Aggregate Job Search of the Employed, Unemployed, and Non-Participants*

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Abstract

Using data from the American Time Use Survey, I document a substantial rise in the proportion of job seekers who are classified as out of the labor force. In 1980, about 9.5% of people classified as out of the labor force were searching for a job, whereas in 2020, 13% actively searched for a job, an increase of nearly 7 million job seekers. The increase in search effort from non-participants is attributed to an increase in education among individuals classified as out of the labor force, and changes in the composition of race and gender. Accounting for these searchers increases the unemployment rate by 5.2 percentage points on average and rids the unemployment rate of its downward trend. The paper also delivers a total searcher rate, including employed job seekers, and adjusted labor market flows. Contrary to estimates with the standard unemployment rate, estimating the Phillips curve with the adjusted unemployment rate (or total searcher rate) shows no sign of a flattening output-inflation relationship in the post-2008 recession period.

Keywords: Unemployment, Labor Force Participation, Worker Flows, Phillips Curve

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1 Introduction

In 2019 in the Untied States, 50% of new hires were workers who were previously classified as out of the labor force, 31% came from a different job and only 19% of new hires were from the pool of individuals considered to be actively searching: the unemployed. This startling statistic is not unique to 2019, Figure 1 shows that the proportion of hires coming from non-participation has increase since 1980. In the face of this fact, the unemployment rate, considered by many as the "best single indicator of current labor market conditions"[1], is abysmal at capturing potential hires.

The paper makes three points. First, I show that the fraction of non-participants who are actively searching for a job has increased since 1980. I show that education, gender and race are strong predictors of search effort of non-participants. Second, I construct an adjusted unemployment rate and total searcher rate (including employed job seekers) by estimating a monthly probability that an individual is searching for a job, and classifying individual as job seekers based on these probabilities rather than reported labor market status. I also adjust labor market flows using the estimated probabilities. Third, I show that the miss-classification of job seekers has a significant effect on macroeconomic implications by estimating the Phillips Curve using the adjusted unemployment rate and total searcher rate. The results show no flattening of the output-inflation relationship in the post-2008 recession period.

The main source of data for job search comes from the American Time User Survey (ATUS). Time use diaries from the ATUS allow us to see search effort by all individuals, regardless of labor market status (employed, unemployed, or out of the labor force). Using the 2003-2019 ATUS diaries, I show that nearly 12% of people classified by as out of the labor force are actively searching for a job during the month. I show that women, and women with children are more likely to be classified as non-participants, but they are more likely to be searching for a job from outside the labor force than their male counterparts. Similarly education is a strong predictor of labor market status classification, with more educated people less likely to be classified as non-participants but more likely to be searching for a job if classified so.

Next I estimate a model of the probability an individual is searching for a job based on observable characteristics. To estimate these probabilities I use machine learning on the American Time Use data to inform about which demographic characteristics are the strongest predictors of job search. Using the estimated model, I then predict search effort of all individuals in the Current Population Survey. I classify the non-employed as job seekers probabilistically based on the estimated search probability, rather than deterministically based on reported labor market status. I classify employed

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

as job seekers, in the same fashion. Using these classifications I create an adjust the unemployment rate since 1980. The adjusted unemployment rate is on average 5.2 percentage points higher than the standard unemployment rate and does not display the same low frequency downward trend observed in the standard unemployment rate. The differences in level is attributed to the large fraction of job seekers classified as non-participants. The difference in trends is attributed to the fact that the fraction of job seekers classified as non-participants has increase from 9.5% in 1980 to 13% in 2020.

Using the predicted search probabilities I also adjust labor market flows. The adjusted labor market flows are substantially different than the standard flows calculated from the matched Current Population Survey. 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 probability to non-participation is only 0.04, implying that unemployment is a much more persistent state than previously thought.

Finally, I show that the estimates of the Phillips Curve differ substantially when using the standard unemployment rate rather than the adjusted unemployment rate (or total searcher rate). Many papers have investigated the changing output-inflation relationship following the Great Recession, often using the unemployment gap, measured as the difference between the Congressional Budget Office's Natural Rate of Unemployment (NRU) and the standard unemployment rate, as a measure for the output gap (Ball and Mazumder, 2011; Coibion and Gorodnichenko, 2015; Blanchard, 2016). I show that with estimates using the adjusted unemployment rate and total searcher rate, there is no flattening in the post 2008 recession period. This suggests that the change in the output-inflation relationship may be driven my measurement issues.

The paper contributed to the literature exploring the effects of miss-classification of individuals on the level of the unemployment rate (Abowd and Zellner, 1985; Feng and Hu, 2013; Ahn and Hamilton, 2019). These studies suggest that the true unemployment rate may be somewhere between 2 and 4 percentage points higher than the reported one. The method used here differs from the existing studies by using data on job search to estimate misclassification probabilities for the non-employed, rather than reported labor market status. Similarly to Ahn and Hamilton (2019), I show that miss-classification has increased over time due to demographic changes. These results are consistent with Perry (1970); Flaim (1979); Shimer (2001); Barnichon and Mesters (2018) who find that demographic changes decreased the unemployment rate by 1-2 percentage points since 1980.

I also contribute to the literature exploring miss-classification on the flows between labor market states, which has focused on tying 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 constructed here. Similarly, Elsby et al. (2015) correct labor market transitions to get ride of oscillations between non-participation 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.[2] The adjusted flows presented here show these large oscillations between unemployment and non-participation are in fact due to measurement error, suggesting that transitory shocks to the disutility of search are not necessary in understanding participation decisions.

This paper also adds to a small literature focused on constructing a better measure of labor underutilization for the United States.[3] 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. I contribute to this literature by estimating labor slack with data on search effort, instead of ex-post transition probabilities, and constructing a total searchers rate which includes employed job seekers. Currently all aggregate measures of total search effort in the economy include the part time employed based on the reason for part time employment. To the best of my knowledge this is the first such measure constructed from reported search effort.

