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

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May 27, 2013

Abstract

We use Google search data to construct the first high-frequency, location-specific index of job search activity (GJSI). We demonstrate the GJSI's validity and study the effect of increased unemployment insurance (UI) on job search activity. Using the universe of administrative Texas UI records from 2006-2011, we show that individuals receiving UI search less than individuals who are unemployed and who are not receiving UI. We also find that individuals with 0 to 10 weeks of UI remaining search over two times more than those with more than 10 weeks remaining. We document that the GJSI temporarily decreases by up to 4.3% in the 4 weeks after expansions in UI policy. Our calculations suggest that, while expansions in unemployment insurance do drive temporary changes in job search, the immediate effects of expansions are unlikely to result in large changes to unemployment rates.

*Thanks to Caroline Hoxby, Doug Bernheim, Nick Bloom, Hal Varian, David Card, Camille Landais and for the many helpful comments and suggestions from seminar participants at Stanford, Google, the SF Federal Reserve, and the American Economic Association Meetings. Thanks to Jack Bao, David Summers, and Holly Faubion at the Texas Workforce Commission for assistance in obtaining administrative UI data. This research was supported by the Shultz Graduate Student Fellowship in Economic Policy through a grant from the Stanford Institute for Economic Policy Research

1 Introduction

The amount of job search exerted by unemployed individuals is a key choice variable in theories of optimal social insurance and business cycles. However, the absence of high-quality job search data has made it difficult to test economic theories of job search directly. We construct, validate, and demonstrate the utility of a flexible, high-frequency index of job search. We use our index in conjunction with the universe of administrative UI records from Texas from 2006-2011 to test the reaction of job search to both the number of weeks of UI remaining among recipients and to expansions in the UI program.

The Google Job Search Index (GJSI) is a weekly index based on the volume of search for the term 'jobs' at a given time in a given location. We show that the GJSI is a valid proxy for overall job search by comparing it to other measures of job search and by establishing a relationship between the GJSI and hypothesized macroeconomic drivers of job search. We develop a methodology to extract economically meaningful parameters from the GJSI using non-linear least squares and demonstrate it using administrative UI records from Texas. We find that individuals with 0-10 weeks of UI eligibility remaining search more than 2 times as much as individuals with more remaining weeks of benefits. Furthermore, aggregate job search dropped by over 2% in the four weeks after policy changes which extended or expanded UI benefits.

Our identification strategy uses both high frequency variation in the precise timing of expansions to the UI system over the past 6 years as well as the composition of the unemployed. For example, due to the differential timing of layoffs among metropolitan statistical areas (MSAs), some MSAs will have relatively more individuals than other MSAs with a given number of weeks of UI left. Further, federally mandated expansions and extensions of UI provide shocks to the potential UI eligibility of the unemployed. The variation in the composition of the UI claimants across MSAs allows us to describe the typical pattern of job search over the average unemployment spell as well as to determine differential effects of expansions across MSAs.

Texas administrative UI data allows us to measure the composition of the unemployed in a given MSA-week much more precisely than other frequently used data sources such as the CPS. On average, the mean number of observed unemployed individuals per state-month in the CPS is only 23. The small sample size in the CPS, in combination with the inability to accurately gauge the number of weeks left of UI or even if an individual is receiving UI, makes the CPS unsuitable for our research methodology.

The GJSI also has several advantages over the American Time-Use Survey (ATUS), another frequently used data set for job search research. Firstly, the ATUS's small sample size leads to situations in which state-month level data often contain fewer than 5 unemployed respondents, making them unsuitable for state-level or fine time-series analysis. Google search data represents an aggregate measure of the amount of online job search based on total search activity in a location and thus does not suffer as acutely from small-sample bias. Online search data also sidesteps the known problems of survey data where inaccurate recall and the nature of surveyed responses can create biased results. Lastly, the immediate availability of Google Trends data makes it possible to diagnose large behavioral response to policy changes in real time (Choi and Varian 2012 and 2013).

The rest of this paper is organized as follows: Section 2 describes prior literature on job search and optimal UI design. Section 3 describes our job search and tests of its validity. Section 4 describes the expansions to the unemployment insurance system in the United States during the Great Recession and Section 5 describes the administrative UI data from Texas used in our analysis. Section 6 discusses our empirical strategy and presents our results and Section 7 concludes.

2 Previous Literature

Economists have been interested in understanding the costs and benefits of UI for a long time. Prior literature, such as Meyer (2007), Card and Levine (2000), Katz and Meyer

(1990), and Moffit (1985), has focused on the effects of benefit levels and duration on hazard rates out of UI. Employing a variety of empirical strategies (regression discontinuity, natural experiments, cross-state variation), the literature generally finds elasticity of unemployment with respect to benefit levels of around 0.5. However, due to the difficulty of observing search effort and reservation wages, the mechanisms behind the elasticity are only addressed indirectly.

2.1 Empirical Evidence on Job Search

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

In another study, Krueger and Mueller (2011) (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 and that their results are contrary to prior, cross-sectional, evidence which found increasing search as individuals neared expiration. This discrepancy may be due to unobserved heterogeneity across UI claimants that jointly drive 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. However, their identification strategy for the effects of the 2009 expansion of Emergency Unemployment Compensation (EUC) cannot separate time trends from the policy change as 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, the weather and seasonality. They find that after the policy change, there is, on average, 11 - 20 minutes less job search per day per individual.

Given survey evidence, the rapid increase in both access to the internet (as of 2010, approximately 80% of Americans had internet access from home), and the increase in the number and size of job search related sites, it is safe to assume that online job search currently represents an important component of overall job search. We also believe that online search behavior is an interesting behavior to explain, not only as a proxy for overall job search, but also in and of itself. The increased availability of internet job search services and the decreased use of physical classified jobs ads has made online job search more prevalent over the past decade, as documented in Kroft and Pope (2011). Employers increasingly rely on online service to post vacancies. Candidates looking for job naturally rely on search engines to find positions that are suitable to their skills and are in the desired location of employment.

Job search is driven not only by UI but also but other factors impacting the returns to job search. For example, tighter local labor markets may increase the marginal returns to job search. Schmieder et al. (2011) find that the elasticity of non-employment for mature workers in Germany is moderately lower during larger recessions. The type of job search is also an endogenous decision. Holzer (1988) finds that job searchers are relatively efficient in the allocation of their search effort, spending more time in job search activities which are more ‘productive in terms of finding a job.

Data from Google Trends has been used in several other papers. Choi and Varian (2009a and 2009b) and D'Amuri and Marcucci (2011) have demonstrated the utility of Google search data in forecasting several categories of sales and initial unemployment claims. Da, Gao and Engelberg (2011) use Google search data as a proxy for investors' attention to stocks, showing that it predicts stock price movement and Vlastakis and Markellos (2012) show that demand for information about stocks rises in times of high volatility and high returns. We follow such papers in finding value in the high-frequency and timely nature of Google search data.

2.2 Job Search Activity and Optimal Policy

The GJSI offers insight into the moral hazard effect of extending or increasing unemployment benefits. In this vein, Raj Chetty (2009) examines the implications of increases in unemployment benefits on duration of unemployment, separating the impact into a positive 'liquidity' effect and a negative 'moral hazard' effect. Using the Survey of Income and Program Participation, he is able to estimate heterogeneous effects of potential UI duration between households likely to be liquidity constrainted and those unlikely to be constrained. He finds that 60% of the increase in unemployment duration resulting from an increase in UI benefits can be attributed to the 'liquidity' effect. Thus, an observed increase in unemployment duration following an increase in benefits need not be a net welfare loss. Shimer and Werning (2007) study the reservation wage, an alternative channel for the moral hazard and liquidity effects of UI. They show that, in a stylized model, optimal UI policy should be structured so that the unemployed do not experience a decrease in their reservation wage during their unemployment spell. Spinnewijin (2013) uses survey data on UI spell duration expectations and actual UI spell length to provide evidence for systematic biases in expectations among the unemployed. He finds that job seekers are, on average, too optimistic about their chances of quickly finding a job. He then theoretically demonstrates behavioral deviations from rational expectations by job seekers can modify standard results about optimal UI.

Mortensen (1977) develops the canonical model of job search with expiring UI duration. He shows that, holding the match rate constant, job search activity should increase as UI benefits come closer to expiring. Most studies of optimal UI policy focus on the level rather than the duration of benefits, despite the fact that, in practice, duration is the dimension of UI most often affected by policy. Kroft and Notowidigdo (2010) estimate that the elasticity of unemployment duration with respect to the benefit level is -1.10 when unemployment is low, but is only -0.32 when unemployment is high. They use the above difference to calibrate the optimal replacement rate in a Baily-Chetty sufficient statistic framework. They show that the optimal replacement rate should be higher when there is higher unemployment.

