per capita is 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. Both dependent and independent variables are scaled such that each has a standard deviation of 1.

Table 5—: Effect of UI Status and Composition on Job Search (NLLS)

	(1)	(2)	(3)	(4)
Post Legislation		-0.0191**		-0.0115
		(0.00773)		(0.00936)
Number on UI	0.824***	0.840***		
	(0.230)	(0.237)		
Not on UI	1.045***	1.090***	1.082***	1.083***
	(0.246)	(0.269)	(0.269)	(0.269)
Number Employed	0.0915***	0.0940***	0.0943***	0.0945***
	(0.0160)	(0.0163)	(0.0181)	(0.0182)
0-10 Weeks Left			1.563**	1.534*
			(0.730)	(0.733)
10-20 Weeks Left			0.938***	0.920***
			(0.297)	(0.298)
20-30 Weeks Left			0.951***	0.945***
			(0.232)	(0.233)
Over 30 Weeks Left			0.753***	0.766***
			(0.258)	(0.259)
UI Recipients/Employed	11.43	11.60		
UI Recipients/Non-UI Unemployed	0.788	0.771		
DMA FE and Trend	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Observations	5070	5070	5070	5070

Notes: Dependent variable is log(GJSI) at DMA-week level. Analysis spans all Texas DMAs from 2006-2011. Number on UI, Not on UI, and Number Employed are the total number of individuals in each category. Post Legislation is the week of and three weeks following legislation. Unemployed/Employed gives the relative levels of search activity across types. Standard Errors Clustered at DMA level.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 6—: Effects of UI Expansions and Composition by State

	(1)	(2)	(3)	(4)	(5)	(6)
Post Legislation	-0.0264*	-0.0341**	-0.0344**	-0.0627**	-0.0287*	-0.0251
	(0.0154)	(0.0158)	(0.0157)	(0.0298)	(0.0172)	(0.0171)
Fraction On UI		3.587*	2.956		0.814***	0.807***
		(2.119)	(2.163)		(0.273)	(0.285)
Fraction Employed		-2.385**	-2.254*		0.179***	0.185***
		(1.137)	(1.151)		(0.005)	(0.004)
Frac <10 Weeks Left			3.478***			0.235**
			(1.186)			(0.115)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Specification	OLS	OLS	OLS	NLLS	NLLS	NLLS
R-Squared	0.822	0.831	0.832	-	-	-
Observations	3825	3825	3825	3825	3825	3825

Notes: Dependent variable is log(GJSI) at state-month level. Analysis spans all 50 states and Washington DC from 2005-2012. variables represent the fraction of the CPS participants in each category. Data taken from the CPS at a state-month level, imputing weeks left and UI status from the duration of unemployment. Post Legislation is an indicator for the month of and month following an extension. Also included are the fraction of the population who are unemployed but not on UI. Columns 1-3 are OLS while columns 4-5 are NLLS. Standard errors are clustered at state level.
* p<0.10, ** p<0.05, *** p<0.01

Table 7—: Effects of UI Expansion Over Time

	National (1)	National (2)	Texas (3)	Texas (4)
Period of Legislation	-0.0253**	-0.0271**	-0.0560***	-0.0566***
	(0.0117)	(0.0120)	(0.0134)	(0.00900)
Period of Legislation - Lag 1	-0.0200**	-0.0230**	-0.0698***	-0.0695**
	(0.00932)	(0.00940)	(0.0196)	(0.0255)
Period of Legislation - Lag 2	-0.0157*	-0.0184**	-0.0314	-0.0307
	(0.00911)	(0.00900)	(0.0238)	(0.0391)
Period of Legislation - Lag 3	-0.0162	-0.0187	-0.0130	-0.0122
	(0.0130)	(0.0127)	(0.0250)	(0.0361)
Period of Legislation - Lag 4	-0.0151	-0.0176	-0.0201	-0.0193
	(0.0146)	(0.0145)	(0.0268)	(0.0296)
Period of Legislation - Lag 5	-0.0181	-0.0202*	0.00774	0.00826
	(0.0113)	(0.0112)	(0.0276)	(0.0278)
Period of Legislation - Lag 6	-0.0119	-0.0132	0.00441	0.00476
	(0.0127)	(0.0124)	(0.0275)	(0.0245)
Period of Legislation - Lag 7	-0.00151	-0.00205	0.0267	0.0267
	(0.00978)	(0.00942)	(0.0254)	(0.0239)
Period of Legislation - Lag 8	-0.000316	-0.000783	-0.0346	-0.0349*
	(0.0116)	(0.0111)	(0.0216)	(0.0197)
Unemp. Rate		-0.701		0.0246
		(0.832)		(0.0216)
Frac. Employed		-2.378**		-0.680
		(1.173)		(1.057)
Location FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
R-Squared	0.832	0.835	0.659	0.662
Observations	3417	3417	5070	5070