2 Data

The two main data sources are the basic monthly files for the Current Population Survey (CPS) and the American Time Use Survey (ATUS). 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 the household and all members of the household residing

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

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

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; then, people are classified as unemployed if they have made 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.[4]

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 documented 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 the shame carried by admitting, month after month, that they were unable to find a job. However, Flinn and Heckman (1983) find that, at least until the early 1980's, unemployment and out of the labor force are behaviorally distinct states.

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.

In what follows, I present evidence using hires that suggests miss-classification problem is large and that the unemployment rate itself is not a good measure of labor market slack. Then using the ATUS I show how miss-classification can be revisited in the time use diaries and used to estimate aggregate search statistics for the United States.

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

2.1 Hires by Labor Force Status

Figure 1 plots the total number of new hires by previous labor force status, the data come from the matched CPS files. The figure shows that while total hires out of unemployment have remained stable around 2 million per month since 1980, hires from out of the labor force have nearly doubled. In the 1980's workers that were previously classified as out of the labor force made up 60% of total hires from non-employment and by 2019, they made up 72.5%. As a fraction of all hires, workers who were previously classified as out of the labor force have also been increasing, in the 1990's hires from out of the labor force made up 36% of all hires, and 50% in 2019.[5] The figure shows that the pool of unemployed does not capture potential workers well in terms of hires.

Over the same time, the total size of the out of the labor force group also increase by 50% from 63 million in 1980 to 95 million in 2019. However, the composition of the the OLF pool has also seen large changes since 1980. Table 1 shows the percent of each demographic group as a total of the OLF population and a total of the hires from the OLF population. Looking across sex, there were only marginal changes in the percent of the total population as well as total hires. Women made up about 53% of the total OLF population and OLF hires in the 1980's, decreasing to 52% by the 2010's. Similarly, decomposing the total OLF population and hires by race shows only small changes occurring over the past 40 year.

Decomposing changes by age and education show much larger changes. The pool of OLF have become older; people age 56+ made up about 26% of the pool of OLF in the 1980's and increase by 6 percentage point to 32% by the 2010's. However, the precent of hires from OLF by each age group has changes accordingly. Individuals age 56+ made up about 18% of OLF hires in the 1980's and increased 6 percentage points to 24% by the 2010's.

On the other hand, changes in education show that both the percent of each group and the percent of hires has change since the 1980's. There was a general increase in the education level of the OLF population, with more individuals having completed high school and college in the 2010's than the 1980's. However, whereas people who had completed high school make up more the OLF population in the 2010's, the account for less of the OLF hires in the 2010's. And while less of the OLF population had some college education in the 2010's than in the 1980's, they account for more of the OLF hires in the 2010's than in the 1980's.

[5] The decreased level in the job to job transitions after the 2008 recession in the CPS is not consistent with job-to-job transitions from the Longitudinal Employer-Household Dynamics. See Fujita et al. (2020) for a discussion and how some of the difference can be reconciled by the fact that the CPS changed to whom the previous employer question is asked.

2.2 Job Search in the American Time Use Survey

The CPS also asks several questions about job search efforts, however, these questions are limited to people who are classified as unemployed. One the other hand, with the American Time Use Survey, job search effort can be observed by all participants. The 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. Selected 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. Each activities recorded 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.[6] 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 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 any person is searching for a job.

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. Due to the cross-sectional nature of the ATUS, 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 identical and independent across days.[7] That is, if p is the daily probability of searching for a job, then the corresponding monthly probability is calculated as $1 - (1 - p)^{30}$. The monthly probability is the probability that the individual spent some time searching on at least one day during the month, this

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

[7] In the subsequent analysis, this restriction will be relaxed and the propensity of search effort can vary across days however remains independent across days, again due to data limitations.

corresponds well to the CPS definition of unemployment of having made at least one active search effort during the past 4 weeks.

Table 2 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 single 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 (34.7). 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 (24.4) from outside the labor force is higher than the probability of observing an employed person, age 25-55, searching for a job (15.1). The fact that the probability of observing a person classified as out of the labor force searching for a job is positive is further evidence of the measurement issues discussed above.

The intensive margin of search (minutes spent searching) is reported in Table 3. Both the unconditional average and conditional on positive search time is reported. First, 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. The extensive margin of job search in the ATUS is similar to that presented in Faberman et al. (2017) who use data from the Survey of Consumer Finances, however the intensive margin among job seekers differs between the two surveys.

In the CPS classification scheme, the type of job search activity, active vs passive, also determines if non-employed individuals are classified as unemployed or out of the labor force. Table 4 reports the percent of time each group spends 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 states and both samples, the majority of time is spent in active job search.

Employed individuals spend about 14% of the time interviewing whereas, unemployed individuals spend only about 6% of the time interviewing. Consistent with the fact that people classified as out of the labor force should not to be actively searching for a job, they spend up to 5% of the reported job search time in the “Other" category; however, they spend the majority of the time actively searching for a job, between 85% and 90%. The evidence presented in Table 3 and Table 4 suggest that people who are classified as out of the labor force but exert positive search effort, may not be behaving differently from those classified as unemployed.

2.2.1 Who is searching from outside the labor force?

To understand which characteristics make individuals more likely to search while being classified as out of the labor force I run a two stage Heckman selection model on the the non-employed. Selection is estimated as the probability of getting classified as out of the labor force on the set of demographic characteristics (sex, married, child, age, race, education) and interaction terms for sex, married and child. The instrument for selection is an indicator for whether or not the ATUS respondent is the same as the respondent in the final CPS interview. Krueger et al. (2017) show that respondents answer question differently based on how long they have been in the CPS, implying that ATUS respondents that were also the CPS respondents may be classified differently from others but this should not affect their search efforts. For selection I run a Probit on an indicator if the non-employed individual was classified as out of the labor force (y_i) on the set of covariates (x_i):

$$P(y_i = 1|x_i) = \phi(\beta x_i + \gamma_d + \gamma_m + \gamma_y) \tag{1}$$

where ϕ is the standard normal p.d.f., γ_d are day of the week fixed effects, γ_m are month fixed effects, and γ_y are year fixed effects. Then on the subset of people classified as out of the labor force I estimated a linear probability model on an indicator if the individual searched for a job on the interview day (s_i), the set of covariates (x_i) and the selection probability (inverse Mill ratio, λ_i):

$$s_i = \beta x_i + \gamma_d + \gamma_m + \gamma_y + \delta\lambda_i + \varepsilon_i \tag{2}$$

where the fixed effects are as before.

