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

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Job search is a key choice variable in theories of labor markets but has proven difficult to measure directly. We develop and validate the Google Job Search Index (GJSI), a measure of job search based on Google search data. The GJSI is publicly available, high-frequency, and location specific. We use the GJSI to study the effects of the unprecedented unemployment insurance (UI) expansions which occurred between 2008 and 2011. We show that states with higher potential durations of UI experience decreased search during the expansions, even after controlling for local labor market conditions. We use our estimates to calibrate a model of job finding. Our model suggests that the decrease in job search due to UI expansions had minor effects on unemployment rates during the recession.
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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. Furthermore, 49 states impose a job search requirement for unemployment insurance (UI) eligibility, demonstrating the perceived importance of job search by policymakers. However, job search has proven difficult to measure. Most prior research on job search has measured it using limited surveys or hard to access proprietary data. In this paper we address this gap in measurement by constructing and validating a new measure

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of job search which is publicly accessible and observable at a daily and metropolitan area level.[1] Our measure, the Google Job Search Index (GJSI), is constructed using the Google Trends tool and is derived from the total amount of Google searches including the term 'jobs'.

We use the GJSI to study the relationship between job search and unemployment insurance. Our identification relies on variation in the potential duration of benefits caused by expansions of UI during the Great Recession. We show that an increase of 10 weeks in the potential benefit duration is associated with a 3.2% decrease in the GJSI. We also find evidence that individuals closer to UI expiration search more than individuals with many weeks of UI remaining. Lastly, we conduct a calibration exercise to show that changes in job search in response to UI expansions likely had minor effects on the aggregate unemployment rate.

We first discuss why measuring job search is useful even when data on other labor market outcomes is available. We then validate the GJSI as a proxy for overall job search. We show that the GJSI is correlated with both searches for 'jobs' in the Comscore web panel and aggregate job search of all types in the American Time Use Survey (ATUS). Furthermore, the GJSI 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.

Next, we use across state and over time variation to estimate how the potential benefit duration of UI is related to aggregate job search as measured by the GJSI. Specifically, we regress the GJSI on the potential benefit duration and controls for labor market conditions to show that an additional 10 weeks of benefits is associated with a 3.2% decrease in aggregate job search. However, we do not find statistically significant effects of UI on the GJSI immediately after a UI expansion. We use an event study methodology to confirm the robustness of this result.

Next, we use administrative UI data from Texas to supplement state-level data from the Current Population Survey (CPS) (the CPS data was used by Rothstein (2011) and Farber and Valletta (2013) alongside many others) in studying UI. Administrative data allows us to precisely measure the composition of the unemployed in a given DMA-week in terms of their weeks left of UI. 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

[1] The GJSI is measured at the Designated Market Areas (DMA) level. This designation is based on geographical areas which can receive the same radio and television signals. DMAs are generally similar to but not identical to Metropolitan Statistical Areas.

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 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 administrative 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.[2] 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 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. Our estimates suggest that, although UI expansions affected job search, these expansions had minor effects on overall unemployment rates during the great recession.

II. Why Measure Job Search?

The outcome variable throughout this paper is a measure of job search rather than job finding rates as in other studies of UI during the recession (e.g. Rothstein (2011) and Farber and Valletta (2013)). Understanding the behavior of job search is important for at least two reasons, even when data on job finding rates and vacancies is available. First, theories of optimal UI in response to economic fluctuations (e.g. Landais et al. (2015), **?**, Schmieder et al. (2012)) define the labor market tightness as a function of aggregate job search effort and this variable is typically not directly observable. In such a model, a decrease in job search per person holding labor market tightness constant should optimally result in less generous

UI. Alternatively, if job search per person remains relatively constant but the labor market tightness decreases because of changes in labor demand, then the optimal policy may actually be to make UI more generous. Given the small responses of the GJSI to UI expansions, our results support the latter story.

Second, data on job search can be helpful for determining the causal mechanisms for observed changes in job finding rates. For example, a particular policy might affect both job search intensity and reservation wages. In that case, changes in job finding rate do not identify the welfare effects of a policy (Chetty (2009)). Furthermore, moral hazard effect due to job search could be mitigated by job search requirements as shown in Lachowska et al. (2015). However, moral hazard effects due to increases in reservation wages would require a different set of policies to address.

Google Search data provides several advantages compared to survey-based data and proprietary data from online labor platforms. The primary advantage that Google data provides relative to survey data is that it is based on millions of searches which can be then be disaggregated geographically and at a high-frequency. In comparison, the American Time Use Survey (ATUS), which is the most commonly used survey of job search, often contains fewer than 5 unemployed respondents per state-month. The GJSI allows policymakers to measure changes in local labor market conditions (down to DMA-day granularity) or behavioral responses to policies in real time in a way that is impossible with publicly available data.[3] Furthermore, although we focus on aggregate job search, Google Trends allows for more specific queries such as 'tech jobs', 'new york jobs', or 'walmart jobs'. This data can be used to study how search is directed across sectors, regions, and employers.

Several recent papers have used proprietary data from online platforms such as CareerBuilder (Marinescu (2015)) and SnagAJob (Kudlyak et al. (2013)) to study job search. This propriety data is very useful, especially because it contains individual-level behavioral data. However, access to this data is limited due to some combination of privacy restrictions, management changes, and lack of personal connections. An open data source like Google Trends enables researchers and policymakers to easily replicate and expand on earlier work.

III. 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[4] has focused on the effects of benefit levels and duration on hazard rates out of UI. This researches uses 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) conduct a review of the literature on the topic of the

[3] See Choi and Varian (2009) and Choi and Varian (2013) for examples of real-time analysis using Google Trends data.

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 use data on job search effort, they cannot tell whether a change in job-finding rates 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 (2011b)(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 estimates 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 (Schmieder et al. (2012)), 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

[4] For example, see Meyer (1990), Card and Levine (2000), Katz and Meyer (1990), Lalive (2008) and Meyer and Mok (2007)

effect on subgroups of the population even if there is no large effect on aggregate job-finding rates. For instance, both Rothstein (2011) and Farber and Valletta (2013) find negative but small effects of the UI expansions on exit from UI. Furtherermore, they find that most of the effect of the expansions comes through reductions in labor force exits rather than reductions in job finding rates.

