Look Who's Searching: Revisiting Unemployment and Labor Market Flows*

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Abstract

The unemployment rate is the most used single indicator of labor market conditions, but its measure is black and white, lacking any notion of intensity. This paper introduces a continuous unemployment rate; a measure in which people are weighted by their relative search effort. The measure of relative search effort is a monthly probability of exerting search effort, estimated from the American Time Use Survey. The paper delivers a continuous unemployment rate, as well as adjusted labor market flows, for the United States from 1980 onward. On average, the continuous unemployment rate is 4.8 percentage points higher than the standard unemployment rate and recovers slower after every recession since 1990. While the participation margin accounts for 40% of the volatility of the standard unemployment rate, it accounts for only 16% of the volatility of the continuous unemployment rate. The continuous unemployment rate displays a strong negative correlation with nominal wage growth and inflation and is a better predictor of both than the standard unemployment rate.

Keywords: Unemployment, Labor Force Participation, Worker Flows, Business Cycles

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1 Introduction

Summarizing a complex system, such as the labor market, in one comprehensive statistic, is a daunting task. For decades, the most undisputed candidate for this statistic has been the unemployment rate. Over 120 years after the first attempts to measure unemployment at a national level, Federal Reserve Chair, Janet Yellon, stated "the unemployment rate is probably the best single indicator of current labor market conditions."[1] Despite being the most influential statistic in assessing the health of the labor market, the modern concept of unemployment in the United States has remained unchanged since 1940, when unemployment was first alined with the notion of active job search.[2]

Today, a person is considered as unemployed if they are available to work and have had at least one active search attempt in the last 4 weeks. This discrete view of labor market attachment implies that all unemployed people contribute with equal weight to the unemployment rate. In reality, the degree of attachment to the labor market varies across individuals. Some people may be searching for only part time work or accept only jobs with only certain characteristics, while others may be searching broadly and accept any job offered to them. People differ in terms of their labor force attachment or unemployment intensity. The current measure of unemployment lacks any notion of intensity – a concept widely accepted when measuring employment as total hours worked or full time equivalents.

In this paper, I create a new continuous unemployment rate, in which people are weighted by their relative search intensity. The measure of search intensity is a monthly probability of exerting search effort, estimated from the American Time Use Survey. All non-employed individuals contribute to the continuous unemployment rate and those with higher search probabilities enter with more weight. I argue that the estimated search intensity is a predictor of labor force attachment by showing that search intensity is positively correlated with the job finding probability, subsequent hours worked and the probability of full time employment. Along with the continuous unemployment rate, I also construct a measure of total search effort in the economy, i.e., including those searching while employed, and adjusted labor market flows.

I show three empirical differences between the discrete measure of unemployment and the continuous measure of unemployment. First, the continuous unemployment rate is on average 4.8 percentage points higher than the standard unemployment rate and is nearly half as volatile as the standard unemployment rate. By the end of 2017, the standard unemployment rate had fallen about 0.4 percentage points below its pre-2008 recession minimum, whereas the continuous unemployment rate remained nearly 1 percentage point above its pre-2008 recession minimum. This discrepancy is attributed to the

[1]Yellen, Janet L. Speech at the 2013 National Association for Business Economics Policy Conference. www.federalreserve.gov/newsevents/speech/yellen20130302a.htm

[2]See Card (2011) for a brief history of the theory and measurement of unemployment.

cyclicality of search effort. Similar to previous research, Kudlyak and Faberman (2014) and Mukoyama et al. (2018), I show that search effort is countercyclical. During recessions, people increase their search effort, making it more likely for less attached individuals to enter the official unemployment statistics in bad times. As the economy begins to recover, people decrease their search effort and less attached individuals fall out of the official unemployment statistics, despite potentially having a positive job finding probability. I show that for this reason, the participation margin contributes 40% to the variation of the standard unemployment rate, whereas it contributes only 16% to the variation of the continuous unemployment rate.

The increase in the level of the continuous unemployment rate is no surprise in light of the fact that nearly 70% of new hires every month are people who were previously classified as out of the labor force. In 2017, an average of 4.1 million hires per month came from out of the labor force, that is nearly 2.5 times as many hires as from unemployment.[3] The level of any statistic used to asses the health of the labor market is, in general, not as important as it is for that statistic to be comparable over time, and across space. Unfortunately, this is not the case with the standard unemployment rate. The percent of people classified as out of the labor force who are actively seeking a job was about 9.5% in 1980 and increases rapidly in every subsequent recession, reaching over 12% in 2017. This upward trend in search effort from individuals who are classified as out of the labor force can account for about 1 percentage point (25%) of the decrease in labor force participation rate since 2000.

Second, I show that the adjusted labor market flows are substantially different than the standard flows calculated from the matched Current Population Survey (CPS). Matching individuals across consecutive months to calculate transition probabilities had become the standard in calculating labor market flows and these flows are published monthly by the Bureau of Labor Statistics. The most notable difference is along the unemployment/non-participation margin. The standard flows suggest that the probability a person leaves unemployment for non-participation (0.21) is nearly as large as the probability he leaves for employment (0.25). The adjusted flows show that the unemployment exit rate to non-participation is only 0.05, implying that unemployment is a more persistent.

Several papers have tried to understand the large oscillations between unemployment and non-participation. Using the reinterview surveys conducted by the CPS, Abowd and Zellner (1985) and Poterba and Summers (1986) show that the largest margin of misclassification is along the unemployment/out-of-the-labor-force margin; however, their adjustments decrease the flow from unemployment to out of the labor force by half and it remains 50% higher than the flow found here. Similarly, Elsby et al. (2015) correct labor market transitions to get ride of oscillations between non-participation

[3] Fujita et al. (2019) show that the number for the hires from employment are downward biased by a change in the current population Survey that occurred between 2007 and 2009.

and unemployment, but conclude that unemployment to non-participation exit rate remains above 0.1. These large and volatile movements between unemployment and non-participation are difficult to match using standard calibrations of search and matching models (Garibaldi and Wasmer, 2005). More recently, Krusell et al. (2017) show that the only way to match such large movements into and out of the labor force is through relatively large transitory shocks to the disutility of search effort.[4] I argue that, unless matching a distribution of labor market flows, a more accurate aggregate flow target is the continuous measure presented here.

Third, I show that the negative correlation between nominal wage growth and inflation growth is stronger for the continuous unemployment rate than the standard unemployment rate. It is well documented that the relationship between inflation and labor market slack has weakened over the past two decades Roberts (2006), the phenomenon referred to the flattening of the Philips Curve. Many explanations of this empirical fact have been proposed (Coibion and Gorodnichenko, 2015; McLeay and Tenreyro, 2019; Galí and Gambetti, 2019). However, I show, using a simple OLS specification, that the correlation between the continuous unemployment rate and nominal wage growth remains strongly negative since 1980 and is a better predictor than the standard unemployment rate. In fact, the correlation between the total searcher rate (including employed search effort) and nominal wage growth is even more negative and an even better predicted than the continuous unemployment rate. This suggests that the flattening of the Phillips curve may in part be driven by unemployment rate becoming a less accurate measure of the health of the labor market since 1980.

There exist two empirical challenges when attempting to create a consistent aggregate labor market statistic. First, long run trends in the demographic composition of the pool of job seekers make the standard unemployment rate hard to compare across time. Many papers have worked to ride the standard unemployment rate of this bias (Perry, 1970; Flaim, 1979; Shimer, 2001; Barnichon and Mesters, 2018), finding that demographic changes decreased the unemployment rate by 1.2-2.2 percentage points since 1980. Second, the misclassification errors pointed out by Abowd and Zellner (1985) and later explored by Feng and Hu (2013) and Ahn and Hamilton (2019), suggest that the true unemployment rate may be somewhere between 2 and 4 percentage points higher than the reported one. What remains constant across all the corrections is the extensive definition of unemployment. Here, the continuous unemployment rate deals with both challenges simultaneously. First, the weights are demographic specific but the effect of demographics does not change across time. Second, the weight is calculated for all non-employed individuals, so misclassification between unemployment and non-participation is not an issue.

[4]See Krusell et al. (2008, 2010, 2011) for a complete explanation of how aggregate and idiosyncraty shocks affect labor market flows.

The continuous unemployment rate adds to a small literature focused on constructing a better measure of labor underutilization for the United States.[5] Hornstein et al. (2014) construct a non-employment index (NEI) in which they weight all non-employed people by the average transition probabilities to employment on a coarse grid of observable characteristics. Faberman et al. (2019) construct a measure of labor market underutilization by differentiating people by the difference between their hours worked, zero if non-employed, and their desired hours worked. The measure is constructed for the entire population and tries to measure labor market slack as the difference between hours available and actual hours worked. The method proposed in this paper is advantageous because the continuous unemployment rate is created using the same data used to create the official labor market statistics for the United States, the Current Population Survey, and a publicly available supplement of the survey, the American Time Use Survey. The measure can be reconstructed for any demographic group or region and does not rely on the outcome of job search.

The remainder of the paper is structured as follows: section 2 describes the data and gives summary statistics of the American Time Use Survey, and describes the methodology used to estimate and predict search effort. Section 3 describes how the continuous unemployment rate and the adjusted flows between labor market states are constructed and summarizes each series. Section 4 compares the properties of the continuous unemployment rate and adjusted labor market flows to the standard unemployment rate and flows. Section 5 compares the continuous unemployment rate to other, more inclusive measures of unemployment and Section 6 concludes.

2 Estimating Search Effort

Unlike the standard unemployment rate, which counts all unemployed equally, the continuous unemployment rate weights all non-employed people by a measure of the relative search effort. The measure of relative search effort use is the probability person exerts positive search effort in a given month. The two main sources of data used to estimate the probability that a person exerts positive search effort are the basic monthly files of the Current Population Survey (CPS) 1980-2018 and the time diaries from the American Time Use Survey (ATUS) 2003-2018.