Similarly, Landais, Michaillat, Saez (2011) analyze optimal UI policy over the business cycle and develop a general equilibrium model where search activity imposes a negative externality on other job searchers. Their model implies that job search activity has little effect on aggregate unemployment in recessions due to job rationing. They demonstrate that the welfare relevant elasticity in the sufficient statistic framework is the macro elasticity of unemployment with respect to benefits. They show that in a calibrated DSGE model, UI should be more generous in recessions.

Lastly, Bender et al. (2011) study the effect of thresholds in benefit durations within the German UI system on job finding probability, then applying the estimated elasticities to the US recession. They derive a formula for optimal UI duration and show that duration should increase during a recession, at non-recession level of UI maximum duration. Our paper contributes by providing a credible estimate of the elasticity of search effort with respect to UI durations for the US. We then use the above estimate to approximately quantify the effect of changes in search effort on job finding. We abstain from calculating an optimal UI rate because our estimates are micro-level and do not account for general equilibrium or long run effects of changes to the UI system.

Rothstein (2011) examines the impact of the UI extensions over the past several years on UI hazard rates. He uses data from the CPS to gauge the change in exit rates over time and between individuals with different number of weeks left. He finds small negative effects of UI expansions on exit from UI, concentrated among the long-time unemployed, which could account for a 0.1-0.5% rise in the unemployment rate over the past years.

3 Google Search Data Description and Validity

The GJSI is constructed from indices of search activity obtained from Google Trends. Google Trends allows us to obtain a geographic-specific time series of the relative amount of search activity for specific search terms on Google.com.[1] The numerical values we obtain are normalized and scaled measures of this search activity. Specifically, for a given time period, the values represent the number of searches on Google.com for the specified search term relative to the total number of searches on Google.com derived from a sample of all Google search data. To reduce noise stemming from this sampling, we resample Google Trends during 4 different weeks and take an average. The values on Google Trends are normalized such that the highest value for the entire time period is set equal to 100. Thus, the range of values is always between 0 and 100, where higher values represent higher fractions of total searches on Google.com were for the indicated search term. An example of the results from a Google Trends search can be seen in Figure 1.

It is difficult to ascertain the total historical amount of searches for 'jobs' on Google because Google prefers to keep these numbers secret. However, several tools available as of 2013 provide greater visibility 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. An alternative measure of the total searches for jobs is provided by the Adwords traffic estimator where, as of April 2013, Google estimates that the top placed ad for 'jobs' in Texas 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 Google Trends data in three ways. Firstly, we use data at a daily level, allowing

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

for comparison to ATUS and comScore day-of-week data. Secondly, we construct a weekly series by MSA to use measure MSA-specific job search trends in Texas. Lastly, we use nonlinear least squares to extract coefficients representing the relative amount of job search done by individuals on UI compared to individuals not on UI (See Section 6).

For all methods, we choose the search term 'jobs' (excluding search about Steve Jobs and Apple) as our term of interest. One concern with this measurement technique may be the applicability of the particular search term 'jobs'. We perform extensive tests and find this term to be highly correlated with a multitude of plausibly job search related terms, such as 'state jobs', 'how to find a job', or 'tech jobs'.[2] The query, 'jobs', also has very high volume compared to related terms and is thus less prone to measurement error, especially at the fine-grained MSA-week level. Furthermore, 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 and our measure using 'jobs' will encompass the majority of such queries. We also use Google Correlate[3] to determine which search terms that do not contain the text 'jobs' and are most correlated with Google searches for 'jobs'. 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').

3.1 Importance of Online Job Search

A natural concern with our Google measure of job search is the representativeness of online job search in terms of overall job search activity. Online job search has been a rapidly expanding segment of internet use, with sites like CareerBuilder.com, Monster.com, and Indeed.com receiving tens of millions of unique visitors per month.

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

[3]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.'

For additional evidence, we turn to the National Longitudinal Survey of Youth (NLSY). The NLSY includes a question that asks respondents about the usage of the internet for job search from 2003 to 2008. In 2003, 53% of NLSY job seekers used the internet whereas 83 percent did in 2008, which is the midpoint of our sample period. The most internet intensive activities are resume submissions, placing ads, and contacting schools' career centers. Rates of internet usage in job search increased with education but did not vary systematically by census region. However, we may be concerned about the nature of the population of the NLSY. The Internet and Computer use supplement of the Current Population Survey (CPS) also contains data on internet use among the job seeking population and, from the 2011 supplement, we find that over 75% of individuals who were searching for work in the past 4 weeks had used the internet to do so.

Kuhn and Skuterud (2004) discuss the prevalence of online search as a component of job search activity. They note that, as of 1998, more unemployed job seekers used the internet than private employment agencies, contacting friends, or utilizing unions to find a job. Finally, Stevenson (2009) finds that, while a majority of online job searchers are currently employed, over the past 10 years unemployed job searchers have come to use the internet much more extensively. Furthermore, as the penetration of internet access increases, the unemployed devote a greater fraction of their job search time to online search and the proportion of job seekers directly contacting potential employers increases. In mid-2002, prior to many of the largest job search websites becoming operational and widespread and well before the start of our sample period, Stevenson reports that 22% of job seekers found their jobs online.

3.2 ComScore

Our search term of choice, 'jobs', is a reliable proxy for all job search on Google because it is highly correlated with other potential Google job search terms. However, Google job search activity may be a different type of behavior from online job search in general. 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. We determine whether a person is searching for a job by summing the time spent on websites that contain job relevant terms.[4] We then note if a visitor to a job search related site was referred there by Google, giving us a relationship between Google-related job search and online job search in general. Using this measure, we find a strong relationship between the total online job search time and the number of job search related Google searches.[5]

3.3 ATUS

We use the American Time Use Survey (ATUS) as another check of the consistency of our Google measure. 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.

We use the ATUS data and Kreuger and Mueller's (2010) methodology in order to compare our Google measure of job search activity to their ATUS measure of job search. ATUS job search activity is calculated using the amount of time that individuals spend in job search

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

[5] See Appendix Table 1. Each Google search for a job in the comScore data is associated with approximately 7.5 minutes spent on job sites. Another worry about Google search is that the ratio of Google search activity to true online job search activity is not constant across regions or time periods.

related activities.[6] As a first pass, we examine the monthly correlation between the national measured averages of job search per capita from the ATUS and the GJSI. The overall correlation is approximately 0.51, and is robust to inclusion or exclusion of job-related travel time, removing the oversampling of weekend days, or using alternate Google search terms to measure job search activity. As a more thorough comparison, we take the state averages of job search time per capita for each month. Table 1 shows results of a number of regressions of Google Search measures on ATUS job search. We find a significant relationship between the Google and ATUS measure both looking at overall ATUS search time as well as with an indicator of non-zero job search. The job search indicator may be a better measure of job search effort in the ATUS due to the fact that it has less measurement error than the job search time variable (due to individual recall biases or other survey-based factors). Furthermore, the table shows a placebo test, regressing the Google Search measure for an unrelated phrase, 'weather', on the ATUS job search measure. We repeat this test with other terms such as 'sports' or 'news' with similarly insignificant results.

Although the two data sets are clearly related, they are not identical. Differences might arise because Google search and the ATUS are measuring different underlying behavior due to biases in survey answers or because online job search differs from offline job search. Further, different populations might be sampled by the two measures. Lastly, the Google data inevitably picks up some searches that are unrelated to searching for jobs but which involve the word 'jobs'.

3.4 Day of Week and Holiday Effects

Job search should follow strong day, month, and year trends, with predictable declines in search on weekends and holidays due to social commitments and general societal norms. We

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

also expect search to increase in the late spring because graduating students are looking for jobs and other students are looking for summer jobs. The GJSI increases in January after a holiday lull and also increases at the end of the spring as expected.

We study the American Time Use Survey, comScore data, and the GJSI in order to determine whether there are consistent 'day of the week' and 'holiday' effects across measures of job search. Figure 2 displays these day-of-week results graphically (full regression results in Appendix Table 2), with coefficients plotted as relative to the Monday coefficients. This relative plotting shows the consistency in day of week effects among the three different measures of job search effort. We see consistent day-of-week effects across measure of job search, with large drops in search on Fridays and weekends across all three measures. The daily effects are statistically indistinguishable from one another across the entire week.