Column (1) of Table 5 shows the parameters from the first stage. Non-employed women, married women, and women with children are all more likely to get classified as out of the labor force than their male counterparts. People with higher levels of eduction are less likely to get classified as out of the labor force than people with less than a high school degree. The estimated coefficient on the

"Same Respondent" dummy is negative and significant, implying that people who were also the CPS respondent are less likely to get classified as out of the labor force.

Column (2) of Table 5 shows the parameter estimates from the linear probability model. The significant coefficient on the inverse Mills ratio implies that there is statistically significant selection on observables. Conditional on selection, women are more likely to search for a job from out of the labor force. Married men are less likely to be classified as OLF but conditional on selection, they are 20 percentage points more likely to search for a job when they are. Similarly, higher educated people are less likely to be classified as out of the labor force, but conditional on selection they are more likely to search. For example, college educated workers are 31 percentage points more likely to search for a job on the interview day.

3 Estimation and Prediction

The previous section documented an increase in the fraction of hires coming from out of the labor force, suggesting that the CPS definition of unemployment does not capture labor underutilization well. This is also supported by the fact that about 12% of those classified as out of the labor force are searching for a job during the month. The probability that an individual searchers for a job while being classified as out of the labor force differs across gender, age and education, demographic characteristics along which individuals classified as out of the labor force have changed substantially since 1980.

In this section I estimate search effort among ATUS respondents based on labor force status and demographic characteristics. Using these estimates I predict the probability that individuals in the CPS are searching for a job during the interview month. Finally, by matching people across consecutive months, I show that the estimated search probability is correlated with job finding probabilities and subsequent hours worked.

3.1 Estimating Search Effort

Search effort (the daily search probability) is predicted from the subset of individuals that participate in the ATUS and predicted for all individuals in the CPS. To maximize the predictive power of the covariates, I use machine learning to choose the set of best predictors. The potential covariates are all demographic variables (a quadratic in age, race, education, sex, marital status, and an indicator for having a child), day of the week fixed effects, a full/part time indicator for the employed, and interactions between sex and education, and all other covariates. The total number of potential covariates for the employed group is 57 and for the unemployed and out of the labor force groups is 51. To ensure that the adjusted unemployment rate is comparable over time, i.e. is not biased by changes in the demographic composition of the pool of job seekers, all demographic variables and day of the week fixed effects enter the machine learning algorithm without penalty, while all interaction terms enter with a standard penalty function described in detail below.

I estimate the daily search probability for each labor market state, including those classified as unemployed. Estimating search probabilities that depend on demographic characteristics for the unemployed, again ensures that the adjusted unemployment rate is not biased by changes in the demographic composition of the unemployed. This also allows for miss-classification error among the U-O margin, that is, workers classified as unemployed that should be classifies as out of the labor force.

For each CPS defined labor market status, I run a net-elastic logistic regression, where the dependent variable is an indicator for if the individual spent any time searching for a job on the interview day. Demographic information for each person is collected in the CPS and matched to their ATUS interview. For each individual in the ATUS, let y_i be an indicator that takes on the value one if they spent any time searching for job on the interview day and x_i be the vector of covariates. The probability that the individual searched for a job is modeled using the logistic function,

$$P(y_i = 1|x_i) = \frac{\exp(\beta_0 + x_i'\beta)}{1 - \exp(\beta_0 + x_i'\beta)} \tag{3}$$

and the log-likelihood function is

$$\mathcal{L}(\beta_0, \beta|\{y_i, x_i\}) = \left[\frac{1}{N}\sum_{i=1}^{N} y_i(\beta_0 + x_i'\beta) - \ln[1 - \exp(\beta_0 + x_i'\beta)]\right] + \lambda\left[(1-\alpha)\sum_{k\in K}\beta_k^2 + \alpha\sum_{k\in K}|\beta_k|\right] \tag{4}$$

where α is set to 0.95, implying more weight on the LASSO penalty and the tuning parameter, λ, is chosen through cross validation of ten folds of the data with the area under the receiver operating characteristic curve as the selection criteria. The penalty is only over the interaction terms (the set K) to ensure that all demographic variables and day of the week fixed effects are always included in the estimation. Final ATUS weights are used in all calculations.

Table 6 shows the selected covariates and resulting parameter estimates for each labor force status. For the employed group, 5 of the interaction terms are included in the estimation. For the unemployed and out of the labor force groups 17 and 8 interaction terms are included. Figure 2 plots the receiver operating characteristic curve for each labor force group. The out of the labor force group has the best fit with an area under the curve (AUC) of 0.873, the employed AUC is 0.753 and the unemployed AUC is 0.735.

3.2 Predicting Search Effort

The CPS contains all the same demographic information as the ATUS and labor market status is determined equivalently in both samples. Therefore, although the ATUS sample begins in 2003, search effort can be predicted using the CPS starting in 1980. The estimated search probability is a daily probability, therefore, seven probabilities are predicted for each person in the CPS, one for each day of the week fixed effect. The predicted daily probability is:

$$\hat{p}_i^d = \frac{\exp(\hat{\beta}_0 + x_i'\hat{\beta})}{1 - \exp(\hat{\beta}_0 + x_i'\hat{\beta})} \tag{5}$$

for $d \in \{1, 2, \ldots, 7\}$ where $\hat{\beta}_0$ and $\hat{\beta}$ are the estimated coefficients.