2.1 Data Sources

The CPS is the main source of data used for calculating aggregate statistics regarding the labor force status of U.S. residents. The survey is conducted monthly, the interview unit is based on the address of

[5] Schweitzer (2003) and Jones et al. (2003) attempt similar exercises for the United Kingdom.

the household and all members of the household residing at the address are interviewed. A household is in the survey for 4 months, then out for 8 months, and then back in for 4 months. Given this rotating-panel element of the CPS, in theory three quarters of the each month's sample can be longitudinally linked to the prior month. In practice however, only about two-thirds of the sample can be linked due to households moving. The survey asks a variety of questions related to labor market attachment and people are classified as unemployed if they have had at least one active search effort during the past 4 weeks and are available to work. All other non-employed individuals are classified as out of the labor force.[6]

This broad classification of labor force status is advantageous in many respects, but needless to say, not perfect. Misclassification of people across labor market states in the CPS is a well document fact. Abowd and Zellner (1985) and Poterba and Summers (1986) show that misclassification happens along all margins using data from the reinterview surveys conducted by the CPS on a subset of individuals. The largest error occurs among people that are at first classified as out of the labor force and later reclassified as unemployed. Similarly, Ahn and Hamilton (2019) show that two-thirds of people who were classified as out of the labor force last month and unemployed this month report having an unemployment duration of longer than 4 weeks. Krueger et al. (2017) document that people are more likely to get misclassified as out of the labor force the longer they stay in the survey, which Halpern-Manners and Warren (2012) suggest may be due to some shame carried by admitting, month after month, that they were unable to find a job.

Despite measurement issues, the CPS data have become, not only the standard source for labor market stocks, but also the main source for estimating the flows across labor market states. The Bureau of Labor Statistics publishes the flows across labor market states beginning in 1990 and many others have calculated the flows using the linked microdata, see for example Shimer (2012) or Elsby et al. (2015). Beginning with the 1994 redesign of the CPS, Fallick and Fleischman (2004) show that it is possible to observe employment to employment transitions as well.

The American Time Use Survey (ATUS), which began as a supplement to the CPS in 2003, randomly selects households that have completed their eighth and final month in the CPS; households are interviewed one time about how they spent their time on the previous day, where they were, and whom they were with. The main goal of the survey is to collect information about how the respondent spent his or her time starting at 4 a.m. the previous day and ending at 4 a.m. on the interview day. For each activity reported, the interviewer asks how long the activity lasted. For most activities, the interviewer also asks who was in the room or accompanied the respondent during the activity and

[6] A detailed description of how labor market status is determined can be found at https://www.bls.gov/cps/definitions.htm.

where the activity took place. The activities are then coded into over 400 categories.

Of particular interest are the categories devoted to job search which include: job search activities, job interviewing, waiting associated with job search or interview, security procedures related to job search/interviewing, and other job search.[7] These categories are the focus of this paper as they provide an opportunity to see if and how much people are searching for a job, regardless of their labor force status. Given these categories, the ATUS has recently become a common data set used to study the cyclical behavior of job search among the unemployed (Mukoyama et al., 2018) and the employed (Ahn and Shao, 2017).

The ATUS interview is conducted between 2 and 5 months after exiting the CPS. Because of the delay between the persons' final CPS interview and the ATUS interview, the questions pertaining to labor force status are asked again, in the same fashion as during the CPS interview, and respondents are classified as employed, unemployed, or out of the labor force accordingly. Regardless of a person's labor market status, if he spent any time searching for a job on the interview day, the time will be recored as job search activity. Therefore, the ATUS data can be used to estimate the probability that a person is searching for a job for the entire population.

The main disadvantage of using the ATUS to study job search behavior is that people are only surveyed about one day in the month. In what follows, search effort, in terms of minutes per day, is reported both unconditionally and conditional on observing positive search effort and the probability that a person searches for a job is reported as a daily probability and converted to a monthly probability under the assumption that job search is independent across days. That is, if p is the daily probability of searching for a job, then the corresponding monthly probability is calculated as $1 - (1 - p)^{30}$.

Table 1 shows the probability of observing a person searching for a job on a single day, calculated as the sample mean of a dummy variable that takes on the value 1 if the person reports spending any time that day looking for a job. Also reported is the corresponding monthly probability. Not surprisingly people classified as unemployed have the highest probability of searching for a job on a day and with almost certainty, search for a job throughout the month. For the employed, those at work have a lower monthly probability (15.9) of searching for a job than those absent from work (30.5). Those classified as out of the labor force also report searching for a job throughout the day, in fact the probability of observing a person age 25-55 searching for a job throughout the month (24.3) is higher than the probability of observing an employed person age 25-55 (15.1) searching. The fact that the probability of observing a person classified as out of the labor force searching for a job is positive (11.4 for the age 16+ sample) is further evidence of the measurement issues discussed above.

The intensive margin of search is reported in Table 2. Both the unconditional average and conditional

[7] Categories 50401-50499 in the ATUS lexicon.

on positive search time is reported. First, notice that across both samples, the unemployed have the highest unconditional search intensity, searching for an average of about 30 minutes per day. The unconditional average for the employed and out of the labor force is mostly below one minute across both samples, stemming from the fact that no more than 25 percent of each group is searching for a job. However, when looking at the conditional search times the three groups look strikingly similar. The unemployed, again, have the highest search intensity, spending on average 2.5 hours per day searching for a job. However, conditional on searching for a job, those classified as out of the labor force spend almost as much time per day (2.2 hours) searching as the unemployed. Employed people spend the least amount of time searching for a job, about 2 hours per day. However, the standard errors are large for all samples due to the small sample sizes.

Since the type of job search activity, active vs passive, matters for how non-employed individuals are classified, Table 3 reports the percent of time each group sends in three types of job search activities. The first activity labeled “Active Job Search" consists of ATUS category number 50401 which includes contacting employers, sending out resumes, ect. The second category is “Interviewing" and the third category “Other" includes all other ATUS categories (50403-50499) which are: waiting time associated with interviewing, security procedures related to job search/interviewing, and all other job search activities not elsewhere specified. Across all three labor market state and both samples, the majority of time in spent is in active job search. Employed individuals spend about 15% of the time interviewing whereas, unemployed individuals spend only about 5-6% of the time interviewing. Consistent with the fact that people classified as out of the labor force are more likely not to be actively searching for a job, they spend up to 5% of the job search time in the “Other" category; however, they do spend a large majority of the time actively searching for a job, between 85% and 90%. The evidence presented in Table 2 and Table 3 suggest that people classified as out of the labor force but exert positive search effort, may not be behaving differently from those classified as unemployed.

Table 4 gives the summary statistics of demographic characteristics, education, and the day of the week each interview occurred by labor force status. The demographic and education information is matched from the respondents CPS interview. Women, as well as married women, are more likely to be unemployed and out of the labor force, with the differences being statically significant. Married men are more likely to be employed than unemployed and more educated people are more likely to be employed. The summary statistics also suggest some selection on the day of the week that the person was interviewed: People interviewed on Saturday and Sunday are more likely to be out of the labor force.

2.2 Estimating Search Effort

Since demographics and the state of the economy may have differential effects on search effort based on labor market status, I estimate the probability that an individual searches for a job for each labor market status. However, demographics, and importantly the state of the economy may play a key role in determining which labor market state we observe individuals in. To control for selection issues I use a two-state Heckman Selection approach in which the first state estimates the probability of belonging to each state conditional on demographics and the state of the economy and the second stage estimates the effect of demographics and the state of the economy on the probability of an individual searching conditional on selection into each state.

Demographic information for each person is collected in the ATUS interview. The measure of the state of the economy, I use the monthly state Coincidence Index (CI) provided by the Federal Reserve Bank of Philadelphia as a proxy for the state level state of the economy in which the worker is searching.[8] The state CI is created using a dynamic single factor model that

> combine[s] four state-level indicators to summarize current economic conditions in a single statistic. The four state-level variables in each coincident index are nonfarm payroll employment, average hours worked in manufacturing by production workers, the unemployment rate, and wage and salary disbursements deflated by the consumer price index (U.S. city average).

Although employment outcomes are endogenous to a worker's search effort, since the index is aggregated at the state level some exogeneity is gained by assuming that a change in an individual's search effort is not strong enough to change all four statistics in a significant way. The trend of the state level index is set to the trend of the state's Gross Domestic Product; therefore, the final monthly state level indicator of the state of the economy is the coincidence index per capita.

The first stage for the selection probability is estimated using a probit where the outcome variable is an indicator that takes on the value 1 if the individual is in the labor force state $S = j$ where $j \in \{\text{employed, unemployed, out of the labor force}\}$. I allow for selection into each state on all the demographic variables listed in Table 4 as well as a quartic in age and the day on which the respondent was interviewed. The selection model is identified if there exists an observable characteristics that determines selection but does not determine search efforts. For this variable I use an indicator which takes on the value one if it is the interviewees first month in the sample.[9] Krueger et al. (2017) show that individuals in later months are more likely to get misclassified, therefore, information on how

[8] https://www.philadelphiafed.org/research-and-data/regional-economy/indexes/coincident/

[9] In the ATUS each individual is only observed once, however the files contain information if the individual is the sample person who was interviewed in the corresponding CPS interview.

many months an individuals has been in the sample should be correlated with which labor market state they get categorized into, but should not determine their search effort. The final specification for the selection process is:

$$P(S_i = j) = \Phi(\beta_0 + \beta_1 Economy_{sm} + \beta_2 Demographics_i + \beta_3 FirstMonth_i + \gamma_d^1) \tag{1}$$

where $Economy_{sm}$ is the CI per capita of the state, s, that the individual lives in, in month m, $FirstMonth_i$ is an indicator that takes on the value 1 if it is individual i's first time in the sample, γ_d^1 are day of the week fixed effects and $\Phi(\cdot)$ is the normal c.d.f.

In the second stage I estimated the probability that an individual searches, where the outcome variable is an indicator variable that takes on the value one if the individual records any positive amount of time searching for a job on the interview day. Included in the probit model are all the demographic variable in Table 4 as well as a quartic in age and the day of the week the individual responded to the survey. The final specification is:

$$P(search_i = 1) = \Phi(\delta_0 + \delta_1 Economy_{sm} + \delta_2 Demographics_i + \gamma_d^2 + \rho\tilde{\lambda}_i) \tag{2}$$

where $Economy_{sm}$ is the CI per capita of the state, γ_d^2 are day of the week fixed effects, $\Phi(\cdot)$ is the normal c.d.f. and $\tilde{\lambda}_i$ is the selection corrections.[10] Final ATUS weights are used in all calculations.

Table 6 contains the estimated coefficients for selection into the three labor market states. Demographics and education are significant predictors of labor market status: for example, married women and women with children are more likely to be out of the labor force and more educated individuals are more likely to be employed. The state of the economy is also a strong predictor of labor market status: in a good state there is positive selection into employment and negative selection into unemployment.

Table 5 contains the estimated coefficients on search effort, here the effects of demographics are mixed. Women are less likely so search on the job and while unemployed. Age also remains a significant predictor of search effort on the job and when out of the labor force after controlling for selection. However, the effects of age on the search effort of the unemployed are not significant after controlling for selection. Search effort also does not display any significant differences by education in any labor market state after controlling for selection; although, the high school educated are less likely to search on the job than those without a high school degree. There are significant differences in the day of the week that individuals search. The employed and unemployed are more likely to search for a job during the week than on the weekend. The people out of the labor force are more likely to search

[10]See de Ven and Praag (1981) for a derivation of the selection correction in a probit model.

at the beginning of the week.