IV. Google Search Data and Validity as a Measure of Job Search

The GJSI is constructed from indexes of search activity containing the term 'jobs' 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.[5] 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.[6] We re-sample Google Trends data at 4 different months (eg. pulling all data from 2004-2012 in March of 2014, April of 2014, and May of 2014). With these four separate indexes, we 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 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-

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

[6] 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.

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' as our term of interest.[7] 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'.[8]

As a test of the applicability of our chosen term, we also use Google Correlate to determine which search terms that do not contain the text 'jobs' are most correlated with Google searches for 'jobs'.[9] 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.

Lastly, 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 and Gao (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. 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.[10] Similarly, the 2011 Internet and Computer Use supplement of the CPS reports that 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 Skuterud (2000), the most internet intensive activities are resume

[7] We remove searches that contain 'Apple' or 'Steve', as there was a large surge in Google searches containing 'Jobs' upon the death of Steve Jobs. This can be accomplished in Google Trends by searching, 'jobs -apple -steve' rather than simply searching for 'jobs'.

[8] See Appendix Table 1 for a partial list of alternate terms tested.

[9] 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.'

submissions, placing ads, and contacting schools' career centers. Even as early as 2002, 22% of job seekers found their jobs online (Stevenson (2009)), suggesting that a much larger fraction used the internet as part of their search. Finally, the increased availability of the internet has decreased 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.[11] We determine whether a person is searching for a job by summing the time spent on websites that contain job relevant terms.[12]

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 Use Survey

In this section we compare the GJSI to the job search related portion of the American Time Use Survey.[13] We use the methodology from Krueger and Mueller

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

[11]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.

[12]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 identified and removed the most common websites which were unrelated to job search but contained the word 'job'.

[13]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.

(2010) to measure the quantity of job search using the ATUS. ATUS job search activity is calculated using the amount of time that individuals spend in job search related activities.[14] 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 oversampling of weekend days, or using related Google job-search terms to measure job search activity.

Table 2 shows results of regressions of the GJSI on job search as measured by the ATUS at a state-month level. There is a statistically significant relationship between the Google and ATUS measure across all specifications. Columns 1-4 display the relationship between the GJSI and average ATUS job search activity both without controls and with state and month fixed effects. The dependent variable is either amount of job search time, or an indicator for non-zero job search activity. The five fold increase in R^2 between columns 1 and 2 highlights a drawback of the small samples in the ATUS, where most state-month observations have no reported job search activity. This makes any meaningful estimation using the ATUS difficult at a geographically disaggregated or high-frequency level. Across specifications, we find that increases in the GJSI are associated with more job search.

Columns 5 and 6 display placebo regressions that include other search indexes derived from Google Trends. In column 5, we include an index of search for the term 'weather' alongside our Google Job Search Index. We find no significant relationship between searches for weather and job search as measured by the ATUS. Moreover, the coefficient on our GJSI is virtually unchanged. In column 8, we include two other measures of Google search that could be related to unemployment rates or benefits rather than job search. 'Google Unemp/Emp' refers to an index of all searches containing either the term 'unemployment' or the term 'employment'. 'Google Unemp Rate' refers to an index including the term 'Unemployment Rate'. Neither of these terms are significantly related to ATUS job search time when we include the baseline GJSI.[15]

C. Day of Week and Holiday Effects

Another way in which we validate the GJSI is to study its behavior across days of the week and holidays. 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.[16] It should also increase in the late spring because

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

[15] Other terms which were similarly non-significant in this specification include 'economy', 'economic', 'unemployment insurance', 'unemployment benefits', 'gdp', 'layoffs'.

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. 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 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.

We also apply the same methodology to other placebo search terms related to the economy, unemployment, and unemployment insurance. We illustrate results in Appendix Figure 1 and Appendix Table 2. In Appendix Figure 1, we plot day of week coefficients from regressions using three placebo search terms alongside the daily coefficients from our ATUS and comScore data. Google Unemp Benefits tracks the frequency of Google searches for the term unemployment benefits or unemployment insurance, Google Unemployment tracks searches for the term unemployment, and Google Unemployment/Employment tracks searches for the term unemployment or employment. We find little similarity between the weekly patterns of these Google search terms and the weekly patterns in the ATUS and the comScore web panel. We take this as further confirmation that the link between our GJSI and the amount of job search as measured by other datasets is not due solely to chance or to any mechanical feature of the Google Trends data. Rather, it represents a true link between the amount of job search undertaken in the real world and that observed through Google search behavior (and in particular through Google searches including the term 'jobs').

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. 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.

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

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.

V. Data and Institutional Background on Unemployment Insurance

Individuals eligible for unemployment insurance can typically draw on benefits for up to 26 weeks at a maximum weekly benefit amount that varies across states. For example, to qualify in the state of Texas 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.[17] 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 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, adding 13 and 7 weeks of eligibility respectively. The most common trigger condition used during the recession for the first tier occured when the three month moving average of a state's seasonally adjusted three month total unemployment rate (TUR) hits 6.5%. The second level (7 additional weeks beyond the initial 13 weeks) became available when the TUR hit 8%.[18] Note, not all states chose to institute EB even when eligbile (see Marinescu (2015) for a more thorough description of the EB program).

Due to the severity of the recession, the federal government passed the Emergency Unemployment Compensation(EUC) Act to extend the potential duration of UI. This act was amended several times due to the severity of the Great Recession. This timeline for this program is as follows:

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

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

[18] There are addition nuances to EB eligibility. First, states have the option of using the insured unemployment rate (IUR) rather than the total unemployment rate for the triggers. This option is typically more stringent and most states chose the TUR option. Second, the unemployment rate must be higher than 110% of the same average in the past two years. A similar condition holds if states choose the IUR option.

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% three months average TUR.

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% TUR, and an additional 6 weeks for states with TUR 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. 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 amended several times to extend the period for which individuals were eligible for these expanded benefits (see Appendix Table 3 for details).