Notes: Dependent variable is log(GJSI) at state-month level in columns 1 and 2; DMA-week level in columns 3 and 4. Analysis spans all 50 states and Washington DC from 2005-2012 in columns 1 and 2 and all Texas DMAs from 2006-2011 in columns 3 and 4. represents the fraction of the population who are employed, by the CPS definition. Post Legislation and it's lags are indicators for the month of a UI extension or expansion law (or lags of this variable). Standard errors are clustered at a state level for columns 1 and 2 and at a DMA level in columns 3 and 4.
* p<0.10, ** p<0.05, *** p<0.01

Appendices

A. Results Using the "Current Policy" Assumption

Appendix Table 5 estimates the effect of potential weeks left on job search intensity under the assumption of 'current policy' beliefs among UI recipients. In this world, we assume that individuals project the 'current policy' about potential UI durations, without regard to the expiration date present on any UI laws. With this assumption, the estimates fail to show the expected pattern of job search. In our preferred specification, in column (4), we find that those individuals with 20 - 30 weeks left search the most. This difference is caused by the fact that many individuals who have a large number of weeks left under the current UI policy only have a few weeks left under current law as the extended benefits they are relying on were set to expire. The fact that the 'current law' results yield an elasticity with respect to potential duration that is much closer to the what is predicted by theory suggests that most UI recipients were of the 'current law' type. Further, in contrast with these results, most estimates in the literature show that individuals closer to UI expiration search more.

An alternative interpretation of our 'current policy' results is that they confirm KM's panel data. KM find that individuals who are on UI for more than 10 weeks search approximately 30% - 50% less than those who just enter UI. We test for the above alternative by including the number of newly unemployed individuals in column (4). We find a small and insignificant coefficient on the number of new UI recipients. Therefore, we do not think that KM's story is driving the results in the 'current policy' specification.

B. Calibration Setup

The calibration requires data on the composition and exit rates of the cohort of individuals that was eligible for UI at the time of the first UI expansion. We include all individuals who were on UI during the week of the expansion or those that re-joined UI after a break with fewer than 13 weeks left of UI following the expansion. This leaves approximately 110 thousand individuals on UI who are part of the simulation. Many individuals in the dataset temporarily leave UI and return within several weeks. We therefore define exit from UI as follows. An individual who leaves UI must be gone from UI for at least 180 days and if they subsequently return to UI, it must be considered a new UI spell by the Texas Workforce Commission. An individual leaves to find a job in Texas if we observe that that individual is paid this quarter or next quarter and leaves UI. Otherwise, a UI leaver is considered to have left UI permanently (presumably to exit the labor force or to move to another state). The base rate of temporary exit in the same is 3.8% per week and the base rate of return conditional on a temporary exit is 9%. Appendix Table 6 displays estimates of nj_w, the probability of individuals to exit UI without a job as a function of their weeks left. Lastly, Appendix Figure

2 displays the weekly exit rates from UI. The blue line displays the exit rate per person and the red line displays the effort adjusted rate used for the simulation. We ran 100 simulations under both the UI expansion and non-expansion scenarios according to the procedure described in section VIII.