The ratios of weekend to holiday search are approximately the same for all 3 measures. Furthermore, the intra-week pattern is similar for Google job search, overall online job search time measured by comScore, and total job search time measured by the ATUS. The three measures intra-week trends are statistically indistinguishable from one another. We interpret these results as evidence that Google search for 'jobs' is a good proxy for overall job search.

3.5 Macroeconomic Drivers of Job Search

The GJSI should also follow macroeconomic drivers of job search activity. Table 2 displays the results of regressions of the GJSI on labor market conditions. While these results are not causal, they all appear to move in the 'expected' direction.

Column 1 reports the results of a regression of the change in our measure, month to month, on the change in unemployment rate, as well as month and year fixed effects. There is a positive correlation between the unemployment rate and the GJSI. The magnitude corresponds to an increase in online job search activity of 1.3% when a state undergoes a 1%

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

increase in unemployment rate. In Column 2, we add the number of initial unemployment benefit claims per capita to our regression. There is a predicted 3.5% increase in job search activity when the number of initial claimants rises by 1 percentage point of the population.

We expect that current job search will be positively correlated with the number of final claims in the following month for two reasons. Firstly because those who search more in the current month are more likely to be exiting unemployment benefits in the following month, and also because recipients whose benefits will be expiring in the following month will most likely search at a higher rate in the current month. We find that an increase in job search of nearly 3% is correlated with a rise in next month's final claimants of 1 percentage point of the population. Columns 4 and 5 add the change in vacancies and tightness (given by the number of vacancies divided by the monthly unemployment rate) to the regression. As labor market tightness increases, we expect people to increase their job search activity due to the higher marginal return to one more minute of job search (although the effect depends on the convexity of the cost of job search effort). Indeed, we still find positive effects of all variables, though the coefficient on vacancies is insignificant.

4 Unemployment Insurance and EUC

In normal times, individuals eligible for unemployment insurance in Texas can draw on benefits for up to 26 weeks at a maximum weekly benefit amount of around $440.00. To receive UI benefits, an individual needed to satisfy a number of criteria. Firstly, an individual needed to have earned a sufficient amount of wages, generally equal to 37 times their weekly benefit amount, 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. Secondly, an individual needed to have been laid off for economic reasons, fired without work-related misconduct, or quit for a valid reason. Finally, to maintain eligibility, workers must be able to work, be available to work, be registered with Texas Workforce Solutions, and search for full-time work unless exempted.

In addition to these normal benefits, during times of high unemployment, individuals have access to additional weeks of unemployment insurance through the federally-funded Extended Benefits program. This program consists of two tiers, of 13 and 7 additional weeks, and are made available at a state-level when a state passes certain thresholds of unemployment. For the first level (13 weeks), a state becomes eligible when the three month moving average of its unemployment rate hits 6.5%. The second level (7 additional weeks beyond the initial 13 weeks) is available when the three month moving average hits 8.0%.

Due to the severity of the 2007-2009 recession, Congress and the President undertook additional measures to extend the number of weeks of unemployment insurance that individuals were eligible for. On June 30th, 2008, the Emergency Unemployment Compensation (EUC) program was created, allowing individuals who have exhausted their normal weeks of benefits to be eligible for a further 13 weeks of benefits. During the ensuing 18 months, the EUC program was expanded with two additional pieces of legislation:

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

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

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

The combination of the EUC and EB programs had the effect of increasing the maximum weeks of unemployment insurance from 26 to 99 weeks in many states, including Texas. This was an unprecedented expansion, representing a fourfold increase in unemployment insurance benefit duration. Moreover, the program was 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 subject to numerous extensions, seen in Table 3, which extended the period for which individuals were eligible for these expanded benefits.

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

An important consideration is the extent to which individuals can anticipate the legislative changes to UI policy, given our reliance on the timing of the policy changes in identifying causal effects on job search. On balance, we feel that these policies were relatively unexpected by individuals on UI for a number of reasons. The first is that the expansions and extensions were often politically contentious and it was uncertain whether they would be passed or in what exact form. In the UI extension bills in 2009-2011, some bills were even passed retroactively, with individuals losing benefits for a short time before regaining them. In addition, many of the expansions came at predetermined thresholds of unemployment rates by state. Such expansions would be unpredictably at a high-frequency level given the difficulty for individuals to predict precise unemployment rates in their state in the coming rates. Finally, we also do not see evidence of increased news coverage in the weeks leading up to expansions in unemployment benefits. Figure 3 displays counts from newspapers in Texas of articles about the EUC or EB system for the 15 days before and 15 days following each expansion or extension. We see a marked increase in coverage only 2 days before the policy change and the level remains persistently higher for some time afterwards. This gives us more cause to believe that individuals were not exposed to much information about the potential for extended UI benefits until very near to their availability. However, to the extent to which some individuals did anticipate the imminent expansion in UI benefits (eg. the perceived probability of expansion went from somewhere above 0% to 100% instead of from 0% to 100%), our estimates would most likely represent lower bounds on the true effects on search.

We measure the impact of each expansion using indicators for the date of each policy change and the period following the policy change. If there exists considerable moral hazard in these programs, with those claiming unemployment not actively seeking work, we would expect to see a fall in job search activity following an expansion of benefits. This effect would be driven both because more individuals were newly eligible for UI after having exhausted their previously available benefits and because all UI recipients would now have greater numbers of weeks left prior to exhaustion. Using our administrative UI data from Texas, we are able to precisely track individuals with varying numbers of weeks of benefits remaining and to determine the effects of the number of weeks remaining on job search. If the spike in exits from unemployment benefits in the last weeks of availability seen in Meyer (1990) is due to relatively high search activity around the time of benefit expiration, we would expect to find a fall in search activity driven by shifts in the number of weeks of benefits remaining for UI claimants. However, if the spike in exits is due primarily to a fall in the reservation wage or exit from the labor force, we may observe little change in the amount of job search activity.

5 Texas UI Data Description

Our sample of Unemployment Insurance data comes from administrative data from the Texas Workforce Commission, spanning from 2006-2011 and including every recipient of unemployment insurance in Texas during that time period. In total, over 2 million individuals received unemployment insurance over 2.7 million unemployment spells during this period. Utilizing administrative data from Texas offers a number of advantages over alternate data sources and a few disadvantages. The primary benefit is that the data is both accurate and highly granular. Due to aspects of the UI system like waiting periods, part-time work allowances, and variable claim amounts, 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 starkly incorrect results. Moreover, possessing data on the entirety of the population of the UI system allows us to precisely calculate the distribution of indiv-duals currently receiving UI with regards to the number of weeks remaining they are eligible for. In addition, we are able to use relatively fine locational data to match to MSA-specific search trends, whereas other data sources are often restricted to state or Census region level analyses.

The main downside of focusing on Texas is a narrowing of the scope of analysis and that we lose some variation in the timing of the UI expansions that we are focusing on. While the timing of the expansions differed across states according to the unemployment rates, it did not differ within state. However, we are able to use variation in the composition of the UI recipient population by using the panel of data across MSAs in Texas. While we focus on a single state, it has the benefit of being the second most populus state in the United States with a wide range of unemployment rates across its various MSAs and regions.

The data covers a number of important demographic and economic characteristics for individual UI recipients. We observe an individual's age, gender, and zip code of residence. We utilize this locational data to assign individuals to MSAs and match them to the Google Search data. We also observe a recipient's tier of benefits, received retroactive payments, weekly eligible benefit amount, and weekly amount received. The latter two variables can differ if a claimant works part time, which can offset some of his UI benefits and lengthen a claimants' UI spell. Using the Texas data in conjunction with details of the UI legislation in effect at the time, we calculate how many weeks of eligibility recipients had remaining in their spell before their benefits expired.

Figures 6 displays the evolution of the UI system in Texas over time. Figure 6 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 rise was in concert with the overall rise in the unemployment rate in Texas during the same period, though it is important to recall that not all unemployed individuals receive unemployment insurance during their job loss spell.

Following Rothstein (2011), we study the effects of the potential UI duration under two different sets of assumptions. Under Assumption 1 (A1), we assume that UI recipients expect UI expansions to be extended indefinitely (such that the current policy lasts indefinitely). Under Assumption 2 (A2), we assume that UI recipients expect UI expansions to expire according to current law with no additional laws passed. We refer to these assumptions as a 'current policy' assumption and a 'current law' assumption, respectively. A sample trajectory of maximum number of weeks eligible for all new UI recipients under the two assumptions is displayed in Figure 4. The practical difference in these assumptions is evident in Figure 5 which shows the average expected remaining duration of UI benefits under each assumption. For some weeks in 2009, the average expected remaining duration differs by over 30 weeks.