A. Data on the Composition of UI Recipients

Changes in job search can be driven not only by legislative changes but also by differences in the composition of UI recipients across areas and over time. We use two data sources to measure the composition of individuals on UI during the recession — survey data from the Current Population Survey and administrative UI data from Texas. With regards to the CPS, we follow Rothstein (2011) in constructing a panel of individuals on unemployment insurance across states, using repeated survey observations and data on job loss reasons to determine the lengths of UI spells and eligibility for UI.

While the CPS is the standard dataset for studying the composition of the unemployed, it has several drawbacks. 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' often gives incorrect results.

As an alternate data source, we use administrative UI data 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. 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.

This data allows us to account for the nuances of UI receipt when calculating the potential weeks left an individual level. 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.

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. Therefore, we view our results using Texas data as complimentary rather than superior to our cross-state results using the CPS.

B. Assumptions Regarding Expectations of Benefit Duration

The UI policy changes over the time period which we study are complicated, so some UI recipients were unlikely to fully grasp the nuances of cutoff dates and eligibility for benefits. For example, extra weeks of UI benefits sometimes expired and were reinstated retroactively by legislation. This led some individuals to lose benefits for a short time before regaining them. On the other hand, there was a population of sophisticated UI recipients who understood the nuances of the EUC and EB programs. We see evidence of this group on www.city-data.com, a popular forum about unemployment and unemployment benefits. This forum has a large number of posts regarding detailed analysis of changes to UI, EUC, and EB. Posted questions were often answered within hours and were eventually read millions of times.

Rather than take an a priori stand on the correct model of expectations, we follow Rothstein (2011) in considering two assumptions regarding the potential duration of beneits for individuals: "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.

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.

VI. The Aggregate Effects of UI Expansions on the GJSI

We now test whether the expansions in the potential benefit duration (PBD) of UI affected aggregate job search. We use both benefit duration shifts that occur due to the changes in the EUC program at the time of legislation as well as those due to hitting state-level unemployment thresholds for increases in PBD. This latter category includes both thresholds set by the new EUC program as well as the previously enacted EB program.

An important consideration for our analysis is the extent to which individuals can anticipate increases in PBD. If some individuals did anticipate the imminent expansion in UI benefits (i.e. the perceived probability of expansion went from somewhere above 0% to 100% instead of from 0% to 100%), our estimates represent lower bounds on the true effects of expansions on search. There are several reasons, however, why these increases were unlikely to be expected by unemployed individuals. First, expansions were often politically contentious and it was uncertain whether they would be passed or in what exact form. Second, some of the expansions came at predetermined thresholds of unemployment rates by state. Such expansions would be unpredictable at a high-frequency level because it is hard to predict short-run unemployment rate changes. As evidence, we look at media articles regarding benefits around the time of new legislation to see whether the media anticipated these changes. Figure 3 displays counts of newspaper articles in Texas 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.

Our identification comes from 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.

Our baseline specification is:

$$\log GJSI_{st} = \alpha PBD_{st} + \beta X_{st} + \gamma_t + \gamma_s + \epsilon_{st} \tag{1}$$

where PBD_{st} is a measure of the potential weeks of UI for a newly unemployed individual on month t in state s. X_{st} are covariates representing local labor market conditions and the composition of weeks until UI expiration of the unemployed. γ_t

and γ_s are year-month and state fixed effects, respectively.

We estimate the above specification using data from January 2004 through March of 2011. The main coefficient of interest in these specifications is α, which we interpret as the effect of the PBD on job search activity. The results of this specification are shown in 5. The coefficient on this variable is negative and statistically signficant across all specifications. The magnitude of the coefficient in our preferred specification (5), which includes year-month and state-month fixed effects, suggests that an additional 10 weeks of UI benefits result in a 2% drop in aggregate job search in the state.

Columns 4 - 6 display the same sets of specifications but replacing the potential benefit duration with a post expansion indicator which equals 1 in the month and month following an expansion of UI benefits. The coefficient on post expansion is small and not statistically significant across specifications which include various fixed effects (state, year-month, state-month) and labor market controls (share of labor force on ui, share employed, and share with fewer than 10 weeks of benefits before expiration).

Why do we detect an effect of potential benefit duration but not an immediate decrease following an expansion? We hypothesize that the effects of these expansions are likely to be long-lasting.[19] The potential weeks of benefits that a new UI claimant has access to typically remains elevated months or years past a given UI expansion. Furthermore, UI claimants may only realize they have many additional weeks when they need to change tiers of UI benefits. Therefore, the job search of UI claimants should be affected by the potential UI duration long after a given expansion and the effect should be larger, the more people there are on UI.

Including just a post-expansion indicator does not capture these potentially long-lived effects. For example, the second month after an expansion may have even lower job search than the first month. One solution would be to include indicators for a full dynamic effect on expansion in the panel regression. However, multiple UI changes (both increases and decreases in potential benefits) often occurred within months of each other. Therefore, we cannot use Equation 1 to study the full dynamic effect of an expansion.

A. *Robustness: Event Study Analysis*

As a robustness check, we turn to an event study approach similar to Marinescu (2015) as an alternate way to estimate the effects of UI expansions. The event study approach requires strong assumptions about the behavior of job search. First, in a simple before and after specification, states experiencing jumps must not experience concurrent changes in labor market conditions or internet usage around the time of a jump. Second, even in a difference-in-differences specification, it is not clear

[19] Indeed, Marinescu (2015) uses an event study to find a more than three times larger decrease in job search on Careerbuilder 7 months after a large UI expansion.

whether any true 'control' states exist. Specifically, since all states experienced UI increases and if expansions had long-lasting and time-varying effects, there would be no true 'control' states. Lastly, an event-study strategy can only be done for changes in UI that are not concurrent with legislation that affects UI in all states.