Using the predicted daily probability, the weekly probability that a person is searching for a job is 1 minus the probability he does not search any day during the week, i.e.

$$\hat{p}_i^w = 1 - \sum_{d=1}^{7} (1 - \hat{p}_d). \tag{6}$$

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

$$\hat{P}_i = 1 - (1 - \hat{p}_i^w)^{4.17} \tag{7}$$

with 4.17 weeks per month. Equation 7 is one minus the cumulative product of not searching each week in the month, that is, it is the probability that person i searched at least once during the month. The probability is in line with the CPS definition of unemployment of having at least on active search effort during the month.

Table 7 reports percentiles of the predicted search probabilities for each labor market state over the entire sample. The unemployed have the highest predicted search probabilities and the distribution of search probabilities is skewed towards one, with the 50th percentile at 0.997. Not surprisingly, many predicted search probabilities are very close to zero for the out of the labor force group, in fact, the 25th percentile is at 0.04. However, the out of the labor force group still has many predicted search probabilities that are larger than the employed group. The 95th percentile of search probabilities for out of the labor force group is 0.44 and 0.35 for the employed group.

3.3 Search Effort and Labor Force Attachment

For the adjusted unemployment rate to be a useful measure of labor underutilization, it should weight non-employed people with a higher labor force attachment more than those with a lower labor force attachment. In term of labor force attachment, three statistics can be calculated from the basic CPS files. First, for the full sample of individuals matched across two consecutive months in the CPS from 1994-2019 an indicator variable that takes on the value one if they found a job (or switched jobs for the employed), that is, a job finding probability is constructed as a measure of labor force attachment. Second, for the subset of non-employed individuals who found a job, their subsequent usual hours worked is used as a measure of labor force attachment. Third, for the subset of employed individuals who switched jobs, the change their usual hours worked is used as a measure of labor force attachment. For all three statistics, the estimated job search probability is an indicator of labor force attachment if it correlated positively with the outcome.

The correlation between the predicted job search probability and the three measures of labor force attachment is estimated as follows:

$$y_{it} = \beta \hat{P}_{it-1} + \delta_t + \varepsilon_{it} \tag{8}$$

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

The estimated correlation between an indicator for new employment (job finding probability) 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 and large relative to the mean job finding probability over the sample (0.04). The correlation between search effort and subsequent hours worked for the non-employed job finders subsample is reported in columns (3) and (4) of Table 8; the correlation is positive and significant. The correlation between changes in hours worked and search effort for the subset of employed job switchers is also positive and significant as reported in the last two columns of Table 8. The positive correlation between predicted search effort and job finding probabilities and hours worked suggests that the predicted search effort is indeed a good proxy of labor force attachment.

4 Aggregate Unemployment and Labor Market Flows

4.1 Aggregate Unemployment

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

$$U_t^s = \sum_{i \in U_t} wgt_{it} \times \hat{P}_{it} \tag{9}$$

$$E_t^s = \sum_{i \in E_t} wgt_{it} \times \hat{P}_{it} \tag{10}$$

$$O_t^s = \sum_{i \in O_t} wgt_{it} \times \hat{P}_{it} \tag{11}$$

where U_t, E_t, and O_t are the sets of all individuals in the respective CPS defined labor market state and wgt_{it} is the CPS sampling 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, seasonally adjusted using the Census X13-ARIMA and then aggregated to a quarterly frequency. A complete description of the process can be found in Appendix A.1.

Figure 3 plots the predicted fraction of people searching in each labor market state (O_t^s/O_t, U_t^s/U_t, E_t^s/E_t), and the population as a whole. The shaded regions depict recessions using the National Bureau of Economic Research's classifications. All series clearly display a counter cyclical patter, with the exception of employed search effort during the 2020 recession. The fraction of people searching while employed rose dramatically during the 2008 recession, increasing by about 1 percentage point from trough to peak. Nearly all those who are unemployed are searching for a job, with the percent varying between 95% and 98%. The fraction of people searching for a job who are classified as out of the labor force has risen by nearly 4 percentage points since 1980, which corresponds to nearly 7 million extra job seekers. The final panel of Figure 3 plots the total fraction of the population that is searching for a job, on average about 16.5% of the population is searching for a job over the sample period.

The fraction of searchers among all three labor force groups in Figure 3 display a clearly countercyclical patter, rising during each recession. 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. 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. While the fraction of people searching among people classified as out of the labor force has risen by one third since 1980, the rise is also countercyclical, rising quickly during recessions and flattening or decreasing during expansions.

The adjusted unemployment rate is defined as the ratio of the weighted sum of all non-employed people, weighted by their search probabilities, to the total number of non-employed searchers and employed, that is:

$$\tilde{U}_t = \frac{U_t^s + O_t^s}{U_t^s + O_t^s + E_t}. \tag{12}$$

Analogously, the total searcher rate is the ratio of the weighted sum of all people, to the total number of participants,

$$S_t = \frac{U_t^s + O_t^s + E_t^s}{U_t^s + O_t^s + E_t}. \tag{13}$$

The total searcher rate is in spirit most similar to the Bureau of Labor Statistic's most inclusive measure of labor slack, U-6, which includes the unemployed, the marginally attached and all part time employed for economic reasons. However, the total searcher rate may better capture total labor under utilization since it weights individuals by their propensity to begin new employment. Finally, a adjusted measure of labor force participation is constructed by taking the ratio of the weighted average of all non-employed plus all employed to the total population,

$$\tilde{P}_t = \frac{U_t^s + O_t^s + E_t}{U_t + O_t + E_t}. \tag{14}$$

Panel (a) of Figure 4 plots the standard and adjusted unemployment and the total searcher rate. The average standard unemployment rate over the sample is 6.4. Both the average adjusted unemployment rate (11.6) and the average total searcher rate is (24) are higher than the standard unemployment rate. The most notable difference between the standard and adjusted unemployment rate is that the adjusted unemployment rate does not display the same low frequency downward trend that the standard unemployment rate does. Panel (b) plots the standard and adjusted labor force participation rates. The average adjusted participation rate is 3.9 percentage points higher than the standard participation rate. The standard labor force participation rate drops by 4 percentage points from 2000 to 2015. The adjusted participation rate decrease by only 3 percentage points from 2000 to 2015, implying that the increased misclassification among the non-employed can account for 25% of the drop in the standard participation rate.