The estimated coefficient on the economy variable implies that search effort of the employed is countercyclical. These results are consistent with Ahn and Shao (2017) who show that the search effort of the employed is countercyclical in the extensive and intensive margin; they argue this may be for precautionary reasons. The unemployed also display countercyclical search effort. This result adds to a growing literature that documents that search effort of the unemployed is countercyclical, such as Shimer (2004), Kudlyak and Faberman (2014) and Mukoyama et al. (2018). However, this stands in contrast to DeLoach and Kurt (2013) who show a-cyclical search effort and Gomme and Lkhagvasuren (2015) who show evidence of pro-cyclical search effort. Search effort among people classified as out of the labor force is also countercyclical, but the effect is smaller in magnitude than for the employed and unemployed.

2.3 Predicting Search Effort

The CPS contains all the same demographic information as the ATUS and labor market status is determined equivalently in both sample. Therefore, although the ATUS sample begins in 2003, search effort can be predicted using the CPS starting in 1980. Using the estimated coefficients of selection and main effects of demographics and the state of the economy on the probability of observing a person searching for a job I predict the conditional probability that an individual is searching for a job. The probability is conditional on their labor market status since we can observe the individual's labor market status in the CPS, that is, we can observe the selection outcome of each individual. Since the estimates are of the daily probability of observing a worker searching for a job, and the probability differs across the days of the week, I predict 7 probabilities for each worker in the sample. The predicted conditional probability is:

$$\hat{p}_i^d = \frac{\Phi_2(\hat{\beta}X_i + \hat{\gamma}_d^1, \hat{\delta}X_i + \hat{\gamma}_d^1 + \hat{\rho}\tilde{\lambda}_i)}{\Phi(\hat{\beta}X_i + \hat{\gamma}_d^1)} \tag{3}$$

for $d \in \{1, 2, \ldots, 7\}$ and where $\Phi_2(\cdot)$ is the joint normal c.d.f., $\Phi(\cdot)$ is the normal c.d.f, $\hat{\beta}$ and $\hat{\delta}$ are the estimates from the selection stage and the second stage, X_i are the demographics and state of the economy.

Using the predicted daily conditional probability, the weekly probability that a person is searching for a job is 1 minus the probability that the person does on search any day during the week, i.e.

$$\hat{p}_i^w = 1 - \sum_{d=1}^{7}(1 - \hat{p}_d). \tag{4}$$

The monthly probability that the person searches for a job is constructed analogously, i.e.

$$\hat{P}_i = 1 - (1 - \hat{p}_i^w)^{4.17} \tag{5}$$

since there are about 4.17 weeks per month.

2.4 Search Effort and Labor Force Attachment

Using predicted search effort probability for each individual in the CPS I now test if search effort is a predictor of labor force attachment. I use three measures for labor force attachment. First, for the subset of individuals that transitioned from non-employment to employment I use usual hours worked and an indicator for full time employment as a measure of labor force attachment. If search effort is a good predictor of labor force attachment, then we should expect to see a positive correlation with search effort in the previous month and subsequent hours worked or full time employment. Second, for all non-employed individuals in the first month I correlate an indicator if they became employed in the second month with their estimated search effort. Again, if the estimated search effort is a predictor for labor force attachment, then we should expect to see a positive correlation with subsequent employment probabilities.

To calculate the correlation between predicted search effort and labor force attachment I match individuals in the CPS over two consecutive months and create two samples. The first sample consists of all individuals who are not employed in the first month and employed in the second month. For this sample, I correlate hours worked and an indicator for full time employment on the estimated search probability. The second sample consists of individuals that are not employed in the first month and either employed or not employed in the second month. For this sample I correlate the estimated search probability with an indicator for if they were employed in the second month. That is,

$$y_{it} = \beta \hat{P}_{it-1} + \delta_t + \varepsilon_{it} \tag{6}$$

where y_{it} is usual hours worked, an indicator for full time employment or an indicator for employment, $\hat{P}_{it-1}$ is the predicted search effort in the previous month, and δ_t are month by year fixed effects.

The estimated correlation between hours worked and predicted search effort are reported in the first two columns of Table 8. The correlation is significantly positive with and without year by month fixed effects. Similarly, there is a positive correlation between the probability of full time employment and search effort, as reported in columns (3) and (4) of Table 8. The correlations between estimated search probability and the job finding probability are reported in the last two columns of Table 8. Again there exists a strong positive correlation between the search effort and the job finding probability. The positive correlation between predicted search effort and hours worked, full time employment and job finding probabilities, suggests that search effort is indeed a predictor of labor force attachment.

3 Unemployment and Labor Market Flows

3.1 Aggregate Number of Searcher and the Unemployment Rate

Using the monthly predicted conditional probability of search effort for each person, the number of searchers within each labor market state, unemployed U^s, employed E^s, and out of the labor force O^s, are constructed as follows:

$$U^s = \sum_{i \in U} wgt_i \times \hat{P}_i \tag{7}$$

$$E^s = \sum_{i \in E} wgt_i \times \hat{P}_i \tag{8}$$

$$O^s = \sum_{i \in O} wgt_i \times \hat{P}_i \tag{9}$$

where U, E, and O are the set of all individuals in the respective labor market state and wgt_i is the CPS weight. The total number of people in each state is calculated as the sum of the weights within each group; the resulting series are monthly.

Figure 2 plots the predicted fraction of people searching in each labor market state and the total fraction of searchers out of the population for people 16 and older. The shaded regions depict recessions using the National Bureau of Economic Research's classifications. All four series clearly display a counter cyclical patter. The fraction of people searching while employed rose dramatically during the 2008 recession, increasing by about 1.5 percentage points or approximately 384,000 people from trough to peak. Although declining after the end of the recession, the fraction of employed job seekers remains above it's trough. Turing to those who are unemployed, nearly all are searching for a job, with the percent varying between 96% and 98% but remaining at its highest level since 1980.

The fraction of people searching for a job that are out of the labor force has be steadily rising since 1980, increasing by 3 percentage point from its minimum to its maximum in 2011, this amounts to about 1.2 million more people searching for a job. When considering that the average number of people who report being unemployed from 1980-2017 is about 8.5 million the addition of 1.2 million job seekers amounts to nearly 14%. Since the end of the 2008 recession, however, the fraction has begun to decrease but remains above its pre-recession value. The final panel of Figure 2 plots the total fraction of the population that is searching for a job. The general shape is close to the the standard unemployment rate, defined as $U/(U+E)$; however, the level of the total searcher rate is much higher than the unemployment rate, which is obvious from the positive fraction of employed and out of the labor force that are predicted to be searching for a job.

Figure 3 plots the unadjusted and adjusted unemployment and labor force participation rates for the full sample. The average unemployment rate over the sample increase from 6.4 to 11.2. While the unadjusted unemployment rate has fallen below its precession minimum of 4.3 in 2007 to 3.9 at the end of 2017, the adjusted unemployment rate remains 0.8 percentage points above its pre-recession minimum. Similarly the average participation rate of the adjusted sample is higher than the unadjusted sample and the fall beginning in 2000 is dampened. While the unadjusted participation rate drops by 4.6 percentage points since 2000, the adjusted participation rate drop by 3.6 percentage points.

3.2 Labor Market Flows

The data used to estimate the flows between labor market states are the basic monthly files from the CPS. The basic monthly files are composed of eight rotations groups. Households in the first through third and fifth through seventh month in the sample will be surveyed in the following month and can thus be linked across month, implying that in theory three quarters of the sample can be longitudinally linked. However in practice only about two thirds of the sample can be linked due to attrition.

Using the longitudinally linked data, estimates for transition probabilities are typically calculated as the average number of workers transitioning across states from month to month. For example, the probability that an employed worker loses his job and moves to unemployment is simply the average number of workers that report being employed in the first month and unemployed in the second month. This method has become the standard in estimating worker flows.

The approach used here is similar, however, non-employed worker transitions are weighted by the predicted monthly search probability. The probability a worker transitions from employment to unemployment is calculated as:

$$f_{EU} = \frac{\sum_{i \in E_1 N_2} wgt_i \times \hat{P}_{i2}}{\sum_{i \in E_1} wgt_i} \tag{10}$$

where the summation in the numerator is over all workers that are observed in employment in the first month and non-employment (CPS defined unemployment and out of the labor force) in the second month. The summation in the denominator is over all workers in employment in the first month. The weight used in the numerator is the CPS sampling weight times the estimated search effort in the second month. Similarly the transition probability from employment to out of the labor force is calculated as:

$$f_{EO} = \frac{\sum_{i \in E_1 N_2} wgt_i \times (1 - \hat{P}_{i2})}{\sum_{i \in E_1} wgt_i} \tag{11}$$

where the weight used in the numerator is now the CPS sampling weight times the probability the worker is not searching for a job in the second month. The transition probability from unemployment to employment is calculated using all individuals that are not employed in the first month and employed in the second month, weighted by their search probability. That is,

$$f_{UE} = \frac{\sum_{i \in N_1 E_2} wgt_i \times \hat{P}_{i2}}{\sum_{i \in N_1} wgt_i}. \tag{12}$$

The transition probabilities between unemployment and out of the labor force are calculated slightly differently. Instead of weighting the individual by the search probability each period, workers are weighted by the change in their search probability. If a person remains not employed for two consecutive month, and his predicted probability of search does not change over those two months then, although he contributes to both the stock of unemployed and out of the labor force, he does not contribute to the flow between these two states. Alternatively, suppose that a person is not employed in two consecutive months, and his estimated probability of searching is $\hat{P}_1 = 0.3$ in the first month and $\hat{P}_2 = 0.5$ in the second month, then he contributes to the flow from out of the labor force to unemployment by only change in his estimated search probability, that is with weight 0.2. Therefore, the flow from out of the labor force to unemployment is calculate as

$$f_{OU} = \frac{\sum_{i \in N_1 N_2} wgt_i \times max\{\hat{P}_{i2} - \hat{P}_{i1}, 0\}}{\sum_{i \in N_1} wgt_i}. \tag{13}$$

Similarly a person that is not employed in two consecutive periods only contributes to the flow from unemployment to out of the labor force if his predicted search probability decrease from the first to the second month. The flow from unemployment to out of the labor force is calculated as

$$f_{UO} = \frac{\sum_{i \in N_1 N_2} wgt_i \times |min\{\hat{P}_{i2} - \hat{P}_{i1}, 0\}|}{\sum_{i \in N_1} wgt_i}. \tag{14}$$

Then, by construction the flow from out of the labor force to employment is zero.