To execute the event study, we use the largest PDB increases that were not concurrent with the passage of legislation regarding UI by congress. In each case, we consider up to 4 months before and after the change. If a change in UI occurred in the 4 months prior to the biggest change, then we exclude observations including and before the month of the prior change. Similarly, if a change in UI occurred after the largest change, then we exclude the month of the change and the months after the change. Consequently, our sample does not represent a balanced panel.

We estimate two specifications using the samples of large changes: a before and after analysis and a difference in difference specification with control states that did not experience jumps during the same time period. The estimating equation for the before and after analysis is:

$$\log GJSI_{st} = \alpha After_{st} + \gamma_s + \epsilon_{st} \tag{2}$$

where $After_{st}$ is an indicator variable for whether the month includes the change in PDB or is after the PDB and γ_s is a state fixed effect. We also try a specification in which we replace the $After_{st}$ with an impulse function ranging from 3 months before the change to 4 months after the change.

The simple before and after analysis is potentially corrupted by state specific changes in other labor market conditions or in overall Google usage, which may occur concurrently with changes in UI. In an attempt to account for time trends, we find control states for each identified jump which do not experience a jump in the same time period. If a 'control' state experiences a jump in potential weeks left before the 'treatment' state, we only keep observations for the 'control' after that occur after that jump. Similarly, if a 'control' state experiences a jump in potential weeks left after the 'treatment' state, we only keep observations for the 'control' that occur before that jump. Our difference in difference specification is as follows:

$$\log GJSI_{stj} = \alpha After_{st} + \gamma_t + \gamma_{sj} + \epsilon_{stj} \tag{3}$$

Here, there are two additional fixed effects. γ_t is a year-month fixed effect and γ_{sj} is a state-by-jump fixed effect. Note, some state-month observations may appear multiple times as controls for different jumps.

Table 6 displays the results of the above specification. Column 1 shows the basic before and after specification using the biggest jumps per state in the sample. There is no statistically significant drop in job search after the increase and the standard errors exclude large responses. Column 2 includes an interaction of the after change indicator with the share of the population on UI in the month before the change. This coefficient on the interaction is negative and significant, suggesting that those states with more individuals on UI experienced larger decreases in search following an expansion. This is consistent with the standard model of job search behavior. In column 3, we include indicator variables for each month relative to the jump in benefits. There is no statistically significant decrease in job search follow an increase in potential duration.

Table 7 displays the result of the difference in difference specification. Column 1 shows a negative and statistically insignificant drop in search after a change. Column 2 shows that the change in search is more negative for states with more individuals on UI. Column 3 includes month relative to UI change indicators. These coefficients decrease in magnitude over time, but the decrease is not statistically significant or discontinuous in the month of the jump. The event study results confirm our panel data specification, which suggests that any immediate effects of UI expansions were small. Although the dynamic effects we estimate are not statistically significant, they are also not statistically distinguishable from the estimates in Marinescu (2015).

VII. The Effect of Unemployment Insurance on Job Search Intensity

The GJSI is an aggregate of all job search and can potentially mask large effects of UI on job search effort for specific sub-populations. For example, in the previous section we found that states with more potential benefits experienced lower job search. This may be due to the fact that a larger share of those on UI in those states have more weeks until benefit expiration. In this next section we study these effects using high-frequency data on the distribution of the UI recipient population in terms of potention weeks of UI left.

We want to understand the contributions made to the GJSI 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 ('WeeksLeftBin') as well as state and year-month fixed effects.

$$\log JS_{it} = \sum_{k=1}^{n} \beta_k WeeksLeftBin_{kit} + \gamma_t + \gamma_s + u_{it} \tag{4}$$

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 explicitly model the manner in which the GJSI is constructed.

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:

$$JS = \frac{1}{\mu}\left[\frac{\gamma_{Ut}N_{Ut} + \gamma_{Et}N_{Et}}{\alpha_{Et}N_{Et} + \alpha_{Ut}N_{Ut}}\right] \tag{5}$$

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 online 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 5:

$$\log JS = -\log(\mu N) + \log(\frac{\kappa_t}{\alpha_t}) + \log(\gamma_U N_{Ut} + \gamma_E N_{E2}) \tag{6}$$

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

$$\log JS_{dt} = \beta_{0d} + \beta_{1dt} + \beta_{2t} + \log(\gamma_E N_{Edt} + \gamma_U N_{Udt}) + \epsilon_{dt} \tag{7}$$

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.[20] 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.

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 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[21] and the GJSI is negative, suggesting that the response of vacancies 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, they search 46 times more than the employed on average according to the ATUS (seen in Appendix Table 4).

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 XI displays estimates from a nonlinear least squares (NLLS) model based on Equation 7 with three types of job seekers: those on UI, those not on UI and the employed (see Appendix Table 5 for OLS version). Columns 1 displays the coefficients corresponding to the γ_i's in Equation 5. 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.

[20]Results are qualitatively unchanged when including a quadratic DMA-specific time trend.
[21]Vacancies are measured at a monthly level by the Job Openings and Labor Turnover Survey.

Next, we 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 XI columns 2 displays 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 66% more than those with 10 - 20 weeks remaining and 108% more than those with more than 30 weeks remaining.. Our results suggest that potential UI duration affects aggregate job search in the expected direction.

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 use our estimates to determine the importance of the decreased job search channel in explaining higher 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.[22] We construct a counterfactual in which these individuals were only eligible for a maximum of 26 weeks of UI rather than the 46 weeks they were actually eligible for. 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:

$$J_{wt} = e_w \frac{J_t}{\sum e_w N_{wt}} \tag{8}$$

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

[21] Appendix Figure 2 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.

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

equal to the appropriate coefficients in column (5) of Table XI. 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 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 8 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. (2015)). 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.[23] 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

[23]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.

the GJSI to a number of alternate measures of job search activity and find consistent evidence that it is a good measure of aggregate job search activity. We then use the GJSI to show that job search decreased moderately following the UI expansions during the recession of 2007 - 2009.

We show that job search was lower in states where the potential UI duration was longer. However, we find no evidence of a large drop in job search in the month following a UI expansion. We also find evidence that those individuals closer to UI expiration search more for jobs. 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.

Lastly, we use our estimates of the effects of UI on job search effort 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.