4.1.1 Accounting for the increase in OLF search effort

Since the OLF search series presented in panel (c) of Figure 3 is constructed using time invariant demographic effects on search probabilities, changes in the series are driven by changes in the demographic composition of the pool of non-participants. To understand which demographic changes had the largest effect on aggregate OLF search effort I construct a counterfactual search series allowing the share of one demographic characteristic to vary at a time. This is done by constructing search effort on 1,000 re-sampled CPS basic monthly files, in which all but one demographic characteristic are fixed at their 1980 shares. The final counterfactual series plotted is the average across the 1,000 series.

Figure 5 plots the resulting fraction of OLF searchers as the percentage point difference from 1980. The series labeled "Aggregate" is the series presented in panel (c) of Figure 3. The figure shows that, changes in sex, race and education contributed to the increase in the search effort of those classified as out of the labor force. For example, the series in which only educational attainment is allowed to vary increases by over 5 percentage points since 1980, implying that the changes in the educational attainment of those classified as out of the labor force had a large effect on the aggregate OLF search effort holding all else equal. Similarly race and gender had a large effect on OLF search effort. The age of the OLF pool, on the other hand, had no effect on search effort among the group. The counterfactual series where age is the only demographic characteristic allowed to vary does does not increase since 1980. In fact, the aging of the pool of the out of the labor force contributed to the decline in search effort after the 2008 recession.

4.2 Labor Market Flows

The standard method used to calculated flows between labor market states uses information on individuals who are matched across consecutive months of the CPS basic monthly files. 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, 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 calculated as the fraction of workers transitioning across labor market states from month to month.

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:

$$f_{EU} = \frac{\sum_{i \in E_1 N_2} wgt_i \times \hat{P}_{i2}}{\sum_{i \in E_1} wgt_i} \tag{15}$$

where the summation in the numerator is over all workers that are observed in employment in the first month (E_1) and non-employment (CPS defined unemployment and out of the labor force) in the second month (N_2). 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 probability in the second month. Similarly the transition probability from employment to out of the labor force is calculated as:

$$f_{EO} = \frac{\sum_{i \in E_1 N_2} wgt_i \times (1 - \hat{P}_{i2})}{\sum_{i \in E_1} wgt_i} \tag{16}$$

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 (N_1) and employed in the second month (E_2), weighted by the probability they were searching for a job in the first month. That is,

$$f_{UE} = \frac{\sum_{i \in N_1 E_2} wgt_i \times \hat{P}_{i1}}{\sum_{i \in N_1} wgt_i}. \tag{17}$$

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 non-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

$$f_{OU} = \frac{\sum_{i \in N_1 N_2} wgt_i \times max\{\hat{P}_{i2} - \hat{P}_{i1}, 0\}}{\sum_{i \in N_1} wgt_i}. \tag{18}$$

Similarly, a person that is not employed in two consecutive months 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

$$f_{UO} = \frac{\sum_{i \in N_1 N_2} wgt_i \times |min\{\hat{P}_{i2} - \hat{P}_{i1}, 0\}|}{\sum_{i \in N_1} wgt_i}. \tag{19}$$

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. A detailed description of how this was done can be found in Appendix A.2. 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. Here the flows and stocks are calculated using estimated search probabilities, so correcting for margin error plays a larger role.

Figure 6 plots the standard and adjusted labor market flows across labor market states. The most notable changes occur along the participation margin. The average flow from out of the labor force to unemployment increases slightly from of 0.024 to 0.027 and the average flow from unemployment to out of the labor force decrease from and average of 0.21 to 0.04. The average flow from unemployment to employment decrease slightly from an average of 0.23 to 0.18. The average flow from employment to out of the labor force decreases by more half from 0.026 to 0.008. The standard flow from employment to out of the labor force is nearly twice as high as the standard flow from employment to unemployment; the adjusted flow from employment to out of the labor force is less than the adjusted flow from employment to unemployment.

Much of the previous work on labor market flows has focused on adjusting the flows to account for the misclassification between unemployment and non-participation. 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. Unfortunately, the CPS has since stopped conducting reinterview surveys. So more recently, Elsby et al. (2015) match individuals up to three months and recode an individual who is observed as unemployed in the first month, out of the labor force in the second month and unemployed in the third month, 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.

5 An Application: The Phillips Curve

The unemployment rate, or unemployment gap, is often used as a measure of labor market utilization in estimating the trade-off between output and inflation, i.e. the Phillips Curve. Since the Great Recession this relationship has gained new interest with many finding that the traditionally strong negative correlation between output and inflation has weakened or even disappeared, the phenomenon referred to as the flattening of the Phillips Curve. Papers investigating the apparent flattening (among many others) include Ball and Mazumder (2011); Coibion and Gorodnichenko (2015); Blanchard (2016); see McLeay and Tenreyro (2019) for a recent review.

I revisit the change in the output-inflation relationship following the Great Recession using the adjusted unemployment rate and the total searcher rate as measures of underutilization. I estimate a Phillips curve, where inflation is determined by the output gap and expected inflation. That is,

$$\pi_t = \phi(x_t - x_t^*) + \gamma E_t[\pi_{t+1}] \tag{20}$$

where π_t is the inflation rate at time t, x_t is a measure of labor market underutilization (the standard unemployment rate, the adjusted unemployment rate or the total searcher rate), x_t^* is the natural rate of each measure, and $E_t[\pi_{t+1}]$ is expected inflation. The parameter of interest is ϕ and how its value changes post the 2008 recession, under different measures of the output gap. I estimate a backwards looking Phillips curve and proxy for inflation expectations with the four quarter average of lagged inflation; that is,

$$E_t[\pi_{t+1}] \equiv \bar{\pi}_t = \frac{1}{4}(\pi_{t-1} + \pi_{t-2} + \pi_{t-3} + \pi_{t-4}). \tag{21}$$

Similar specifications have been used recently by Stock and Watson (2019),Galí and Gambetti (2019) and Ball and Mazumder (2011).