The resulting transition probabilities are seasonally adjusted and corrected for margin error. The correction for margin error is similar to Elsby et al. (2015) and restricts the flows across labor market states to be consistent with the evolution of the labor market stocks. In the standard labor market flows data, margin error can arise from movements into the working age population or attrition of households in the matched CPS data; however, Elsby et al. (2015) show that correcting for margin error has little effect on the standard CPS flows. Since here the flows and stocks are calculated using estimated search probabilities, correcting for margin error plays a larger role and decreases the estimated flow from unemployment to out of the labor force by 43%.

Previous work on riding the estimated flows from the CPS of measurement error is most often concerned with spurious movement between unemployment and out of the labor force. For example, Elsby et al. (2015) match individuals up to three months and recode the data such that an individual who is observed as unemployed in the third month followed by out of the labor force in the second month and then unemployed in the third month is observed as unemployed throughout. Similarly for individuals that are out followed by unemployed and again out, are recoded as out of the labor force for the entire period. Indeed, this correction ("deNUNification") decreases the flow between unemployment and out of the labor force but it does not address the issue of movements from out of the labor force directly to employment and vice versa. For example, an individual who is observed as unemployed in the first month, out of the labor force in the second month and employed in the third month is not recoded, therefore, such an individual adds to the flow from unemployment to out of the labor force as well as the flow from out of the labor force to employment.

Abowd and Zellner (1985) and Poterba and Summers (1986) attempt to understand the amount of measurement error in the CPS classification system by using data from the reinterview surveys conducted by the CPS on a subset of individuals. They show that misclassification happens along all margins, however the largest error occurs among individuals that are at first classified as out of the labor force and later reclassified as unemployed. Unfortunately, the CPS has since stopped conducting reinterview surveys so the methods proposed they can not be updated. While the deNUNification method is at the individual level and time varying, although perhaps in an ad-hoc manner, the reinterview method puts some structure on the probability of being misclassified however, is at an aggregate level and time-invariant.

Figure 4 plots the unadjusted and adjusted labor market flows across states for the full sample. The most notable changes occur along the participation margin. The flow from out of the labor force to unemployment increases slightly from an average flow of 0.027 to 0.029 and the flow from unemployment to out of the labor force decrease from and average of 0.21 to 0.05. The flow from unemployment to employment decrease slightly from an average of 0.25 to 0.20. The flow from employment to out of the labor force decreases by more half from 0.028 to 0.01. In the unadjusted sample the flow from employment to out of the labor force is nearly twice as high as the flow from employment to unemployment; the adjusted flows decrease the flow from employment to out of the labor force enough to make the flow to unemployment larger.

4 Implications of a Continuous Unemployment Measure

Using the continuous unemployment rate and labor market flows I revisit the business cycle properties of both. I also revisit the question of how much the participation margin accounts for in the variation of the unemployment rate.

4.1 Business Cycle Properties

Table 9 shows the cyclical properties of the adjusted and unadjusted unemployment rate, participation rate and labor market flows across states for the full sample. The largest changes appear in the cyclical behavior of the unemployment rate and along the unemployment/out of the labor market flows. The table reports the average values ($E(x)$) of each variable over the sample period along with the standard deviation of the quarterly growth rate ($std(Q/Q)$) and the autocorrelation ($corrcoef(x, x_{-1})$). The volatility of the unemployment rate falls by nearly 50% from 0.047 to 0.027 and unemployment becomes slightly more persistent.

Figure 5 plots the adjusted and unadjusted unemployment rates for each recession since 1980, normalizing each series to 0 at the start of the recession. Panel (a) plots the 1980 and 1981 recession, the two series are nearly identical, with the adjusted series decreasing faster only slight toward the end. Following the 1990 recession, the unadjusted unemployment rate falls below its pre-recession value in June 1996 whereas the adjusted unemployment rate takes nearly a year longer to fall below its precession level in April 1997. Following the 2001 recession, the adjusted unemployment rate rises 0.4 percentage points higher than the unadjusted unemployment rate; the unadjusted unemployment rate fall nearly to its pre-recessions value in April 2007, the adjusted unemployment rate remains 0.6 percentage points above it pre-recession value before increasing into the 2008 recession. The increase in unemployment is nearly identical for the unadjusted and adjusted unemployment rates during the 2008 recession, but again the adjusted unemployment rate displays a slower recovery. The unadjusted unemployment rate falls below its pre-recession value in January 2016, the adjusted unemployment rate remains above its pre-recession value until the end of 2017.

The largest changes to labor market flows are to the flow from unemployment to out of the labor force f_{uo}, which, when unadjusted, is large and pro-cyclical. The adjusted flow decreases by 75%, is more volatile and less persistent. These results are in contrast to the deNUNification approach used by Elsby et al. (2015) and the Abowd and Zellner (1985) correction that decrease the f_{ou} flow by less than 50%. Another notable change occurs along the employment to out of the labor force margin. The average flow decreases by over 65% becomes more volatile and less persistent.

4.2 The Participation Margin

To asses how these changes in the flows between labor market states affect the volatility of the unemployment rate I decompose the variance of the unemployment rate using the method developed by Elsby et al. (2015). Elsby et al. (2015) show that roughly 30% of the unemployment fluctuation can be accounted for by flows into and out of the labor force, and that this finding is robust to correcting the flows using the method developed by Abowd and Zellner (1985) and the "deNUNification" approach. Table 10 show the share of the variance of the unemployment rate for the unadjusted and adjusted flows for both samples. As in Elsby et al. (2015) using the unadjusted flows for the full sample, the out of the labor force margin accounts for about 35% of the variance of the unemployment rate. For the adjusted flows, the share of the variance accounted for they the UE movements increase from 34.5% to 40%, the share accounted for by the OU margin decreases from 16% to 10% and the share accounted for they the UO margin decreases from 19.5% to 6.2%. Together, the labor force margin accounts for only 16% of the total variance of the unemployment rate.

4.3 Correlation with Wage Growth and Inflation

The unemployment rate, or unemployment gap, are often used as a measure of labor market utilization in estimating the trade-off between output and inflation, i.e. the Phillips Curve. Roberts (2006) and others have shown that this relationship has weekend over the past two decades – a phenomenon referred to as the flattening of the Phillips curve. There is still an ongoing discussion regarding if and why the output-inflation relationship has weakened (Coibion and Gorodnichenko, 2015; McLeay and Tenreyro, 2019; Galí and Gambetti, 2019).

Since the standard unemployment rate and the continuous unemployment rate have diverged since the 1980s, revealing different recoveries from each subsequent recession, I estimate a simple correlation between inflation and labor market utilizations and the standard and continuous unemployment rate, and the total searcher rate. For inflation, I use the quarterly growth rate of the consumer price index (CPI)[11] and the quarterly growth rate of median hourly wages of 18 to 80 year old workers calculated from the outgoing rotation groups of the CPS. I regress both measures of inflation on each labor market indicator and a constant.

Table 11 shows the estimated correlations and the r-squared from each regression. For median wage growth, the estimated coefficient on the standard unemployment rate is negative but insignificant and the R-squared is small. The estimated coefficient on the continuous unemployment rate and the total searcher rate is negative, three times large and statistically significant. The R-squared for the

[11] FRED series CPIAUCP. https://fred.stlouisfed.org/series/CPIAUCSL

continuous labor market measures is an order of magnitude larger that of the standard unemployment rate. The estimated coefficient of the standard unemployment rate on the growth rate of the CPI, is small, positive and insignificant. Similar to the median wage growth, the estimated coefficients on the continuous unemployment rate and the total searcher rate are negative and statistically significant. The R-squared of the continuous measured are also much larger than the standard unemployment rate. In sum, both the continuous unemployment rate and the total searcher rate continue to display a strong negative relationship with inflation over the past 40 years, whereas the standard unemployment rate does not.

5 Alternative Labor Utilization Measures

There are several alternative measures to the standard unemployment rate that the Bureau of Labor Statistics publishes and include a larger fraction of the non-employed group. These measures aim to be more inclusive by adding workers who would like a job but have stopped searching for one reason or another, and therefore may be more representative of labor under utilization. In what follows, I compare the standard unemployment rate and the continuous unemployment rate to alternative measures of labor underutilization. The measures include the more inclusive measures of unemployment, the non-employment index created by Hornstein et al. (2014), and an additional continuous unemployment rate where the employed are weighted as full time equivalents. All measures are constructed from 1994 to 2018.

5.1 More Inclusive Measures of Unemployment

In addition to the standard unemployment rate (U3), the Bureau of Labor Statistics also publishes more inclusive measures of unemployment. U4 adds to the pool of unemployed workers, discouraged workers, those who would like a job but have stopped searching for work because they believe there is no suitable jobs available for them. U5 takes U4 all other marginally attached worker, i.e. workers that have stopped searching for a job for any other reason. Another alternative measure of labor underutilization, U6, takes U5 and adds to the pool of unemployed individuals that are underemployed in terms of hours, i.e. workers working part time for economic reasons.

Table 12 shows the mean, standard deviation of the quarterly growth rate and autocorrelation for the alternative BLS measures of unemployment. The average level of each measure increase since each measure contains more individuals, however the volatility of each measure remains similar to the standard unemployment rate. Although each measure includes workers which may be less attached to the labor force, they are still subject to the same criticisms since all people categorized as unemployed (or underemployed) are weighted equally once included.

5.2 Non-Employment Index

Hornstein et al. (2014) construct a similar statistic to the continuous unemployment rate called the non-employment index (NEI). The NEI is constructed by weighting all non employed individuals by a relative transition to employment probability. The transition probabilities are calculated within BLS non-employment categories and the weights are the average transition probabilities over the sample relative to the highest transition probability (short-term unemployed). The NEI's main difference is that the weights are not time varying and vary only at the BLS non-employment categories across individuals, whereas the continuous unemployment rate varies at the demographic level and is time varying. Further, the continuous unemployment rate weights by search effort rather than the outcome of search effort, i.e. job finding probability.

Table 12 shows the mean, standard deviation of the quarterly growth rate and the autocorrelation for the NEI. First, The mean value of the NEI is 0.089, about 2 percentage points lower than the continuous unemployment rate. This difference is driven by the fact that the NEI divides by the total population rather than the actively searching population. Second, the standard deviation of the quarterly growth rate is slightly lower than the continuous unemployment rate. This difference is driven by the differences in the weights; since the NEI weights do not vary over time, cyclical movement in the NEI are only driven by compositional changes along the BLS defined non-employment groups.