Under the 'current policy' assumption, recipients only look at the current number of weeks of unemployment insurance that they are eligible for and project that forward. Under the 'current law' assumption, individuals look at current eligibility and also note the expiration date on the legislation, which can often cut short an individuals' benefits. Figure 4 displays the path over time of the total number of weeks an individual would be eligible for had they started a new UI spell in a given week. For 'current policy' recipients, we see a simple stepwise function that increases with each new piece of legislation passed or Extended Benefits threshold met and then plateaus at 93 weeks in late 2009.

In contrast, 'current law' recipients see a much different path and expect about 40-50 weeks of UI benefits through late 2010. Figure 4 show that the difference in expected maximum eligibility time 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, allowing individuals to enjoy their extended benefits for a much longer period of time. We see evidence of a substantial population of more sophisticated UI recipients who understand the nuances of the cutoff dates for the EUC program. For example, one popular forum about unemployment and unemployment benefits, found at www.city-data.com, has a large number of posts regarding the UI and EUC programs in general, and about Texas unemployment insurance in particular. Figure 7 shows a response to a question about extended benefits being answered within hours and in great detail by a user that has answered several thousand questions about unemployment benefits. Importantly, the user's posts have been read millions of times. Forum activity shows at least a subset of individuals receiving UI benefits are well aware of the cutoff dates they face and are not just responding to the headline number of weeks of eligibility.

Figure 5 presents this discrepancy in a different way, looking at the average number of weeks left an individual expects under both the 'current law' and 'current policy' assumptions. The sudden jumps and continuous declines under the 'current law' assumption mirror the timing of multiple short-term extensions, characteristic of the divisive policy-making during the recession. Each extension of EUC is explained in more detail in Table 3. Figures 4 and 5 demonstrate the importance of assumptions when thinking about the responsiveness of individuals to changes in benefit length. While under the 'current policy' assumption, UI recipients see little change in the number of weeks left during 2010, 'current law' recipients see large changes driven by extensions in the EUC program, potentially driving large changes in job search behavior.

The administrative data makes apparent the fact that a large proportion of individuals do not use UI in the straightforward manner that many policymakers and researchers assume. The 'standard' use of UI may be 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. We observe divergences from this timeline at every step by significant numbers of individuals. We observe individuals having no observed income for a number of quarters before applying for UI. We see individuals consistently working part-time (seen in Figure 8 during their entire UI spell and thus greatly extending the actual length of the spell or going without UI for several weeks until they are granted large lump-sum retroactive payments. We also see individuals exiting UI early but not receiving observable income for a number of 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 vast majority of current UI research and policy discussions.

6 The Effect of Potential UI duration on Job Search Intensity

In previous sections we have shown that the GJSI represents a valid measure of aggregate job search. However, if we want to understand the contributions made to the index by different types of searchers, we need to explicitly model the manner in which the GJSI is constructed. Previous work using Google Search data has not modeled the underlying individual level behavior which generates the data. We are the first to show that in order to infer some types of paramaters from the Google Trends data, a different estimation technique is needed.

First, consider the following illustrative example. Suppose that there are two types of job searchers, those that are employed and those that are not. Then the observed measure of job search from Google would be equivalent to:

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

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

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

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

The first assumption states that all types of individuals do not systematically differ in overall search demand. It is unlikely that this assumption will hold precisely, but we have few strong priors on the direction of the difference in overall search behavior. We might expect that the unemployed might use Google more because they are sitting at home on their computers all day. Alternatively, we might expect the employed to use Google more because they are working at a computer. However, all that is necessary for our identification strategy to produce results with little bias is that any systematic differences in overall search behavior by type are dwarfed by differences in job search activity. We also conducted 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 can derive the following equation:

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

Equation (2) can easily be translated into the following estimation equation where each observation is an MSA-week:

$$\log JS_{mt} = \beta_{0m} + \beta_{1m} t + \beta_{2t} + \log(\gamma_E N_{Emt} + \gamma_U N_{Umt}) + \epsilon_{tm} \tag{3}$$

β_{0m} is an MSA specific fixed effect, β_{1m} is an MSA specific time trend (to account for differential trends in internet usage by MSA) and β_{2t} are time fixed effects. We proceed by by estimating equation (3) in several specifications which vary the amount of job searcher heterogeneity. The error term in the above equation represents MSA-time specific fluctuations in job search. Such fluctuations can be caused by other unobserved drivers of search such as MSA specific weather changes or Google's sampling error.

We must also worry about the endogeneity of our estimates. Our identifying assumption is that MSA specific returns to job search are uncorrelated with high frequency changes in the composition of job seekers in that MSA. Suppose that firms drastically increase recruiting in an MSA at the same time that more people's benefits are about to expire in that MSA. 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 MSA because of higher returns to search. We have no direct evidence on MSA specific recruiting intensity. However, the correlation between the JOLTS vacancies series and our search measure is negative rather than positive. Further, 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.

6.1 National Results

We first present results using CPS data across all states before turning to more detailed administrative UI data from Texas. During the recession, states' labor forces underwent very different patterns of unemployment. Due to the structure of federal extended benefits and the EUC program, where various levels of state-level unemployment rates unlocked additional weeks of unemployment insurance benefits, states had different amounts of weeks of benefits available at any given time. We follow Rothstein (2011) in constructing a panel of individuals on unemployment insurance across states and over time from CPS data, using repeated survey observations and data on job loss reasons to distinguish between lengths of UI spells and eligibility for unemployment insurance, respectively.

Table 4 shows results from both an OLS and NLLS analysis using CPS state-level data. In general, we find negative effects of a UI expansion on job search, measured by the GJSI, within a state. Moreover, we find positive effects of increasing numbers of unemployed individuals in a state on job search. When interacting expansions in the UI system with the number of individuals on UI or those who are close to expiration, we see that search drops more in states with larger fractions of the population on unemployment insurance or who are nearing expiration. Columns (4) and (6) break down the population of UI recipients further, generally finding greater search among those who are relatively closer to expiration, as theory would predict. However, for those nearest to expiration we find no significant effect. This may be due to issues arising from systematic measurement error when using the CPS to estimate the number of remaining weeks of UI an individual still has.

The CPS data has a number of shortcomings that lead us to prefer the administrative data from the Texas Workforce Commission. The primary problem with the CPS is it's small sample size, with the CPS often containing fewer than 10 individuals in a given state-month observation. Further, over 50% of state-month observations contain fewer than 18 individuals who are unemployed and seem eligible for UI. Due to this small sample size, the CPS is even less useful for inferring the distribution of the unemployed in terms of the number of weeks remaining in their UI spells. We are forced to construct measures of number of weeks of UI that individuals have used based on maximum UI eligibility in a state even though the eligibility of individuals for UI is very heterogeneous in practice.[7] We must therefore conclude that estimates of job effort response to UI based on CPS data are likely to be biased and lacking in statistical power in comparison to results using administrative UI data from Texas.

[8]In the administrative data from Texas, over 50% of individuals claiming UI are eligible for fewer weeks than the state's statutory maximum

6.2 Texas Results

In Table 5 we turn to results from administrative Texas UI data using the NLLS specification guided by the unique method used to construct Google Job Search Index (OLS results of equivalent procedure describe in Appendix Table 3). We find that the log of the GJSI is related to the total level of unemployment in an MSA. In specifications (1) and (2) we also controlled for indicators for the four weeks after a policy change. When controlling for seasonality and year effects in column (2), we find a negative albeit insignificant effect of the policy changes. In contrast, column (3) finds a strong negative effect on search when restricting the policy change indicator to be equal to one following only expansions in the number of available weeks of UI benefits, thus excluding legislation that merely extended the current benefit regime.

Table 6 estimates a nonlinear least squares (NLLS) model based on equation (3) in which there are three types of job seekers: those on UI, those not on UI and those that are employed. Our preferred specification is displayed in column (5), including year-month dummies as well as an indicator for the four weeks following UI legislation. There are three interesting results to note in this table. First, the coefficient on the number of individuals on UI is approximately 15% smaller than the coefficient on the number of unemployed individuals not on UI. This corroborates previous findings by Krueger and Mueller (2011) and standard models of moral hazard from UI that predict less search among those unemployed who are receiving UI benefits. Secondly, those that are employed search less than one tenth as much as those that are unemployed. Lastly, there is a further drop of search effort of approximately 2.5-3% in the 4 weeks following a policy change. This effect is in addition to the decrease in search caused by shifting individuals from unemployment to UI and prolonging UI spells due to expanded UI eligibility. Together, the above results strongly suggest that there was a significant effect of UI policy changes on the job search of unemployed individuals during the recession. It is also important to note that our results probably understate the immediate effect of policy change on job search activity because some individuals anticipated the changes ahead of time.