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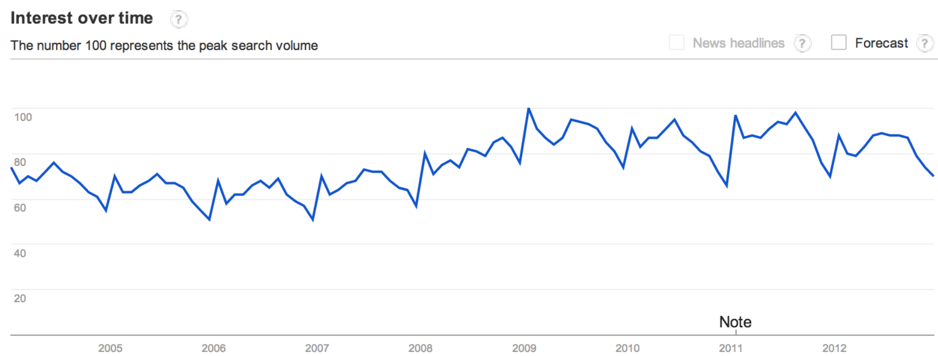
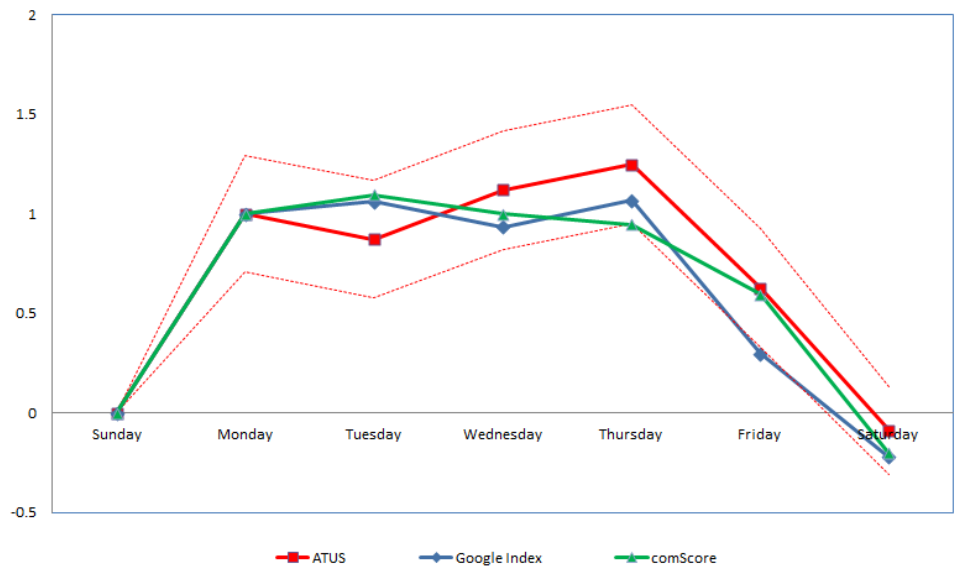
X. Figures

Figure 1. : Google Trends Example Search



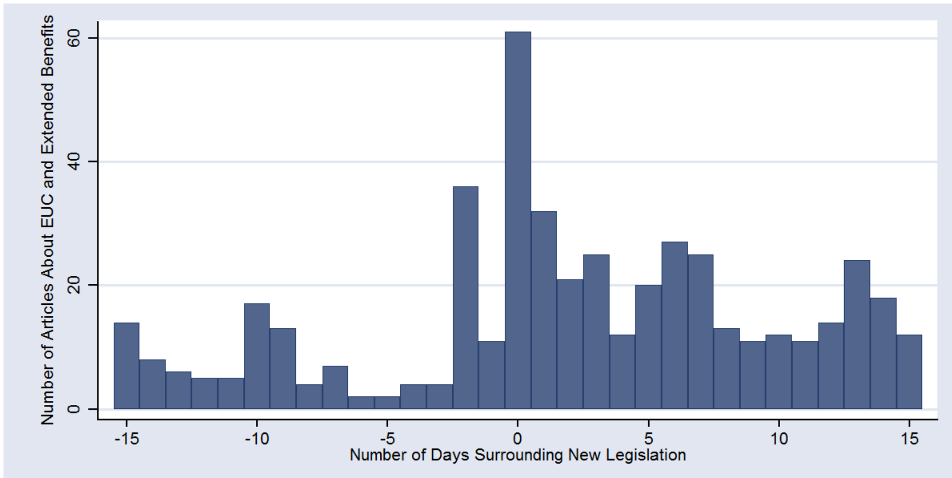
Notes: Figure gives the result of query on Google Trends using the search term ‘jobs in the United States from 2004 to 2013. Displayed data are monthly values. Google Trends accessible at http://www.google.com/trends/.

Figure 2. : Day of Week Fixed Effects



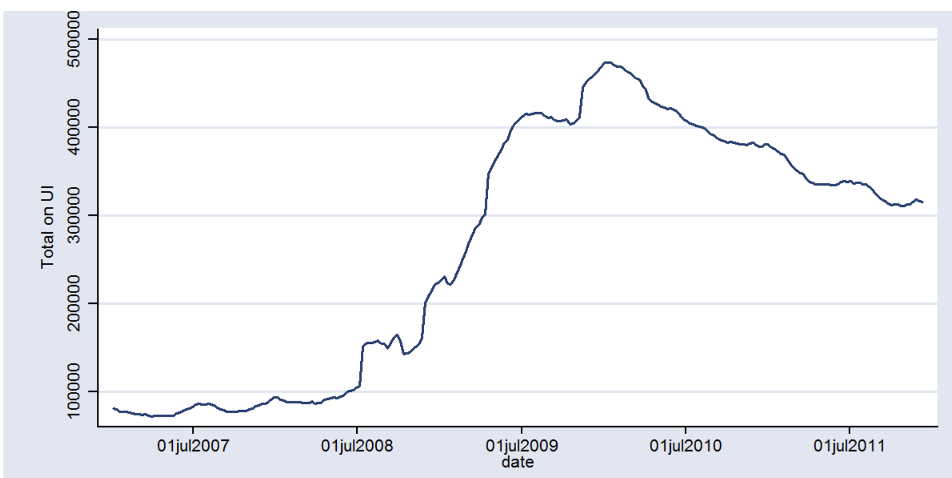
Notes: Figure shows coefficients and standard error bands from three separate regressions. Each regresses a measure of job search on day-of-week dummies and relevant geographic and seasonal fixed effects. ATUS represents coefficients derived from data from the American Time Use Survey from 2003-2010. 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