5.3 Measuring Employment as Full-time Equivalents

The goal of the continuous unemployment rate is create a more continuous measure of labor force attachment for individuals who are not employed. An analogous idea has long been used for employed individuals: often total labor input is calculated as total hours worked or full time equivalents. The standard unemployment rate does not count employed individuals as full time equivalents, however, as a measure of labor underutilization, employed people in the unemployment rate should be measured equivalently to how they are measured in labor input. Starting in 1994, with the CPS redesign each individual is asked about their usual weekly hours. Using usual weekly hours, I recreate continuous unemployment rate with weighted employment in the denominator. Employed people are weighted as a fraction of their usual weekly hours over 40: people working 40 hours are weighted as 1, people working 20 hours are weighted as 0.5 and people working 60 hours are weighted as 1.5.

Panel (a) Figure 6 plots the standard unemployment rate, the continuous unemployment rate, and the employment weighted continuous unemployment rate. The employment weighted continuous unemployment rate is on average 1.1 percentage points higher than the continuous unemployment rate. Panel (b) shows that the participation rate calculated in the standard way, using the continuous definition of unemployment, and as using the continuous definition of unemployment and weighted employment. The employment weighted participation rate lies between the continuous participation rate and the standard participation rate. Both the continuous participation rate and the employment weighted participation rate decrease about 3.5 percentage points since 2000.

Figure 7 plots the evolution of the standard unemployment rate, the continuous unemployment rate, and the employment weighted continuous unemployment rate over the 2001 and 2008 recessions. Each series is indexed to 0 at the start of the recession. The largest difference between the continuous unemployment rate and the employment weighted continuous unemployment rate is during the recession. The employment weighed continuous unemployment rate rises more during both recessions, however, the recovery is similar to the continuous unemployment rate. Table 12 also gives evidence that the cyclical properties of the continuous unemployment rate and the employment weighted continuous unemployment rate are similar. The first panel of Table 12 shows mean, standard deviation of the quarterly growth rate, and the autocorrelation of the three series; the volatility of the employment weighted continuous unemployment rate and the continuous unemployment rate are similar. Overall, allowing labor force attachment to be measured more continuously changes the properties of the unemployment rate more than measuring employment as full time equivalent workers.

6 Conclusion

The paper developed a notion of a continuous unemployment rate. This allows people to enter the unemployment rate with different weights based on their labor force attachment. The notion of using an intensive margin to aggregate individuals has be widely accepted for measures of employment, such as total hours worked or full time equivalents. On average the continuous unemployment rate is 4.8 percentage points higher than the standard unemployment rate and about half as volatile. The continuous unemployment rate recovers slower after every recession since 1980. While the participation margin accounts for 40% of the volatility of the standard unemployment rate, it accounts for only 16% of the volatility of the continuous unemployment rate. The continuous unemployment rate displays a much stronger negative correlation with nominal wage growth and inflation and is a better predictor of both than the standard unemployment rate. The paper also corrects the flows between labor market states; the flow from unemployment to non-participation decreases by about 75%.

In the end, the statistic presented in this paper is only second best. The best approach to measure unemployment moving forward, would be to not simply as if a person has had on active search effort, but to ask how much they have been searching over the past month. This may not circumvent the measurement issues discussed, however it would be a step in the right direction toward taking a more continuous approach to unemployment.

7 Tables

Table 1: Search Effort by Labor Force Status: Extensive Margin

	Age 16+		Age 25-55	
	Daily Probability	Monthly Probability	Daily Probability	Monthly Probability
Employed	0.609	16.739	0.545	15.112
	(0.022)		(0.024)	
At Work	0.573	15.900	0.513	14.306
	(0.022)		(0.024)	
Absent	1.411	34.699	1.343	33.349
	(0.161)		(0.189)	
Unemployed	17.264	99.661	23.053	99.961
	(0.397)		(0.591)	
On Layoff	5.986	84.303	6.313	85.863
	(0.759)		(0.946)	
Looking	18.495	99.783	25.548	99.986
	(0.432)		(0.657)	
Out of the Labor Force	0.402	11.382	0.927	24.386
	(0.025)		(0.072)	
N	198,831	198,831	113,302	113,302

Summary statistics calculated from the pooled 2003-2018 American Time Use Survey (ATUS). The daily probability of observing search within a group is calculated as the mean across the group of a binary variable that takes on the value 1 if the individuals engaged in any positive amount of job search the day of the interview. Job search activities are coded as categories 50401-50499 in the ATUS lexicon. Standard errors given in parenthesis are calculated as $\sqrt{p(1-p)/N}$*, where p is the daily probability and N is the number of observations in the group. Monthly probabilities are calculated as* $1-(1-p)^{30}$*, assuming 30 days per month and that the probability of searching for a job is the same every day.*

Table 2: Search Effort by Labor Force Status: Minutes Per Day

	Age 16+		Age 25-55	
	Unconditional	Conditional	Unconditional	Conditional
Employed	0.711	116.787	0.661	121.284
	(12.778)	(115.267)	(12.750)	(123.499)
At Work	0.615	106.818	0.579	112.871
	(11.010)	(98.708)	(10.949)	(103.476)
Absent	3.02	214.411	2.729	203.194
	(34.165)	(195.248)	(35.296)	(230.840)
Unemployed	25.213	146.039	36.208	157.065
	(78.058)	(132.878)	(91.900)	(132.908)
On Layoff	8.664	144.747	9.792	155.103
	(51.227)	(156.668)	(56.985)	(171.390)
Looking	27.018	146.085	40.145	157.137
	(80.242)	(132.018)	(95.412)	(131.374)
Out of the Labor Force	0.529	131.648	1.263	136.131
	(11.185)	(118.011)	(17.405)	(120.061)

Table 3: Search Effort by Labor Force Status: Percent of Time by Activity

	Age 16+			Age 25-55		
	E	U	O	E	U	O
Active Job Search	81.7	91.0	86.2	81.2	92.4	89.8
Interviewing	14.4	6.7	9.7	14.0	5.1	5.4
Other	3.9	2.3	4.4	4.8	2.5	4.8
N	601	1,382	203	434	982	128

Table 4: Summary Statistics

	Employed	Unemployed	Out of the Labor Force
Female	0.47	0.48	0.62
Married	0.57	0.31	0.52
Female X Married	0.25	0.16	0.32
Child	0.43	0.54	0.29
Female X Child	0.20	0.29	0.21
Age	41.27	33.49	55.38
Less than HS	0.10	0.31	0.25
High School	0.28	0.30	0.34
Some College	0.27	0.25	0.22
Collage	0.22	0.10	0.12
Advanced Degree	0.13	0.04	0.07
Sunday	0.14	0.14	0.15
Monday	0.14	0.14	0.14
Tuesday	0.15	0.14	0.14
Wednesday	0.14	0.15	0.14
Thursday	0.14	0.15	0.14
Friday	0.14	0.14	0.14
Saturday	0.14	0.14	0.14
Full Time	0.78		
Part Time	0.22		
White	0.83	0.71	0.81
Black	0.11	0.22	0.13
Other	0.06	0.07	0.06
Observations	124,631	9,045	65,155

Table 5: Probit Main Effects

	Employed	Unemployed	Out of the Labor Force
Economy	-2.612**	-2.356***	-1.072***
	(1.089)	(0.456)	(0.132)
Female	-0.0957	-0.175***	-0.120
	(0.0691)	(0.0370)	(0.120)
Married	-0.276***	-0.250***	0.0728
	(0.0644)	(0.0376)	(0.162)
Female X Married	0.0546	-0.0325	-0.322
	(0.0890)	(0.0527)	(0.265)
Child	0.132**	-0.0201	-0.0731
	(0.0644)	(0.0440)	(0.121)
Female X Child	-0.212**	0.00765	0.00962
	(0.0980)	(0.0563)	(0.184)
Age	0.632***	0.0758	0.476**
	(0.122)	(0.0930)	(0.218)
Age^2	-0.0239***	-0.00231	-0.0178*
	(0.00483)	(0.00372)	(0.00932)
Age^3	0.000375***	0.0000338	0.000278*
	(0.0000796)	(0.0000617)	(0.000163)
Age^4	-0.00000210***	-0.000000225	-0.00000158
	(0.000000462)	(0.000000361)	(0.000000987)
Black	0.236***	0.236***	0.331***
	(0.0568)	(0.0335)	(0.0698)
Other	-0.0292	0.0578	0.0939
	(0.141)	(0.0662)	(0.136)
High School	-0.0654	0.0743*	-0.0940
	(0.0737)	(0.0445)	(0.122)
Some College	0.0512	0.0800	0.115
	(0.107)	(0.0650)	(0.145)
College	0.0860	0.00248	0.134
	(0.125)	(0.0715)	(0.192)
Advanced Degree	0.159	0.0559	0.177
	(0.147)	(0.0776)	(0.265)
Monday	0.301***	0.341***	0.258**
	(0.0829)	(0.0645)	(0.107)
Tuesday	0.275***	0.256***	0.252***
	(0.0687)	(0.0510)	(0.0922)
Wednesday	0.266***	0.391***	0.389***
	(0.0665)	(0.0654)	(0.113)
Thursday	0.324***	0.313***	0.289**
	(0.0613)	(0.0412)	(0.119)
Friday	0.185**	0.222***	0.0834
	(0.0791)	(0.0503)	(0.0922)
Saturday	-0.00147	-0.0647**	-0.0736
	(0.0702)	(0.0277)	(0.101)
Part Time	0.522***		
	(0.0431)		
Constant	-8.344***	-3.213***	-7.322***
	(1.130)	(0.784)	(1.874)
Uncensored Obs.	124,300	9,012	65,011
Observations	198,323	198,324	198,324

Standard errors shown for demographic variables and day of the week are clustered at the state level. Standard errors shown for the Economic factor are multi-way clustered standard errors by state and year.