Table 1—: Summary of Major Unemployment Legislation

Bill	Date Passed	Effect	Summary
Supp. Appropriations Act	Jun 30, 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. (Tier 1)
Unemp. Comp. Extension Act	Nov 21, 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. (Tier 2)
Worker, Homeownership, and Bus. Asst. Act	Nov 6, 2009	EUC Expanded	Makes Tier 2 available to all states Extends unemployment insurance benefits by up to 19 weeks in states that have jobless rates above 8.5 percent. (Tiers 3 and 4)
DoD Appropriations Act	Dec 19, 2009	EUC Extended	Extends the filing deadline for federal unemployment insurance benefits until Feb 28, 2010.
Temporary Extension Act	Mar 2, 2010	EUC Extended	Extends the filing deadline for federal unemployment insurance benefits until April 5, 2010.
Continuing Extension Act	Apr 15, 2010	EUC Extended	Extends the filing deadline for federal unemployment insurance benefits until June 2, 2010.
Unemp. Comp. Extension Act	Jul 22, 2010	EUC Extended	Extends the filing deadline for federal unemployment insurance benefits until November 30, 2010.
Tax Relief and UI Reauth Act	Dec 17, 2010	EUC Extended	Extends the filing deadline for federal unemployment insurance benefits until Jan 3, 2012.
Temporary Payroll Tax Cut Continuation Act	Dec 23, 2011	EUC Extended	Extends the filing deadline for federal unemployment insurance benefits until March 6, 2012.
Middle Class Tax Relief and Job Creation Act	Feb 22, 2012	EUC Extended	Extends the filing deadline for federal unemployment insurance benefits until Jan 2, 2013.
American Taxpayer Relief Act of 2012	Jan 2, 2013	EUC Extended	Extends the filing deadline for federal unemployment insurance benefits until Jan 1, 2014.

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

Table 2—: Google Search Term Correlations

	Jobs	H.t.F	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	-0.0961	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	-0.514	-0.106

Numbers represent correlations of national weekly Google search for the listed search terms from 2004-2012.

Table 3—: ATUS Summary Statistics

	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%	0.63	0.47	0.78%	81.3
Unemployed	3,252	4.27%	29.1	25.3	18.23%	159.7
Not in Labor Force	14,921	19.61%	0.8	0.6	0.82%	98.1
By Holiday						
Holiday	1,328	1.7%	0.60	0.54	0.68%	80.6
Non-Holiday	74,759	98.3%	1.9	1.6	1.33%	128.6
By Weekend						
Weekend	38,431	50.5%	0.87	0.71	0.64%	109.8
Weekday	37,656	49.5%	2.9	2.4	1.8%	134.8

Sub-sample of ATUS respondents is taken to match the demographic sub-sample used by Krueger and Mueller (2010). 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.

Table 4—: Effect of UI on Job Search (OLS)

	(1)	(2)	(3)	(4)
Post Legislation		-0.0203**		-0.0124
		(0.0101)		(0.0106)
Total on UI	2.328	2.390		
	(1.633)	(1.633)		
Not on UI	4.674***	4.603***	4.259**	4.237**
	(1.740)	(1.740)	(1.743)	(1.743)
0-10 Weeks Left			7.833***	7.611***
			(2.645)	(2.652)
10-20 Weeks Left			1.531	1.399
			(1.134)	(1.139)
20-30 Weeks Left			1.675*	1.625*
			(0.922)	(0.923)
Over 30 Weeks Left			0.481	0.575
			(0.875)	(0.878)
DMA FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
R-Squared	0.703	0.703	0.704	0.704
Observations	5070	5070	5070	5070

Notes: Dependent variable is log(GJSI) at DMA-week level. Analysis spans all Texas DMAs from 2006-2011. variables represent the fraction of the total population belonging to each category. Post Legislation is the week of and three weeks following legislation. Standard Errors Clustered at DMA level.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 5—: Effect of UI Status and Composition on Job Search (NLLS) - Current Policy Beliefs