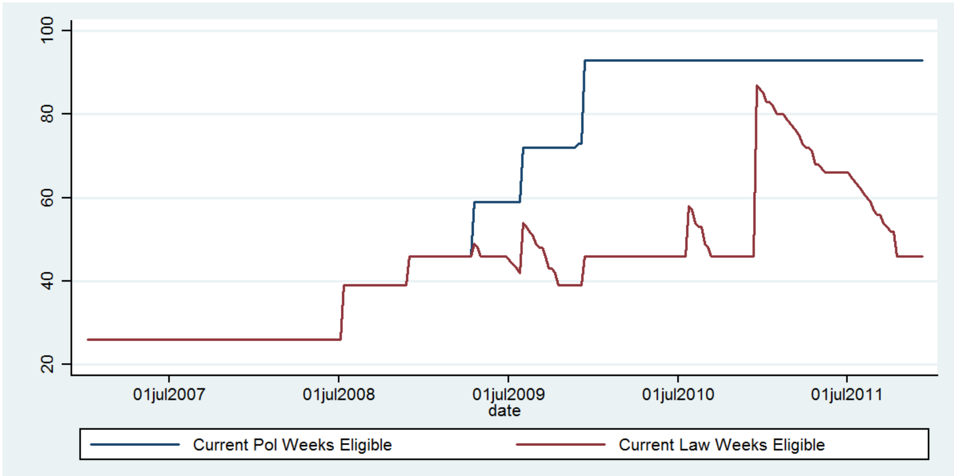
Notes: Columns show the number of articles per day written about the emergency unemployment compensation or extended benefits programs. Searches are run on the Access World News Newsbank archives, which covers more than 1,500 US Newspapers. Search terms include "emergency unemployment compensation" and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

Figure 4. : Total Number on UI: Texas



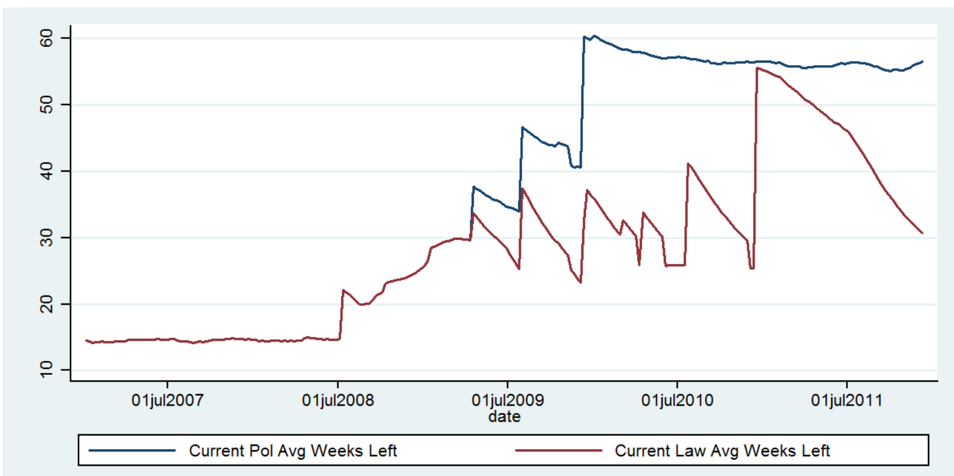
Notes: Graph shows the total number of UI recipients in the state of Texas over time from January 2007 to December 2011. Data obtained from the Texas Workforce Commission.

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 Time	(4) Search Time-NonZero	(5) Search Time	(6) Search Time
log(Google Job Search Index)	0.327***	1.890***	3.268***	6.035*	3.446***	3.067***
	(0.0284)	(0.208)	(0.730)	(3.523)	(0.762)	(1.052)
log(Google Unemp/Emp Index)						0.527
						(0.504)
log(Google Unemp Rate Index)						-0.102
						(0.162)
log(Google Weather Search Index)					-0.378	
					(0.605)	
Observations	3,541	3,541	3,541	3,541	3,541	3,541
R^2	0.049	0.285	0.075	0.619	0.075	0.081
State FE	NO	NO	YES	YES	YES	YES
Month FE	NO	NO	YES	YES	YES	YES

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

'Search Time' refers to ATUS Search Time, the average number of minutes per day respondents report that they spent on job search in a given state-month. Standard errors clustered at a state level. Columns 2 and 4 use the sample of state-month observations with non-zero job search time recorded. Google indexes represents coefficients derived from data from three separate Google Trends queries from 2004-2014. 'Google Weather Search' is an index analogous to the GJSI but using the term 'weather'. 'Google Unemp Rate' tracks the frequency of Google searches for the term 'unemployment rate', and 'Google Unemployment/Employment' tracks searches for the term 'unemployment' or 'employment'.