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

Table 6: Selection

	Employed	Unemployed	Out of the Labor Force
Economy	1.459***	-1.818***	-1.008***
	(0.333)	(0.515)	(0.302)
Female	0.106***	-0.125***	-0.0788***
	(0.0179)	(0.0152)	(0.0193)
Married	0.371***	-0.256***	-0.324***
	(0.0160)	(0.0215)	(0.0151)
Female X Married	-0.594***	0.0876***	0.621***
	(0.0251)	(0.0263)	(0.0263)
Child	0.0356**	0.0101	-0.0873***
	(0.0181)	(0.0250)	(0.0204)
Female X Child	-0.406***	0.0930***	0.474***
	(0.0273)	(0.0254)	(0.0226)
Age	0.0376	-0.125***	0.0163
	(0.0374)	(0.0375)	(0.0316)
Age^2	0.00234**	0.00309**	-0.00408***
	(0.00118)	(0.00136)	(0.000986)
Age^3	-0.0000709***	-0.0000302	0.0000968***
	(0.0000157)	(0.0000206)	(0.0000132)
Age^4	0.000000425***	7.03e-08	-0.000000560***
	(7.51e-08)	(0.000000111)	(6.36e-08)
High School	0.426***	-0.0932***	-0.416***
	(0.0235)	(0.0233)	(0.0253)
Some College	0.561***	-0.178***	-0.531***
	(0.0221)	(0.0217)	(0.0255)
College	0.785***	-0.369***	-0.731***
	(0.0248)	(0.0270)	(0.0265)
Advanced Degree	0.938***	-0.404***	-0.896***
	(0.0331)	(0.0398)	(0.0318)
Black	-0.229***	0.302***	0.108***
	(0.0230)	(0.0291)	(0.0241)
Other	-0.248***	0.0856***	0.246***
	(0.0367)	(0.0298)	(0.0360)
Monday	0.0320**	-0.0232	-0.0279*
	(0.0130)	(0.0199)	(0.0159)
Tuesday	0.0450***	-0.0292	-0.0426***
	(0.0156)	(0.0262)	(0.0135)
Wednesday	0.0161	-0.00403	-0.0201
	(0.0145)	(0.0203)	(0.0156)
Thursday	0.0128	0.0154	-0.0240
	(0.0227)	(0.0252)	(0.0230)
Friday	0.0419***	-0.00209	-0.0490***
	(0.0135)	(0.0209)	(0.0132)
Saturday	0.0314**	-0.00808	-0.0339***
	(0.0137)	(0.0186)	(0.0127)
First Month	0.0455***	0.0180	-0.0637***
	(0.0138)	(0.0174)	(0.0135)
Constant	-1.290***	0.453	0.335
	(0.410)	(0.350)	(0.352)
ρ	-0.238	1.950**	0.507
	(0.236)	(0.932)	(0.532)
Observations	198,323	198,324	198,324

Standard errors shown for demographic variables and day of the week are clustered at the state level. Standard errors shown for the Economic factor are multi-way clustered standard errors by state and year. Employed and out of the labor force selection model would not converge with selection on Age^4.

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

Table 7: Percentiles of Predicted Search Effort

	Employed	Unemployed	Out of the Labor Force
5th Percentile	0.0243	0.8498	0.0000
10th Percentile	0.0340	0.9093	0.0000
25th Percentile	0.0587	0.9768	0.0032
50th Percentile	0.1083	0.9969	0.0480
75th Percentile	0.1856	0.9998	0.1469
90th Percentile	0.2905	1.0000	0.3214
95th Percentile	0.3910	1.0000	0.4601
Observations	468	468	468

Table 8: Correlation between Search Effort and Labor Force Attachment: 1994-2018

Dependent Variable	Hours		Full Time		Job Finding Probability	
	(1)	(2)	(3)	(4)	(5)	(6)
Search Probability	9.725^{***}	9.918^{***}	0.289^{***}	0.293^{***}	0.228^{***}	0.230^{***}
	(0.0491)	(0.0491)	(0.00153)	(0.00153)	(0.000438)	(0.000438)
Mean	29.36	29.35	0.48	0.48	0.064	0.064
Month × Year FE		✓		✓		✓
Observations	639,129	639,129	782,133	782,133	11,860,092	11,860,092

Robust standard errors in parentheses

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

Table 9: Cyclical Property of Stocks and Flows

	Unadjusted							
	unemp.	part.	f_{eu}	f_{eo}	f_{ue}	f_{uo}	f_{oe}	f_{ou}
$E(x)$	0.063	0.654	0.015	0.028	0.250	0.211	0.047	0.027
$std(Q/Q)$	0.042	0.001	0.065	0.033	0.050	0.047	0.034	0.058
$corrcoef(x, x_{-1})$	0.977	0.986	0.910	0.844	0.946	0.875	0.872	0.908
	Adjusted							
	unemp.	part.	f_{eu}	f_{eo}	f_{ue}	f_{uo}	f_{oe}	f_{ou}
$E(x)$	0.111	0.690	0.016	0.009	0.203	0.050	0.000	0.030
$std(Q/Q)$	0.027	0.002	0.049	0.105	0.038	0.073	–	0.046
$corrcoef(x, x_{-1})$	0.981	0.981	0.900	0.605	0.944	0.741	–	0.918

Notes: All series are seasonally adjusted and averaged over the quarter. $E(x)$ is the average value over the sample, $std(Q/Q)$ is the standard deviation of the quarterly growth rate and $corrcoef(x, x_{-1})$ is the autocorrelation.

Table 10: Three State Variance Decomposition

	Share of Variance							Total Between		
	EU	UE	OU	UO	EO	OE	residual	U and E	U and O	E and N
Unadjusted	30.0	40.9	19.0	20.9	-1.8	0.9	-9.8	70.9	39.9	-0.9
Adjusted	36.2	45.5	13.0	2.5	0.2	0.0	2.6	81.8	15.5	0.2

Table 11: Aggregate Wage Growth and Labor Market Correlations: 1980Q1 - 2018Q4

	Median Wage Growth		
	Measure of Labor Utilization		
	Standard Unemployment Rate	Continuous Unemployment Rate	Total Searcher Rate
Coefficient	-0.123	-0.341***	-0.376***
	(0.120)	(0.081)	(0.069)
N	156	156	156
R^2	0.013	0.127	0.142
	Consumer Price Index Growth		
	Measure of Labor Utilization		
	Standard Unemployment Rate	Continuous Unemployment Rate	Total Searcher Rate
Coefficient	0.028	-0.156**	-0.179***
	(0.074)	(0.070)	(0.065)
N	156	156	156
R^2	0.001	0.044	0.054

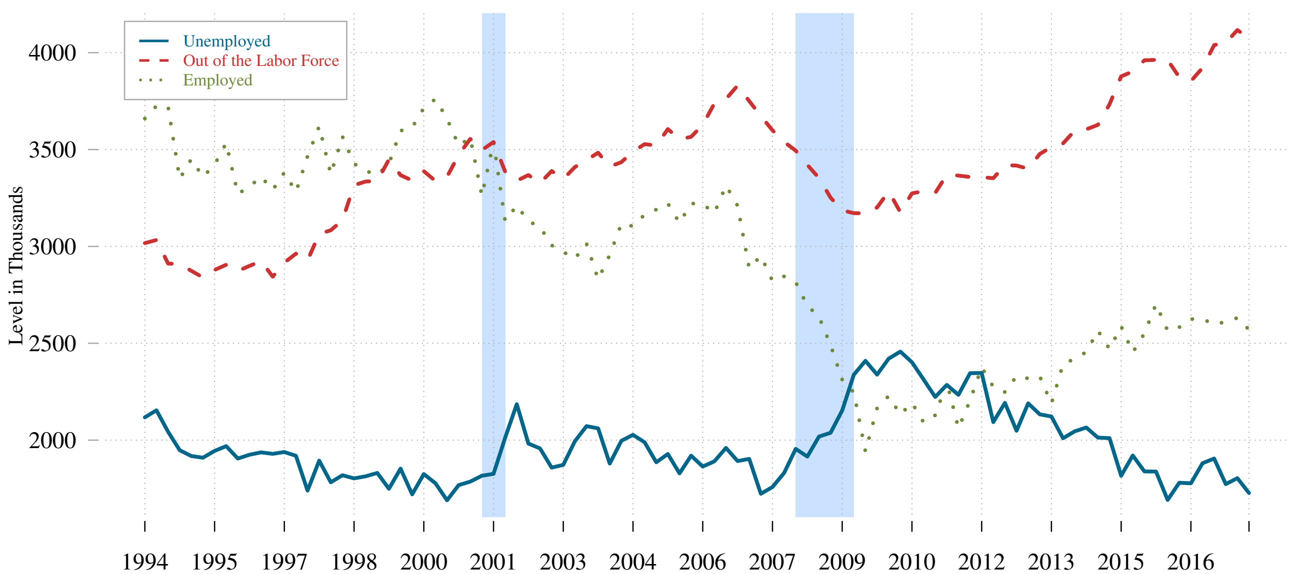
Table 12: Properties of Alternative Unemployment Measures: 1994-2018

	Standard (U3)	Continuous	U4	U5	U6	NEI	Employment Weighted
$E(x)$	0.058	0.109	0.062	0.069	0.105	0.089	0.120
$std(Q/Q)$	0.045	0.025	0.047	0.044	0.042	0.019	0.026
$corrcoef(x, x_{-1})$	0.975	0.985	0.978	0.977	0.981	0.965	0.984

Notes: All series are seasonally adjusted and averaged over the quarter. $E(x)$ *is the average value over the sample,* $std(Q/Q)$ *is the standard deviation of the quarterly growth rate and* $corrcoef(x, x_{-1})$ *is the autocorrelation.*