Along with an inflation Phillips curve I estimate a wage Phillips curve, similar to Galí and Gambetti (2019), again comparing the change in the correlation between wage growth and the three measures of the output gap pre and post 2008 recession. The wage Phillips curve is

$$\Delta w_t = \phi(x_t - x_t^*) + \gamma E_t[\pi_{t+1}] \tag{22}$$

where Δw_t is nominal wage growth, and $x_t - x_t^*$ and $E_t[\pi_{t+1}]$ are the same as above.

The natural rate of unemployment, x_t^*, is defined as the rate of unemployment such that inflation remains stable. This level is thought to change over time due to changes in the demographics of the workforce or changes in the structure of the labor market. There exists a vast literature aimed at estimating the natural rate of unemployment, see Crump et al. (2019) for a thorough review. Although there are many ways to estimate the natural rate of unemployment, Stock and Watson (2019) argue that the disappearance of the Phillips curve is robust to whichever measure one chooses. Therefore, for the output gap measured using the standard unemployment rate is estimated as the difference between the standard unemployment rate and the Congressional Budget Offices natural rate of unemployment (NAIRU). Since the adjusted unemployment rate and the total searcher rate are adjusted for demographic changes in the labor force and no longer display the same low frequency downward trend that the standard unemployment rate does, the natural rate for these measures will be estimated using a constant.

The flattening or disappearance of the Phillips curve, in its simplest form, can be estimated with a change in the parameter ϕ after the start of the great recession. For the standard unemployment rate the change in ϕ is estimated using a similar specification as in Stock and Watson (2019), that is:

$$\pi_t = \phi_1(u_t - u_t^{NAIRU}) + \gamma_1 E_t[\pi_{t+1}] + \phi_2(u_t - u_t^{NAIRU}) \times Post_t + \gamma_2 E_t[\pi_{t+1}] \times Post_t + \varepsilon_t \quad (23)$$

where $Post_t = \mathbb{I}\{t > 2007.25\}$ is an indicator that takes on the value one after the first quarter of 2007 and the parameter ϕ_2 estimates the change in the Phillips curve. For the adjusted unemployment rate and the total searcher rate the specification is:

$$\pi_t = \alpha_1 + \phi_1 x_t + +\gamma_1 E_t[\pi_{t+1}] + \alpha_2 \times Post_t + \phi_2 x_t \times Post_t + \gamma_2 E_t[\pi_{t+1}] \times Post_t + \varepsilon_t \quad (24)$$

where $\alpha_1 = -\phi_1 x^*$ and $\alpha_2 = -\phi_2 x^*$, and ϕ_2 estimates the change in the Phillips curve. Identical specifications are run for the wage Phillips curve.

Table 9 reports the results from the regressions. The sample period is 1980Q1 to 2019Q4. The first three columns show the results from the wage Phillips curve for which Δw_t is the annualized growth rate of average hourly earning of Production and Nonsupervisory Employees[8] and $E_t[\pi_{t+1}]$ is the average of the previous 4 quarters of inflation growth constructed using the annualized growth rate of the Personal Consumption Expenditure Index (PCE). Column (1) shows what has been documented as the flattening of the wage Phillips curve with the estimated effect of the unemployment rate gap on wage growth significantly decreasing post 2007, similar to what Galí and Gambetti (2019) find. Columns (2) and (3) report the estimated parameters when using the adjusted unemployment rate and the total searcher rate as measures of the output gap. Contrary to the standard unemployment rate gap, there is no significant change in the slope of the wage Phillips curve when using these alternative measures, seen by the small and statistically insignificant estimates on the $\tilde{U} \times Post$ and $S \times Post$ variables. The correlation between the adjusted unemployment rate and the total searcher rate, and wage inflation (-0.065 and -0.08) are statistically indistinguishable from the pre-recession estimated correlation with the standard unemployment rate gap and wage inflation (-0.072).

The estimated parameters of the inflation Phillips curve are reported in columns (4)-(6). Column (4) shows the inflation Phillips curve estimated with the standard unemployment gap. The slope coefficient before the Great Recession is estimated at -0.31 and there is a large change in the post recessionary

[8] https://fred.stlouisfed.org/series/AHETPI

period, these estimates are consistent with Stock and Watson (2019) and many others. Column (5) shows the estimated coefficients of the Phillips curve estimated using the adjusted unemployment rate and a time invariant natural rate for the adjusted unemployment rate. In the pre-recession period the estimated slope coefficient is -0.272, similar to the standard unemployment gap coefficient. However, the slope does not change significantly in the post recession period, again, seen by the small and statistically insignificant estimate on the $\tilde{U} \times Post$ coefficient in column (5). When using the total search rate as a measure of labor slack, the pre-recession slope is estimated at -0.476, nearly twice the size of the correlation with the standard unemployment gap in the pre-recession period. The change in the slope when using the total searcher rate is also statistically insignificant. This suggests that the flattening of the Phillips curve may be, in part, due to measurement issues in the output gap. The result stands in contrast to Stock and Watson (2019), who argue that the flattening of the Phillips curve is present regardless of which measure of inflation and the output gap is used.

6 Conclusion

I document a rise in hires from out of the labor force and, using the American Time Use Survey, a large proportion of individual searching actively while being classified as out of the labor force, and argue that the standard unemployment rate therefore does a poor job capture the churning of the labor market. Using estimates from the American Time Use Survey to predict search effort in the CPS, I construct an adjusted unemployment rate, a total searcher rate, and labor market flows since 1980. There has been a substantial increase in the proportion of people classified as out of the labor force that are predicted to be actively seeking employment, which is attributed to increase educational attainment. Adding these job seekers into the unemployment rate nearly doubles its level and rids the unemployment rate of the low frequency downward trend it has had since 1980. An application to the Phillips Curve shows that when using the adjusted unemployment rate rather than the standard unemployment rate as a measure of the output gap, there is no post-2008 flattening.