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

VARIABLES	(1) Google JS	(2) Google JS	(3) ATUS JS	(4) ATUS JS	(5) comScore JS	(6) 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

VARIABLES	(1) Log(GJSI)	(2) Log(GJSI)	(3) Log(GJSI)	(4) Log(GJSI)	(5) Log(GJSI)	(6) Log(GJSI)
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

Notes: 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—: Effects of UI Expansions and Composition by State

	(1)	(2)	(3)	(4)	(5)	(6)
Potential Benefit Duration	-0.00235***	-0.00234***	-0.00324***			
	(0.000714)	(0.000797)	(0.000743)			
Post Expansion				0.00925	0.00228	-0.000317
				(0.0119)	(0.0142)	(0.0179)
Share On UI			3.839			3.428
			(2.441)			(2.556)
Share <10 Weeks Left			0.327			2.067***
			(0.556)			(0.670)
Share Employed			-0.794			0.319
			(1.010)			(0.987)
State FE	Yes	No	No	Yes	No	No
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Month FE	No	Yes	Yes	No	Yes	Yes
R-Squared	0.825	0.844	0.849	0.820	0.839	0.844
Observations	3811	3811	3811	3811	3811	3811

Notes: Dependent variable is log(GJSI) at state-month level. Analysis spans all 50 states and Washington DC from 2005 - March 2011. Observations from Lousiana during 2005 are removed due to Hurricane Katrina. 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 expansion of benefits either due to a trigger or national legislation. is computed using the assumption. Standard errors are clustered at state level.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 6—: Before and After Expansion

	Log GJSI		
	(1)	(2)	(3)
After	−0.004	0.130***	
	(0.014)	(0.042)	
After * Share on UI Before Change		−0.066***	
		(0.019)	
-3 Months After Change			−0.005
			(0.028)
-2 Months After Change			−0.016
			(0.035)
-1 Months After Change			−0.009
			(0.038)
0 Months After Change			−0.032
			(0.036)
1 Months After Change			−0.017
			(0.035)
2 Months After Change			−0.007
			(0.034)
3 Months After Change			0.027
			(0.039)
4 Months After Change			0.012
			(0.041)
State FE:	Yes	Yes	Yes
Observations	253	253	253

Notes: The dependent variable is log(GJSI) at a state/month level. The sample includes observations around and including the largest UI benefit jumps in each state that: a. Did not coincide with federal legislation, b. Occurred after any proceeding jump in the state and before any subseqent jump in the state. 'After' is an indicator variable for whether an observation is after the largest jump in each state. 'Share on UI Before Change' is the share of the population on UI in the month proceeding the jump in benefits. Specification (3) includes indicators for the dynamic effect of the largest jump in potential benefit duration. Standard errors are clustered at the state level.

Table 7—: Difference in Difference After Expansion

	Log GJSI		
	(1)	(2)	(3)
After	−0.007	0.072*	
	(0.012)	(0.042)	
After * Share on UI Before Change		−0.028*	
		(0.015)	
-3 Months After Change			−0.005
			(0.012)
-2 Months After Change			−0.0002
			(0.017)
-1 Months After Change			−0.010
			(0.018)
0 Months After Change			−0.009
			(0.020)
1 Months After Change			−0.012
			(0.021)
2 Months After Change			−0.019
			(0.026)
3 Months After Change			−0.012
			(0.029)
4 Months After Change			−0.018
			(0.032)
Year-Month FE:	Yes	Yes	Yes
Jump-Control FE:	Yes	Yes	Yes
Observations	3,408	3,408	3,408

Notes: The dependent variable is log(GJSI) at a state/month/UI change level. The sample includes observations around and including the largest UI benefit jumps in each state that: a. Did not coincide with federal legislation, b. Occurred after any proceeding jump in the state and before any subseqent jump in the state. For each change, states that did not experience a UI change at the same time are included as 'control' observations. 'After' is an indicator variable for whether an observation is after the largest jump in each state and belongs to the 'treatment' state group. 'Share on UI Before Change' is the share of the population on UI in the month proceeding the jump in benefits. Specification (3) includes indicators for the dynamic effect of the largest jump in potential benefit duration. Standard errors are clustered at the state level.

Table 8—: Effect of UI Status and Composition on Job Search (NLLS)

	(1)	(2)
Number on UI	0.833***	
	(0.235)	
Not on UI	1.091***	1.082***
	(0.267)	(0.269)
Number Employed	0.0934***	0.0943***
	(0.0161)	(0.0181)
0-10 Weeks Left		1.563**
		(0.730)
10-20 Weeks Left		0.938***
		(0.297)
20-30 Weeks Left		0.951***
		(0.232)
Over 30 Weeks Left		0.753***
		(0.258)
UI Recipients/Employed	11.69	
UI Recipients/Non-UI Unemployed	0.763	
DMA FE and Trend	Yes	Yes
Year-Month FE	Yes	Yes
Observations	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. 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

Appendices

A. Results Using the "Current Policy" Assumption

Appendix Table B 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 7 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 3 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—: 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 2—: Day of Week Fixed Effects for Google Placebo Terms

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Google Benefits	Google Benefits	Google Unemp	Google Unemp	Google Unemp or Emp	Google Unemp or Emp
Monday		0.196***		0.158***		0.253***
		(0.0201)		(0.0184)		(0.0121)
Tuesday		-0.000904		-0.0956***		0.138***
		(0.0238)		(0.0238)		(0.0173)
Wednesday		-0.0838***		-0.227***		0.0611***
		(0.0250)		(0.0271)		(0.0197)
Thursday		-0.145***		-0.332***		-0.0107
		(0.0258)		(0.0301)		(0.0217)
Friday		-0.222***		-0.391***		-0.0927***
		(0.0268)		(0.0310)		(0.0217)
Saturday		-0.516***		-0.880***		-0.489***
		(0.0348)		(0.0308)		(0.0253)
Holiday	-0.122**	-0.145***	-0.237***	-0.263***	-0.273***	-0.286***
	(0.0493)	(0.0404)	(0.0428)	(0.0243)	(0.0332)	(0.0249)
Weekend	-0.208***		-0.264***		-0.315***	
	(0.0194)		(0.0121)		(0.00732)	
Observations	4,018	4,018	4,018	4,018	4,018	4,018
Year FE	YES	YES	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

Dependent variables are indexes derived from data from three separate Google Trends queries from 2004-2014. ‘Google Benefits’ tracks the frequency of Google searches for the term ‘unemployment benefits’ or ‘unemployment insurance’, ‘Google Unemp’ tracks searches for the term ‘unemployment’, and ‘Google Unemp or Emp’ tracks searches for the term ‘unemployment’ or ‘employment’. Holiday denotes indicators for all federal holidays.