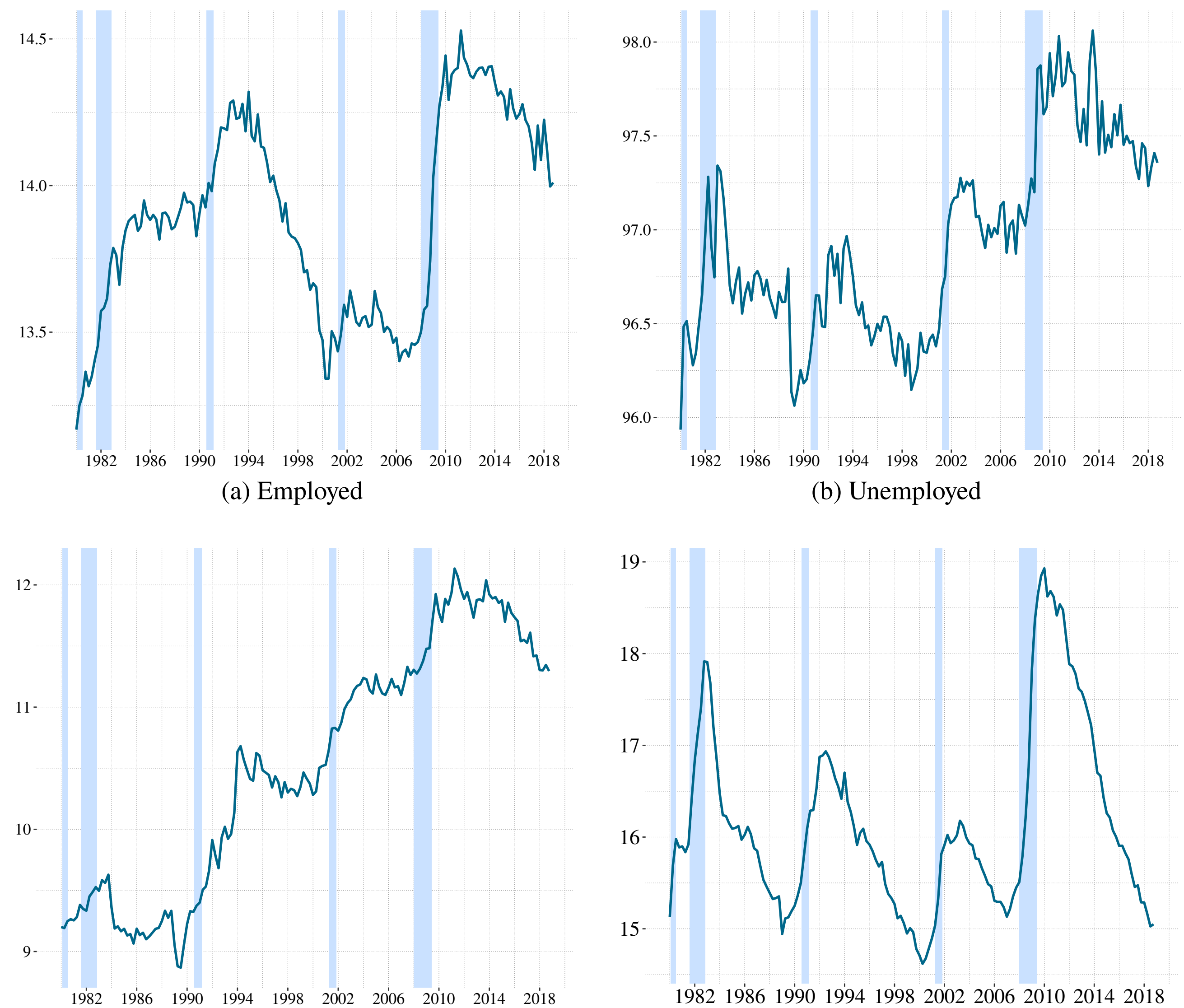
8 Figures

Figure 1: Total Monthly New Job Transitions by Labor Market Status



Plotted are the quarterly average number of individuals age 16 and older each month starting a new job by their previous labor market status. The data comes from the matched basic monthly files of the Current Population Survey.