Tables 7 and 8 estimate the effect of potential weeks left on job search intensity under the assumption of 'current law' and 'current policy' UI recipients respectively. In Table 7 we see that MSAs that have more UI recipients with 0 to 10 weeks left of benefits experience more job search. In our preferred specification in column (5), with month-year fixed effects, the coefficient on an individual having less than 10 weeks left is more than twice as large as the coefficient on the number of individuals with 10 to 20 weeks left. Individuals with higher numbers of potential weeks search even less. Figure 9 displays the coefficients from a NLLS regression with a full set of weeks-left bins, confirming a higher level of search nearer to UI expiration and a flat level of search with more than 15 weeks of benefits left.

If we instead assume that individuals project the 'current policy' about potential UI durations, then the estimates fail to show the expected pattern of job search, as seen in Table 8. In our preferred specification (3) 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, most of the results 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.

7 Conclusion

This paper develops a new measure of job search from Google search data that is easily adaptable to high-frequency analysis across geographical areas and is freely available to researchers. We benchmark the GJSI to a number of alternate measures of job search activity, finding a close correlation, and then show how use it to extract economically meaningful parameters.

Using administrative UI data from Texas, we show that individuals with 0-10 weeks of UI left search more than 2 times more than individuals with more remaining weeks of benefits. Furthermore, we show that job search dropped by over 2% in the four weeks after policy changes which extended or expanded UI benefits. Our identification strategy uses high frequency variation in both the composition of the unemployed as well as the precise timing of expansions to the UI system which caused large changes in the weeks until benefit exhaustion for UI recipients.

We find significant effects of UI policy expansion and UI benefit exhaustion in driving search effort among individuals. However, according to estimates of the elasticity of UI exit rate to job search (eg. Krueger and Mueller (2011)), even a doubling of search time yields little change in job-finding rates. Thus, although we do not simulate the full counterfactual trajectories of UI in the absence of extensions, other estimates of job-finding rate elasticities imply that the partial equilibrium effects of the decreased job search due to UI expansions are economically small. Our 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.

However, there are scenarios in which our estimates could correspond to a meaningful change in the overall unemployment rate. For example, if less job search led to a slower or less efficient sorting of workers to jobs, then the general equilibrium effects of decreased job search could be much higher than the partial equilibrium effects. Alternatively, the intensive vs extensive margin might be very important for job search. It could be that the first several hours of job search yield very high returns while the rest do not. In that case, it would be important to know whether the effects we've estimated are due to the same people searching less or due to some people quitting search altogether. We leave the modeling of such effects for future work.

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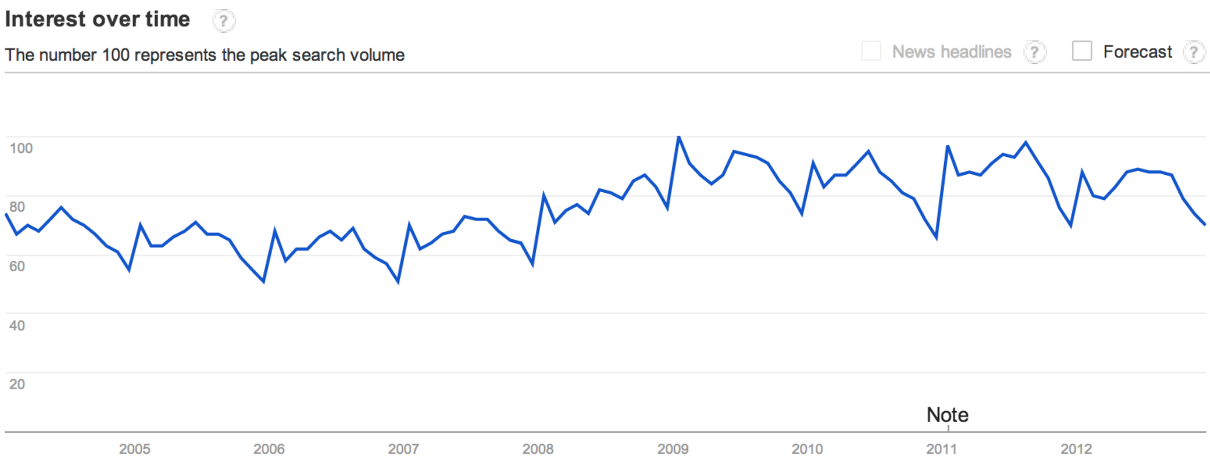