Table 3—: 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 4—: 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 5—: Effect of UI on Job Search (OLS)

	(1)	(2)	(3)	(4)
Number Employed			-2.032**	-2.129**
			(0.855)	(0.817)
Not on UI			2.642	2.130
			(3.657)	(3.546)
Total on UI			0.296	
			(4.011)	
0-10 Weeks Left				6.769
				(5.234)
10-20 Weeks Left				0.467
				(2.158)
20-30 Weeks Left				0.611
				(2.018)
Over 30 Weeks Left				-0.584
				(1.970)
DMA FE	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. variables represent the fraction of the total population belonging to each category.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 6—: Effect of UI Status and Composition on Job Search (NLLS)

	(1)	(2)
Number on UI	1.666***	
	((0.471)	
Not on UI	2.182***	2.133***
	((0.535)	(0.564)
Number Employed	0.187***	0.193***
	(0 (0.0321)	(0.0345)
0-10 Weeks Left		1.155
		(1.023)
10-20 Weeks Left		3.143*
		(1.654)
20-30 Weeks Left		4.192***
		(1.011)
Over 30 Weeks Left		1.434**
		(0.526)
UI Recipients/Employed	11.69	
UI Recipients/Non-UI Unemployed	0.763	
DMA FE and Trend	Yes	Yes
Year and Month FE	No	No
Year-Month FE	Yes	Yes
Observations	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 7—: 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

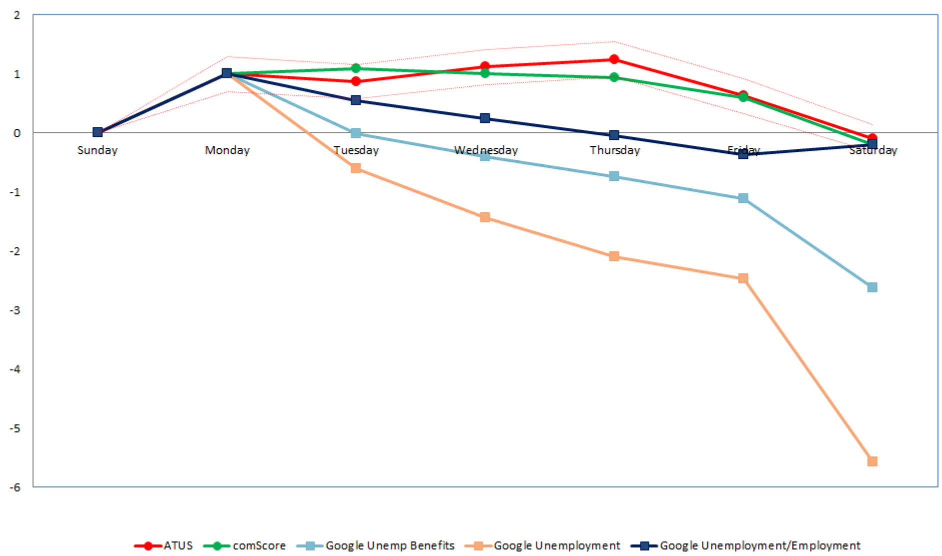
The dependent variable is an indicator whether an individual on UI exited without finding a job. The independent variables are bins of weeks left of UI remaining.
*p<0.1; **p<0.05; ***p<0.01

Table 8—: 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

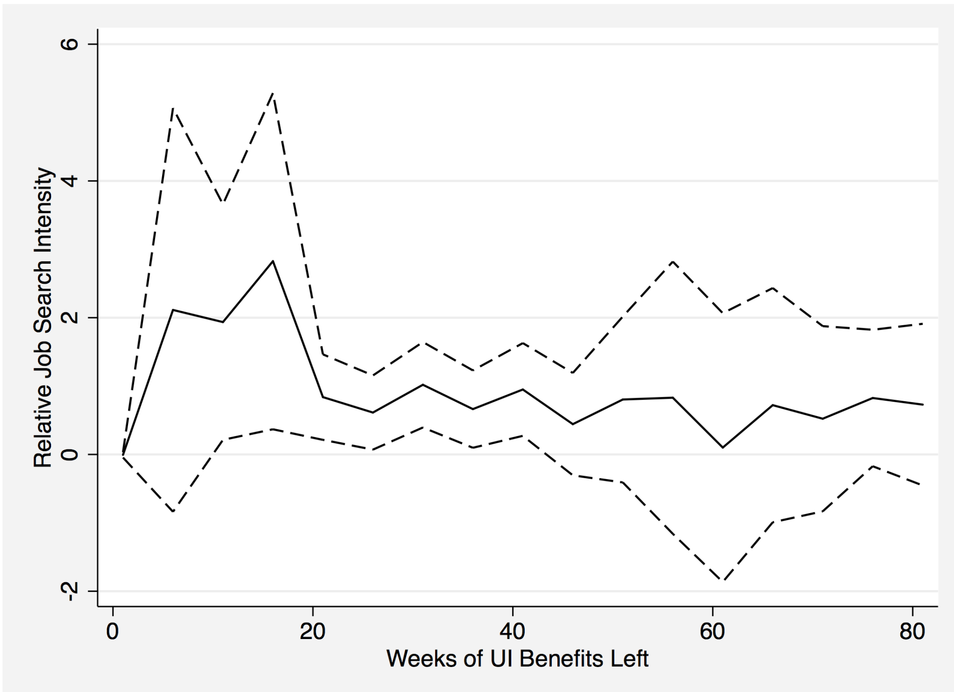
The table displays the mean outcomes for 100 simulations of job finding with and without EUC.

Figure 1. : Day of Week Fixed Effects - Placebo



Notes: Figure shows coefficients and standard error bands from five separate regressions (detailed in Table 3 and Appendix Table 2. 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 indexes represents coefficients derived from data from three separate Google Trends queries from 2004-2014. 'Google Unemp Benefits' tracks the frequency of Google searches for the term 'unemployment benefits' or 'unemployment insurance', 'Google Unemployment' tracks searches for the term 'unemployment', and 'Google Unemployment/Employment' tracks searches for the term 'unemployment' or 'employment'.

Figure 2. : 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 3. : 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.