7 Tables

Table 1: Out of the Labor Force Demographics by Decade

	1980-1989	1990-1999	2000-2009	2010-2018
Men				
% of population	47.4	47.9	48.2	48.3
% of hires	47.5	47.9	48.2	48.3
Women				
% of population	52.6	52.1	51.8	51.7
% of hires	52.5	52.1	51.8	51.7
Age 16-24				
% of population	19.8	16.6	16.3	15.5
% of hires	41.1	38.5	36.8	34.3
Age 25-55				
% of population	54.1	58.2	56.7	52.3
% of hires	41.1	43.3	43.8	42.0
Age 56+				
% of population	26.1	25.2	27.1	32.2
% of hires	17.7	18.1	19.3	23.8
White				
% of population	86.3	84.1	81.9	79.0
% of hires	85.6	82.1	79.2	76.5
Black				
% of population	11.0	11.7	11.9	12.4
% of hires	11.3	12.8	13.6	13.9
Other				
% of population	2.7	4.2	6.2	8.6
% of hires	3.1	5.1	7.1	9.6
Less than HS				
% of population	23.4	20.8	16.8	13.3
% of hires	25.7	21.6	17.8	12.9
High School				
% of population	8.9	35.0	32.4	30.5
% of hires	9.6	7.9	7.3	6.9
Some College				
% of population	48.6	23.9	26.3	27.4
% of hires	48.2	55.4	56.9	58.1
College				
% of population	3.9	13.5	16.4	18.6
% of hires	4.5	4.5	5.4	6.0
Advanced Degree				
% of population	15.4	6.8	8.1	10.1
% of hires	12.1	10.5	12.6	16.0

Table 2: 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 3: 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 4: 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 5: Search Effort of People who are Out of the Labor Force

	Selection Probit	Searching LPM
Female	0.089	0.042
	(0.000)	(0.066)
Married	-0.152	0.212
	(0.000)	(0.075)
Child	-0.067	-0.406
	(0.000)	(0.102)
Age	0.033	0.012
	(0.000)	(0.004)
Race - Black	-0.286	0.206
	(0.000)	(0.065)
Race - Other	0.144	0.369
	(0.000)	(0.098)
High School	-0.344	-0.045
	(0.000)	(0.067)
Some College	-0.343	0.180
	(0.000)	(0.069)
College	-0.379	0.311
	(0.000)	(0.080)
Advanced Degree	-0.435	0.221
	(0.000)	(0.096)
Female $\times$ Married	0.377	-0.079
	(0.000)	(0.098)
Female $\times$ Child	0.206	0.196
	(0.000)	(0.116)
Same Respondent	-0.094	
	(0.000)	
Inverse Mills		3.923
		(0.398)
Diary Day FE	✓	✓
Month FE	✓	✓
Year FE	✓	✓

Table 6: Logit Parameters

Parameter	Employed	Unemployed	Out of the Labor Force	Parameter	Employed	Unemployed	Out of the Labor Force
Monday	0.358	0.512	0.520	Female × Full Time	0.398	Not Included	Not Included
Saturday	-0.563	-0.843	-0.410	College × Age		-0.004	
Sunday	-0.550	-0.674	-0.257	High School × Age			
Thrusday	0.341	0.288	0.604	Less than HS × Age		0.016	
Tuesday	0.275	0.441	0.635	Some College × Age		0.019	
Wednesday	0.247	0.672	1.014	College × Married		-0.056	
Female	-0.670	-0.379	-0.415	High School × Married			
Age	-0.027	-0.003	-0.059	Less than HS × Married		0.176	0.240
College	-0.157	-0.048	-0.065	Some College × Married		0.295	
High School	-0.843	-0.771	-1.041	College × Child		0.276	
Less than HS	-1.296	-2.169	-1.318	High School × Child			
Some College	-0.640	-1.670	-0.305	Less than HS × Child			-0.574
Married	-0.541	-0.101	0.595	Some College × Child	0.152	0.350	0.058
Child	0.048	-0.207	-0.289	College × Race - Other	-0.635	-0.839	
Race - Other	-0.656	0.183	-0.175	High School × Race - Other		-0.740	
Race - White	-0.640	-0.129	-0.921	Less than HS × Race - Other			-1.515
Full Time	-1.397	Not Included	Not Included	Some College × Race - Other		-0.598	-2.003
Female × Age				College × Race - White			
Female × College				High School × Race - White			
Female × High School		-0.053		Less than HS × Race - White			
Female × Less than HS				Some College × Race - White			
Female × Some College		0.221		College × Full Time		Not Included	Not Included
Female × Married		-0.304	-0.803	High School × Full Time		Not Included	Not Included
Female × Child	-0.101	-0.074		Less than HS × Full Time		Not Included	Not Included
Female × Race - Other		0.295	0.029	Some College × Full Time	0.105	Not Included	Not Included
Female × Race - White		0.110	-0.255	Constant	-1.729	-0.329	-1.446

Note: A total of 57 parameters we included in the Logit estimation for the Employed group and 51 for the Unemployed and Out of the labor force. The first 17 (18 for employed) are always included and the remaining interaction terms are chosen with a net-elastic logit with a weight of 0.95 on the LASSO penalty,. The regularization parameter is chosen using cross-validation of 10 folds.