Figure 1: Google Trends Example Search

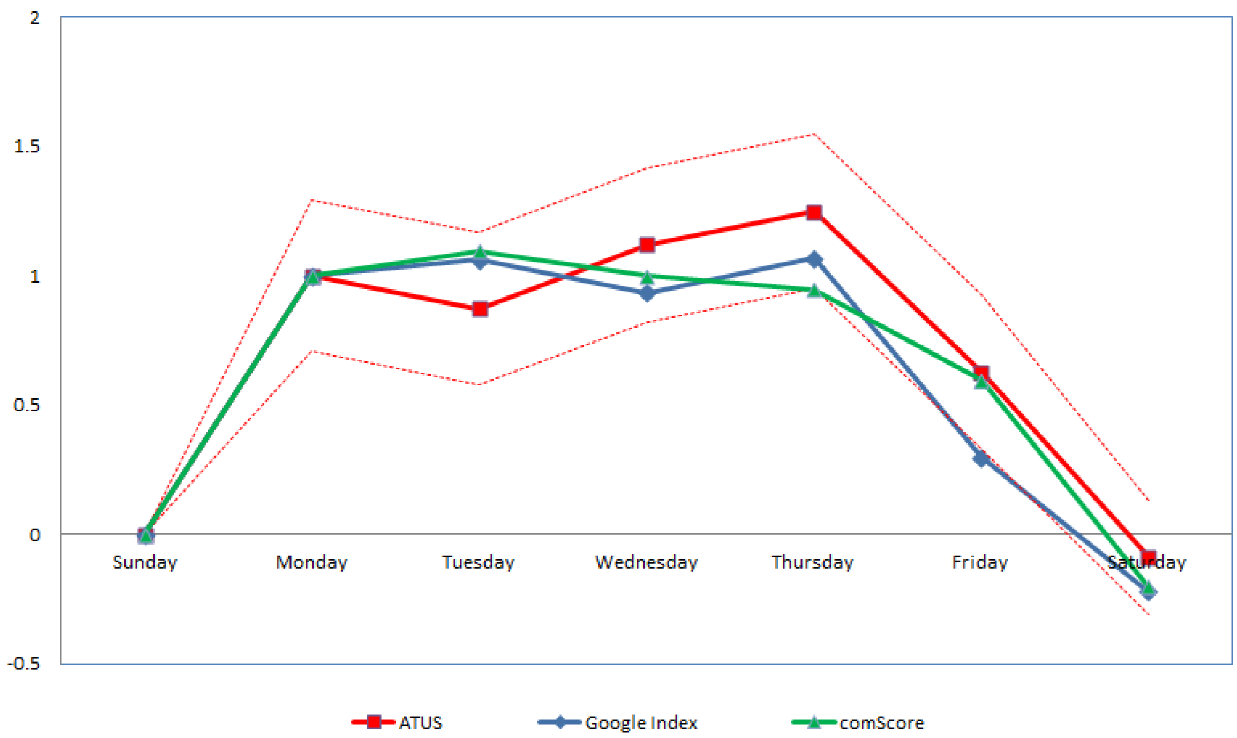

Figure 2: Day of Week Fixed Effects

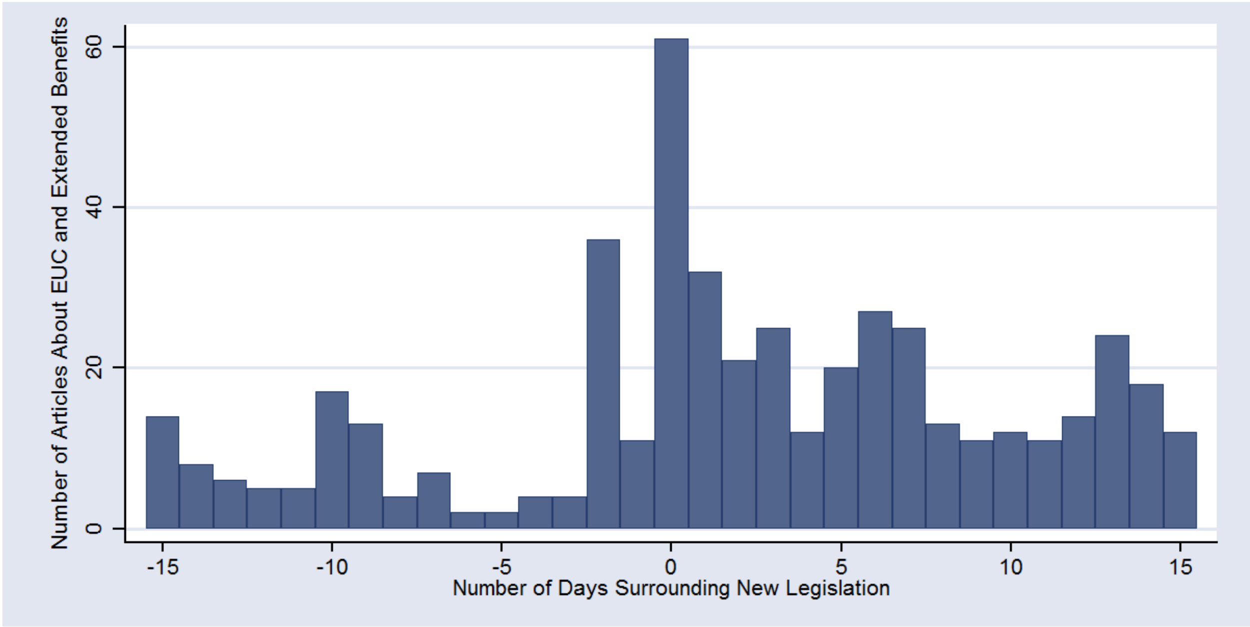

Figure 3: Number of News Articles Regarding EUC

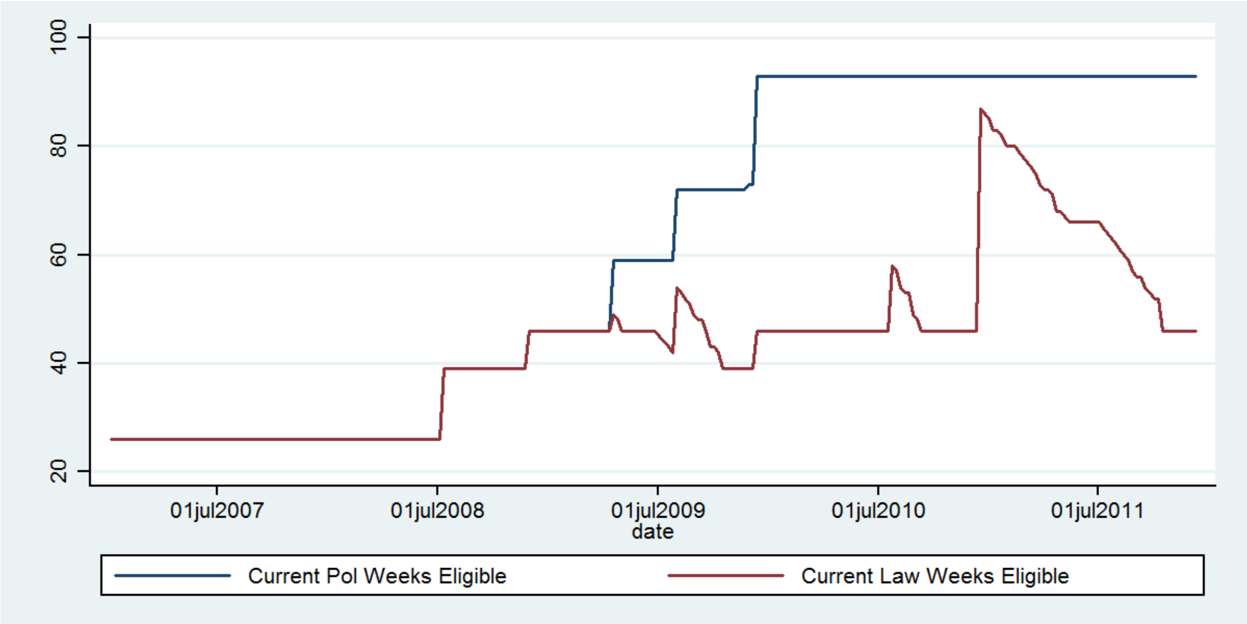

Figure 4: Weeks Eligible for New UI Recipients by Type

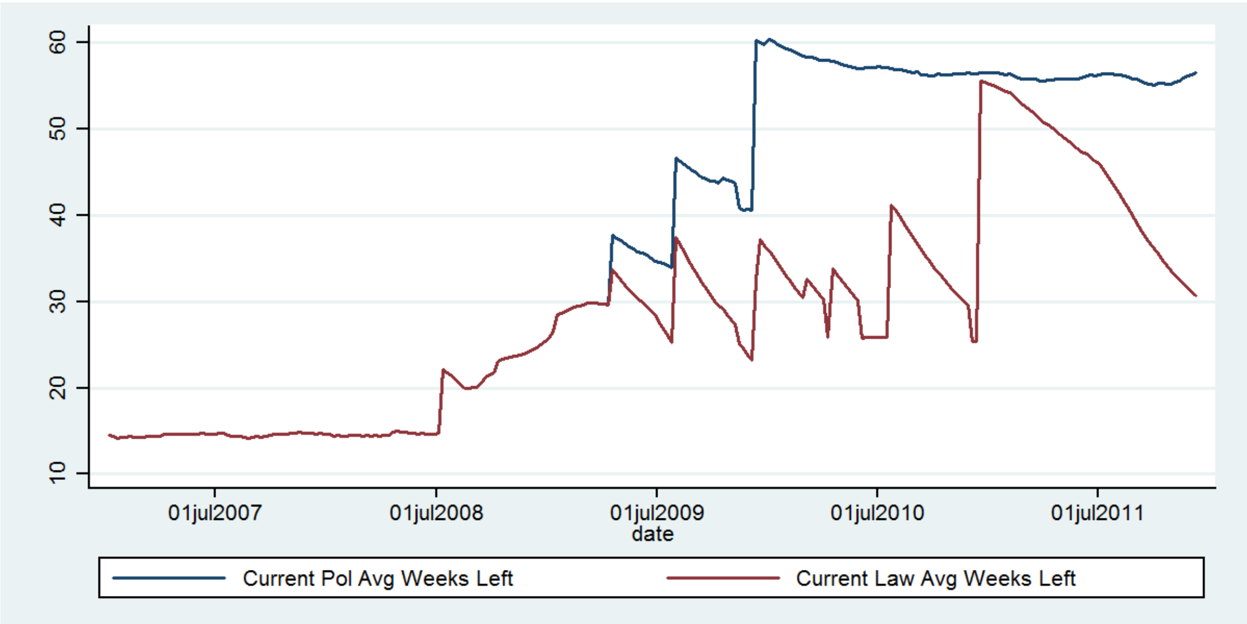

Figure 5: Average Weeks Left by Type

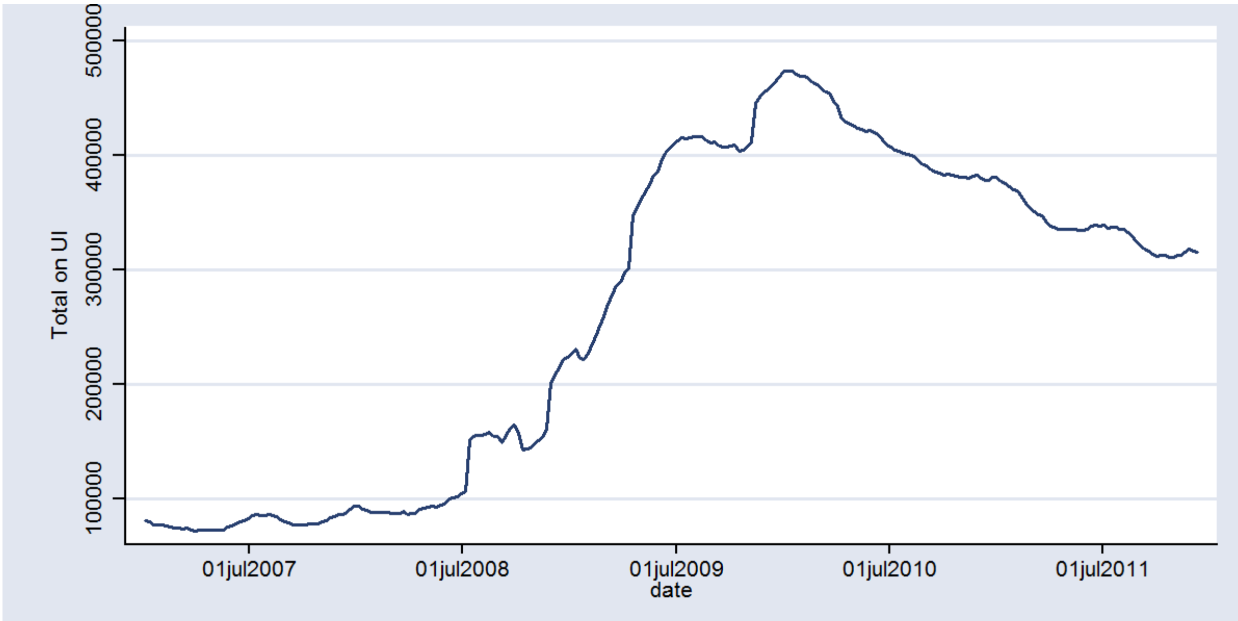

Figure 6: Total Number on UI


08-11-2012, 05:18 AM

[redacted] Original Poster

Location: Fort Worth, Tx
11 posts, read 5,985 times
Reputation: 11

Am I able to file for more benefits if I have exhausted all my benefits in this year?

I was wondering if anyone had any experience with this... I have just been told that I've exhausted all the benefits that I will be getting for this claim year. Is it possible to file a claim for more benefits even if this year isn't over yet? Or is there not any chance for receiving more benefits? I live in TX and was laid off last November and have been unemployed this then. It's my first time to claim unemployment. This job market bites (as I'm sure most of you know)...

Rate this post positively

Quote

08-11-2012, 11:52 AM

[redacted]

Location: Wisconsin
8,446 posts, read 7,109,021 times
Reputation: 3472

It has been about 35 weeks since your unemployment began. Normal state benefits do not exceed 26 weeks. In Texas, federal benefits can add another 34 weeks to that.

We need to know:

1. What is the exact date of your original claim?
2. What is the amount of your original monetary determination?
3. When did you first begin to receive benefits?
4. How much were you paid per week?
5. For how many weeks?

Texas is still paying federal Tier 1 for 20 weeks and Tier 2 for 14 weeks. Current data from TX on federal extensions is here:

http://www.twc.state.tx.us/ui/bnfts/...ionalweeks.pdf

All federal benefit payments end 12/29/2012.

If you had a small claim, it is possible you have exhausted both your state and any available federal benefits by now. If that is the case, you will need to work again and earn sufficient earnings to qualify for another new claim.

You should also read FAQS, posts 2 and 6: Unemployment FAQs

Figure 7: Sample Forum Post Explaining Extended Benefit System

Figure 8: Part Time Work

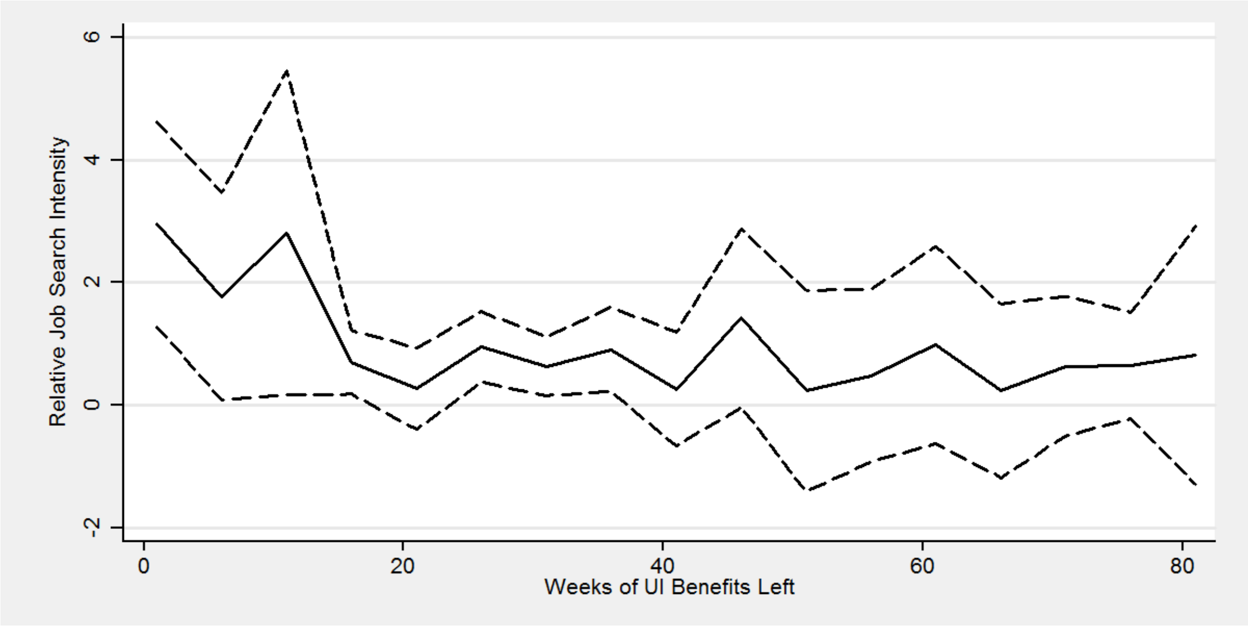

Figure 9: Effect of Number of Weeks Left of UI on Job Search Intensity

Table 1: ATUS Search Time Correlation

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Search Time	Search Indicator	Search Time	Search Indicator	Search Time
log(JSI)	0.327***	0.00277***	3.830***	0.0171*	