	(1)	(2)	(3)	(4)
Post Legislation		-0.0437***		-0.0387**
		(0.0136)		(0.0139)
Number on UI	1.648***	1.693***		
	(0.461)	(0.481)		
Not on UI	2.090***	2.175***	2.133***	2.120***
	(0.491)	(0.547)	(0.564)	(0.580)
Number Employed	0.183***	0.191***	0.193***	0.198***
	(0.0320)	(0.0336)	(0.0345)	(0.0361)
0-10 Weeks Left			1.155	0.919
			(1.023)	(1.045)
10-20 Weeks Left			3.143*	3.168*
			(1.654)	(1.680)
20-30 Weeks Left			4.192***	4.207***
			(1.011)	(1.039)
Over 30 Weeks Left			1.434**	1.445**
			(0.526)	(0.537)
Initial UI Claimants				0.321
				(0.448)
UI Recipients/Employed	11.43	11.40		
UI Recipients/Non-UI Unemployed	0.788	0.778		
DMA FE and Trend	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Observations	5070	5070	5070	5070

Notes: Dependent variable is log(GJSI) at DMA-week level. Analysis spans all Texas DMAs from 2006-2011. Number on UI, Not on UI, and Number Employed are the total number of individuals in each category. Post Legislation is the week of and three weeks following legislation. Unemployed/Employed gives the relative levels of search activity across types. Standard Errors Clustered at DMA level.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 6—: Propensity to Exit UI with No Job

	Exit Without Job
No Weeks Left	0.021***
	(0.0004)
1 - 10 Weeks Left	0.020***
	(0.0002)
10 - 20 Weeks Left	0.012***
	(0.0002)
20 - 30 Weeks Left	0.007***
	(0.0002)
30 + Weeks Left	0.010***
	(0.0002)
N	1,609,165

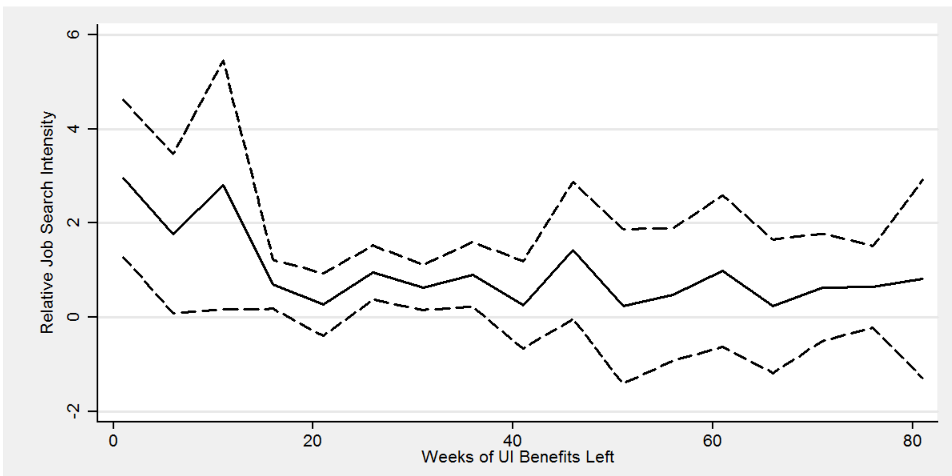
The dependent variable is an indicator whether an individual on UI exited without finding a job. The independent variables are bins of weeks left of UI remaining.
*p<0.1; **p<0.05; ***p<0.01

Table 7—: Simulation Outcomes

Trial	Share Employed	Share Left UI - No Job	Share Temporarily Left UI
EUC	0.250	0.169	0.192
REG	0.277	0.226	0.171

The table displays the mean outcomes for 100 simulations of job finding with and without EUC.

Figure 1. : Effect of Number of Weeks Left of UI on Job Search Intensity



Notes: Graph displays coefficients and standard error bands taken from a non-linear least squares regression of the Google Job Search Index on fractions of the population residing in a range of 5-week bins of weeks left of unemployment insurance. Also included in the regression are the fraction of the population that are employed and the fraction who are unemployed but not on unemployment insurance. Data covers the state of Texas from 2007 to 2011. Unemployment insurance recipient data obtained from the Texas Workforce Commission.

Figure 2. : Job Finding Rates

Notes: The above figure displays two job finding rates for the simulation cohort. The blue line represent the overall job finding rate per person on UI. The red line represents the effort adjusted job finding rate, where each person is weighed in their job finding probability by the effort corresponding to their weeks left.