Figure 2: Fraction of Job Searchers



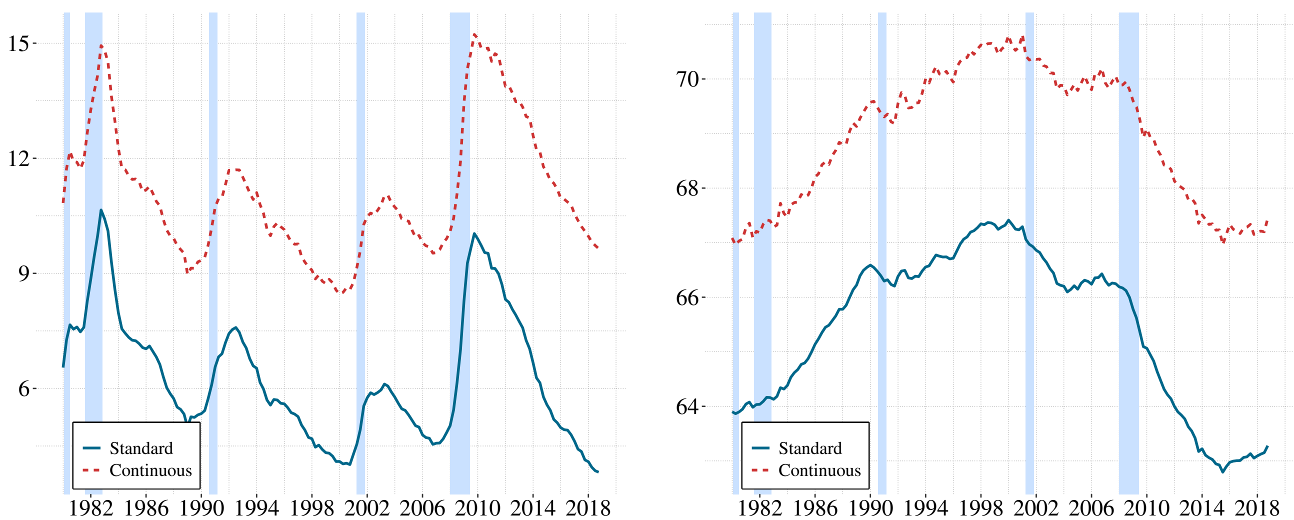
(a) Employed

(b) Unemployed

(c) Out of the Labor Force

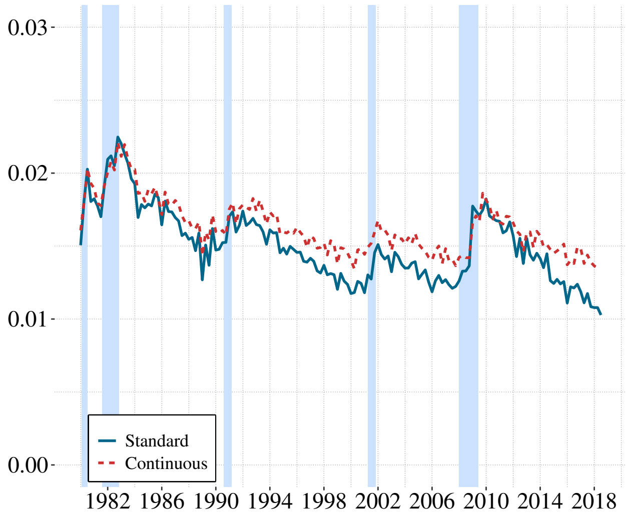
(d) Total Population

Figure 3: Unemployment and Participation Rates

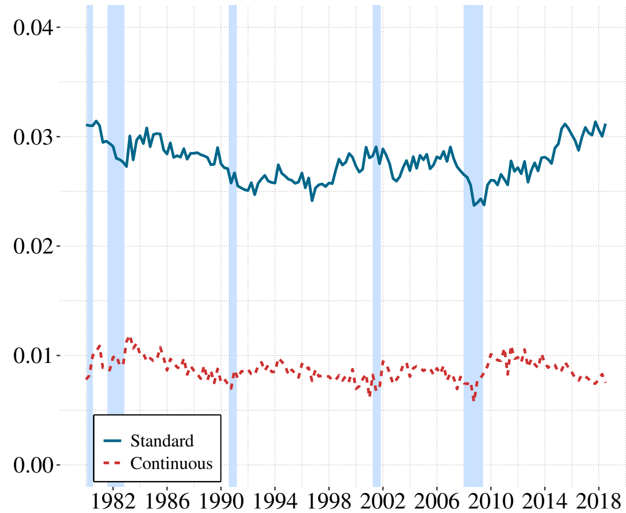


(a) Unemployment Rate (b) Participation Rate

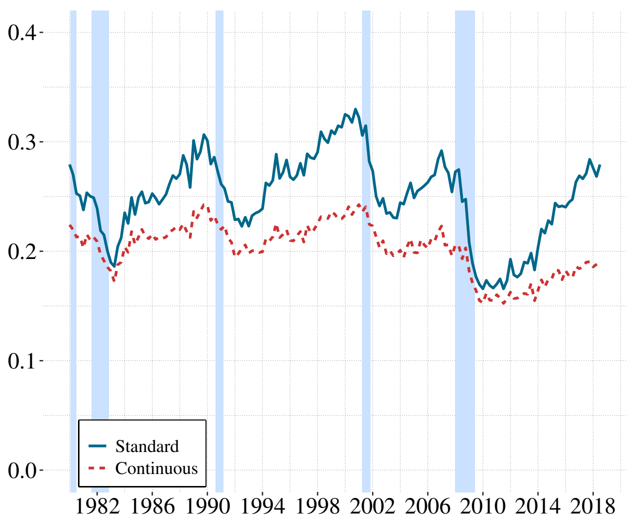
Figure 4: Labor Market Flows



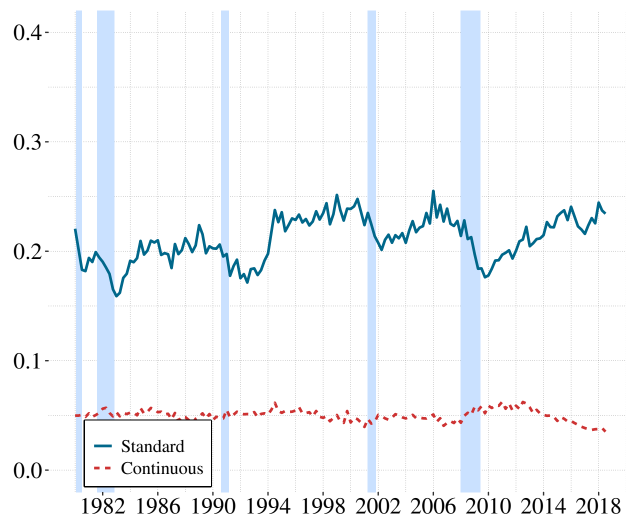
(a) Employed to Unemployed



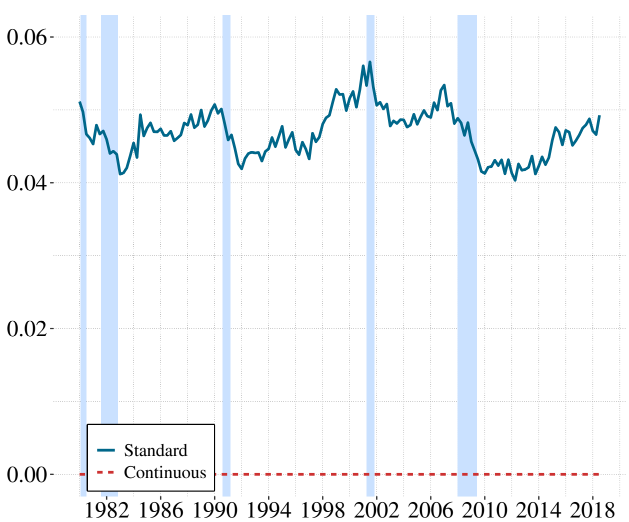
(b) Employed to Out of the Labor Force



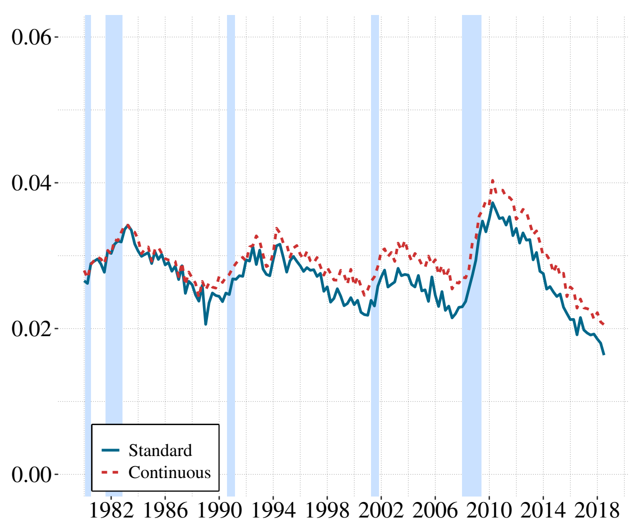
(c) Unemployed to Employed



(d) Unemployed to Out of the Labor Force

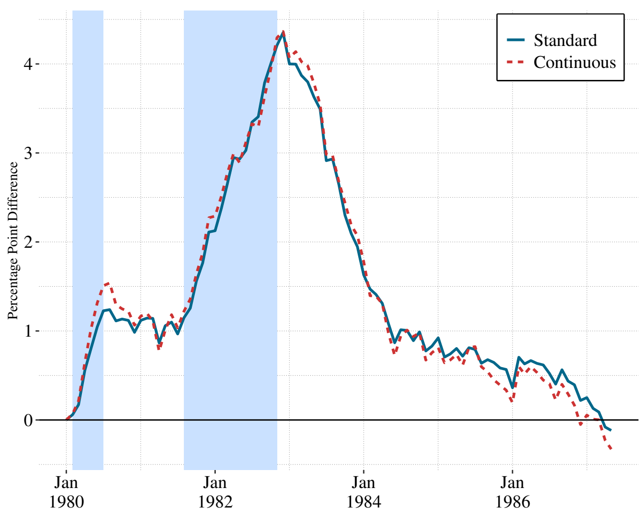


(e) Out of the Labor Force to Employed

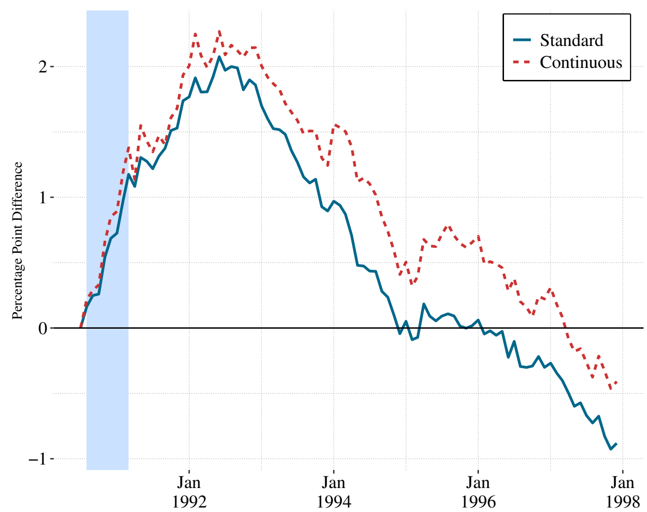


(f) Out of the Labor Force to Unemployed

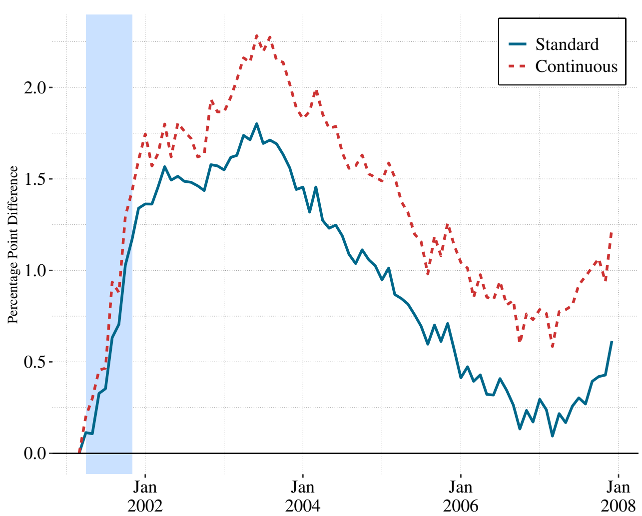
Figure 5: Unemployment by Recession



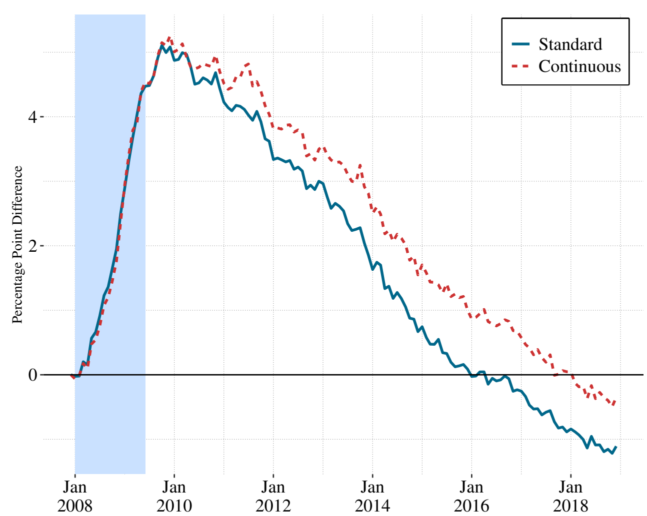
(a) 1980 & 1981 Recessions



(b) 1990 Recession

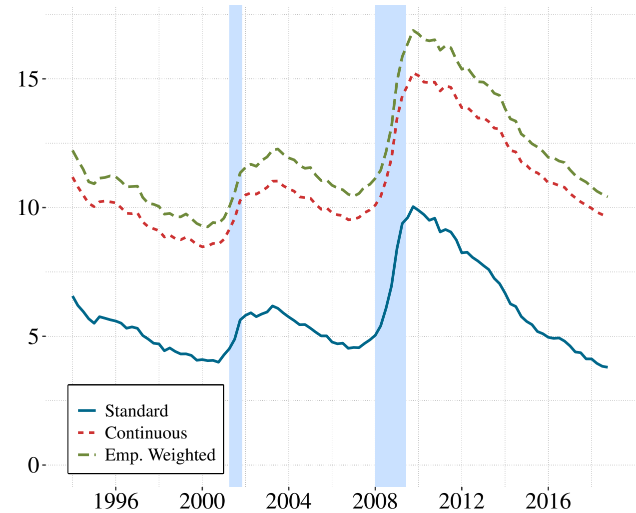


(c) 2001 Recession

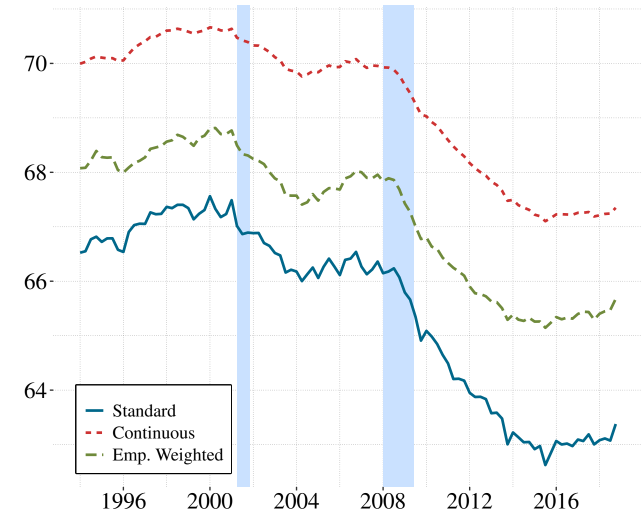


(d) 2008 Recession

Figure 6: Unemployment and Participation Rates: Weighted Employment

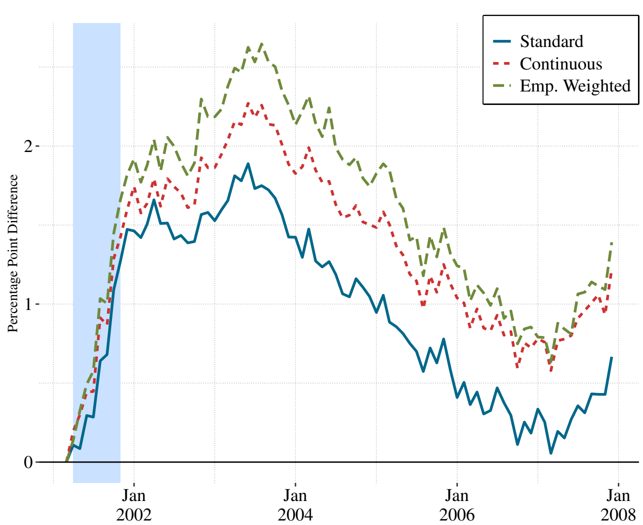


(a) Unemployment Rate

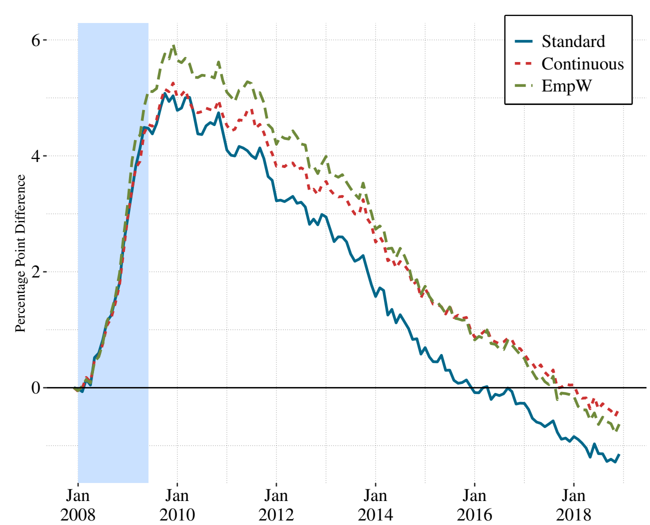


(b) Participation Rate

Figure 7: Unemployment by Recession



(a) 2001 Recession



(b) 2008 Recession

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