	(0.0284)	(0.000182)	(0.845)	(0.00906)	
Google Weather Search					-0.0523
					(0.499)
Observations	3,541	3,541	3,541	3,541	3,541
Year FE	NO	NO	YES	YES	YES
Month FE	NO	NO	YES	YES	YES

Robust standard errors in parentheses

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

Log(GJSI) is the log of the Google Job Search Index. ATUS Search Time is the average number of minutes per day respondents report that they spent on job search in a given state-month. The ATUS Job Search Indicator gives the average fraction of individuals engaging in any level of job search in a given state-month. Standard errors clustered at a state level.

Table 2: Empirical Tests of Google Job Search Measure

VARIABLES	(1) Δ Jobs Search	(2) Δ Jobs Search	(3) Δ Jobs Search	(4) Δ Jobs Search	(5) Δ Jobs Search
Change in Unemp Rate	1.345***	1.080***	1.285***	1.296***	
	(0.253)	(0.258)	(0.263)	(0.263)	
Change in Init. Claims Per Cap		3.488***	3.514***	3.489***	3.495***
		(0.534)	(0.529)	(0.532)	(0.529)
Next Month Final Claims Per Cap			2.913**	2.887**	2.818**
			(1.146)	(1.147)	(1.158)
Change in Vacancies				54.90	
				(69.86)	
Change in Tightness					0.0116***
					(0.00333)
Observations	3,395	3,395	3,293	3,293	3,293
R^2	0.754	0.758	0.766	0.766	0.766
Year FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES

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

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

Table 3: 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: Effects of UI Expansions and Composition by State

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	NLLS (5)	NLLS (6)
UI Expansion	-0.0164***	0.0173	-0.00427	-0.0175***	-0.01274**	-0.0138**
	(0.00531)	(0.0160)	(0.00858)	(0.00550)	(0.00614)	(0.00523)
Fraction on UI	0.646**	0.950***	0.674**		1.0032***	
	(0.287)	(0.285)	(0.308)		(0.3285)	
Frac on UI*Expansion		-2.018**				
		(0.817)				
Frac Near Expir*Expansion			-3.967**		-0.70182	
			(1.793)		(1.0713)	
Frac Under 10 Weeks Left				0.831		0.0308
				(0.574)		(0.1103)
Frac 10-19 Weeks Left				2.797***		0.3233***
				(0.552)		(0.0893)
Frac 20-29 Weeks Left				0.741*		0.1751**
				(0.406)		(0.0780)
Frac 30-39 Weeks Left				1.328***		0.0914
				(0.384)		(0.0653)
Frac 40-49 Weeks Left				0.775		0.1297
				(0.574)		(0.0856)
Frac 50-59 Weeks Left				-0.0911		0.1910
				(0.887)		(0.1449)
Frac 60-69 Weeks Left				-0.249		-0.0987
				(0.990)		(0.1579)
Frac 70 or more Weeks Left				-2.019		0.01726
				(2.310)		(0.1298)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.649	0.650	0.650	0.652	0.628	0.632
Observations	4182	4182	4182	4182	4182	4182

Standard Errors Clustered at state level.

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

Table 5: Effect of UI Expansions on Job Search

	(1)	(2)	(3)	(4)
Four Wks Post Expansion			-0.0433***	
			(0.0108)	
Four Wks Post Legislation	-0.0314***	-0.0117		
	(0.00642)	(0.00700)		
Unemp. Rate	0.0996***	0.0602***	0.0610***	0.0361
	(0.0102)	(0.0118)	(0.0116)	(0.0233)
MSA FE and Trend	Yes	Yes	Yes	Yes
Year and Month FE	No	Yes	Yes	No
Week-Year FE	No	No	No	Yes
R-Squared	0.648	0.706	0.707	0.755
Observations	4527	4527	4527	4527

Standard Errors Clustered at MSA level.

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

Table 6: Effect of UI Status on Job Search

	(1)	(2)	(3)	(4)	(5)	(6)
Number on UI	1.097***	0.652***	0.649***	0.601***	0.616***	
	(0.120)	(0.113)	(0.117)	(0.154)	(0.157)	
Not on UI	1.301***	0.593***	0.592***	0.728***	0.732***	
	(0.0846)	(0.0780)	(0.0783)	(0.148)	(0.150)	
Number Employed	0.0260***	0.0533***	0.0533***	0.0526***	0.0536***	
	(0.00467)	(0.00692)	(0.00690)	(0.00949)	(0.00981)	
Post Legislation			0.00190		-0.0261***	-0.0275***
			(0.00904)		(0.00640)	(0.00645)
Unemployed/Employed	50.04	11.14	11.11	13.85	13.65	
UI/Non-UI	0.843	1.100	1.096	0.826	0.841	
MSA FE and Trend	Yes	Yes	Yes	Yes	Yes	Yes
Year and Week FE	No	Yes	Yes	No	No	No
Year-Month FE	No	No	No	Yes	Yes	Yes
R-Squared	0.646	0.725	0.725	0.721	0.721	0.711
Observations	4527	4527	4527	4527	4527	4527

Standard Errors Clustered at MSA level.

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

Table 7: Effect of UI Duration on Job Search

	(1)	(2)	(3)	(4)	(5)
0-10 Weeks Left	1.525***	0.936**	0.962***	1.454***	1.440***
	(0.402)	(0.401)	(0.289)	(0.497)	(0.459)
10-20 Weeks Left	1.633***	0.747***	0.740***	0.689***	0.672***
	(0.214)	(0.130)	(0.166)	(0.164)	(0.207)
20-30 Weeks Left	1.126***	0.766***	0.755***	0.648***	0.645***
	(0.113)	(0.109)	(0.145)	(0.139)	(0.188)
Over 30 Weeks Left	1.136***	0.598***	0.574***	0.596***	0.623***
	(0.134)	(0.100)	(0.117)	(0.131)	(0.172)
Not on UI	1.308***	0.611***	0.604***	0.724***	0.731***
	(0.0729)	(0.0857)	(0.0791)	(0.118)	(0.161)
Number Employed	0.0251***	0.0528***	0.0529***	0.0525***	0.0532***
	(0.00441)	(0.00683)	(0.00706)	(0.00727)	(0.0105)
Post Legislation			0.0121		-0.0213**
			(0.00906)		(0.00778)
MSA Trend and FE	Yes	Yes	Yes	Yes	Yes
Year and Week FE	No	Yes	Yes	No	No
Year-Month FE	No	No	No	Yes	Yes
R-Squared	0.649	0.726	0.726	0.722	0.722
Observations	4527	4527	4527	4527	4527

Standard Errors Clustered at MSA level.

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

Table 8: Effect of UI Duration on Job Search - Naive Beliefs

	(1)	(2)	(3)	(4)
0-10 Weeks Left	0.0800	0.369	0.486	0.486
	(0.537)	(0.395)	(0.523)	(0.525)
10-20 Weeks Left	2.656***	0.396	1.311**	1.316**
	(0.747)	(0.411)	(0.602)	(0.608)
20-30 Weeks Left	2.361***	1.553***	1.706***	1.721***
	(0.347)	(0.302)	(0.424)	(0.524)
Over 30 Weeks Left	1.085***	0.584***	0.551***	0.555***
	(0.136)	(0.104)	(0.149)	(0.152)
Not on UI	1.317***	0.600***	0.701***	0.700***
	(0.0755)	(0.0851)	(0.129)	(0.131)
Number Employed	0.0244***	0.0542***	0.0572***	0.0574***
	(0.00452)	(0.00673)	(0.00816)	(0.00850)
Post Expansion		-0.0198	-0.0496***	-0.0495***
		(0.0119)	(0.0152)	(0.0152)
New UI Claimants				-0.0217
				(0.317)
MSA Trend and FE	Yes	Yes	Yes	Yes
Week FE	No	Yes	No	No
Month-Year FE	No	No	Yes	Yes
R-Squared	0.651	0.726	0.724	0.724
Observations	4527	4527	4527	4527

Standard Errors Clustered at MSA level.

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

Appendix A

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

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

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

The dependent variable is the total minutes spent by a household on job search for a day. The independent variable is the amount of job sites visited that were referred to by Google search. Job search time is given by time spent on websites related to job search, career building, etc. Specifications are in order without fixed effects, with state fixed effects and with day fixed effects. All numbers taken from 2007 comScore data.

Table 2: Day of Week Fixed Effects for Google, ComScore, and ATUS

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Google JS	Google JS	ATUS JS	ATUS JS	comScore JS	comScore JS
Monday		0.237***		0.0902***		0.111***
		(0.00231)		(0.0134)		(0.00427)
Tuesday		0.251***		0.0689***		0.132***
		(0.00238)		(0.0136)		(0.00430)
Wednesday		0.223***		0.0999***		0.119***
		(0.00233)		(0.0136)		(0.00431)
Thursday		0.169***		0.112***		0.106***
		(0.00232)		(0.0137)		(0.00430)
Friday		0.0709***		0.0560***		0.0623***
		(0.00206)		(0.0137)		(0.00430)
Saturday		-0.0527***		-0.00747		-0.0172***
		(0.00169)		(0.0102)		(0.00429)
Holiday	-0.148***	-0.147***	-0.0497*	-0.0533*	-0.0659***	-0.0664***
	(0.00444)	(0.00397)	(0.0278)	(0.0280)	(0.00629)	(0.00631)
Weekend	-0.217***		-0.0891***		-0.115***	
	(0.00205)		(0.00725)		(0.00256)	
Observations	111,152	111,152	76,087	76,087	18,615	18,615
Year FE	NO	NO	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES

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

'Google Search' refers to the logged value of the GJSI. 'ATUS Job Search' refers to the logged number of minutes of time spent on job search for each ATUS respondent. 'comScore Job Search' refers to the logged number of minutes online job search per capita as measured by comScore. Holiday is an indicator equal to one if the ATUS diary day or the GJSI day was a holiday. Each day represents an indicator equal to 1 if the ATUS diary day was the given day of the week. Weekend is an indicator equal to one if the ATUS diary day was a Saturday or Sunday. Specifications include differing fixed effects because of the differing nature of each dataset. All include, at a minimum, state and time fixed effects. Google data necessarily utilizes Season-State fixed effects, while we use finer time fixed effects with the ATUS and comScore data.

Table 3: Effect of UI on Job Search - OLS

	(1)	(2)	(3)
Post Legislation	-0.0145*	-0.0275***	-0.0219**
	(0.00768)	(0.00630)	(0.00804)
Frac Employed	-0.898	-0.0888	-0.253
	(0.933)	(1.008)	(1.013)
Frac Not on UI	19.11***	5.705	5.132
	(2.067)	(4.630)	(4.529)
Frac On UI	18.27***	5.750	
	(1.753)	(4.779)	
Frac Under 10 Wks Left			23.01**
			(8.727)
Frac 10-19 Wks Left			5.480
			(5.508)
Frac 20-29 Wks Left			5.713
			(4.907)
FracOver 30 Wks Left			4.779
			(4.833)
MSA Trend and FE	Yes	Yes	Yes
Year-Month FE	No	Yes	Yes
R-Squared	0.656	0.727	0.728
Observations	4527	4527	4527

Standard Errors Clustered at MSA level.

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

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

Subsample of ATUS respondents is taken to match the demographic subsample used by Krueger and Mueller (2011). 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: Google Search Term Correlations

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