Table 7: Percentiles of Predicted Search Effort

	Employed	Unemployed	Out of the Labor Force
5th Percentile	0.0285	0.8637	0.0002
10th Percentile	0.0398	0.9181	0.0006
25th Percentile	0.0654	0.9770	0.0044
50th Percentile	0.1086	0.9967	0.0444
75th Percentile	0.1655	0.9998	0.1557
90th Percentile	0.2601	1.0000	0.3073
95th Percentile	0.3504	1.0000	0.4405

Table 8: Correlation between Search Effort and Labor Force Attachment: 1994-2019

	Job Finding Prob.		Hours Worked		Change in Hours	
Search Probability	0.190	0.191	7.728	7.838	22.335	22.275
	(0.000)	(0.000)	(0.067)	(0.067)	(0.250)	(0.249)
Mean	0.037	0.037	30.33	30.33	0.33	0.33
Month × Year FE		✓		✓		✓
Observations	17608693	17608693	345967	345967	188130	188130
Sample	Full	Full	Nonemployed Job Finders	Nonemployed Job Finder	Employed Job Switchers	Employed Job Switchers

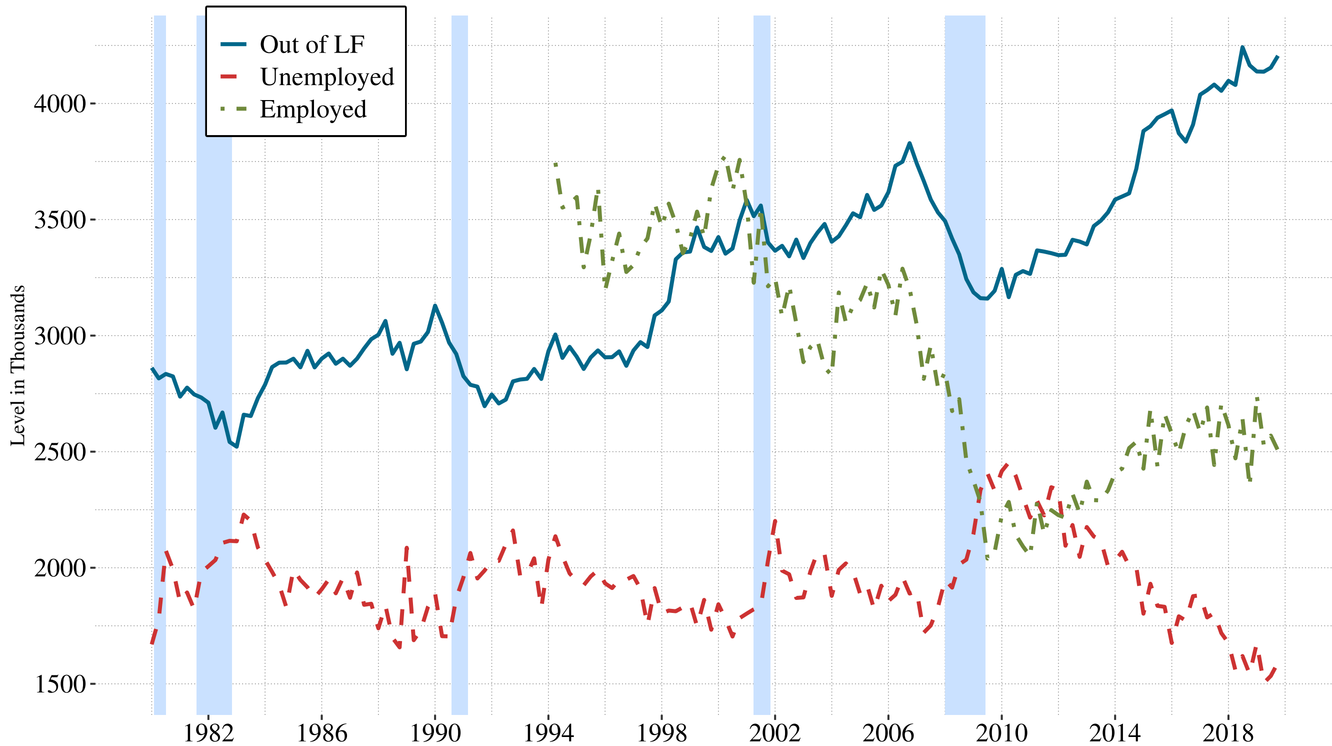
Table 9: Correlations with Inflation and Nominal Wage Growth

	1980Q1 - 2019Q4					
	Average Hourly Earnings			Consumer Price Index		
	(1)	(2)	(3)	(4)	(5)	(6)
U-Gap	-0.073**			-0.242		
	(0.029)			(0.172)		
U-Gap × Post	0.086*			0.668		
	(0.050)			(0.399)		
$\tilde{U}$		-0.065***			-0.272**	
		(0.018)			(0.136)	
$\tilde{U}$× Post		0.004			-0.097	
		(0.024)			(0.456)	
S			-0.080***			-0.476***
			(0.019)			(0.167)
S× Post			0.009			0.029
			(0.027)			(0.553)
$\bar{\pi}_{t-1}^{PCE}$	0.211***	0.088***	0.064***			
	(0.025)	(0.026)	(0.022)			
$\bar{\pi}_{t-1}^{PCE}$× Post	0.029	-0.087**	-0.069**			
	(0.071)	(0.035)	(0.031)			
$\bar{\pi}_{t-1}^{CPI}$				0.972***	0.626***	0.593***
				(0.050)	(0.134)	(0.128)
$\bar{\pi}_{t-1}^{CPI}$× Post				-0.431	-0.898**	-0.880 **
				(0.289)	(0.410)	(0.413)
Intercept		0.009***	0.021***		0.048***	0.130***
		(0.002)	(0.004)		(0.016)	(0.040)
Post		0.003	0.002		0.052	0.036
		(0.003)	(0.006)		(0.065)	(0.145)

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Standard errors are heteroskedastic and autocorrelation consistent. U-Gap refers to the difference of the standard unemployment rate and the Congressional Budget Office's natural rate of unemployment (NRU).* $\bar{\pi}_{t-1}^{x}$ *is the four quarter average of the year-over-year inflation rate measured by the Consumer Price Index (x=CPI) or the Personal Consumption Expenditure Index (x=PCE). Post is an indicator variable that takes on the value 1 after 2007Q2.*

8 Figures

Figure 1: Total Hires by Labor Market Status



Note: The figure plots the number of new hires from each labor market state in thousands.

Figure 2: Receiver Operating Characteristic Curve

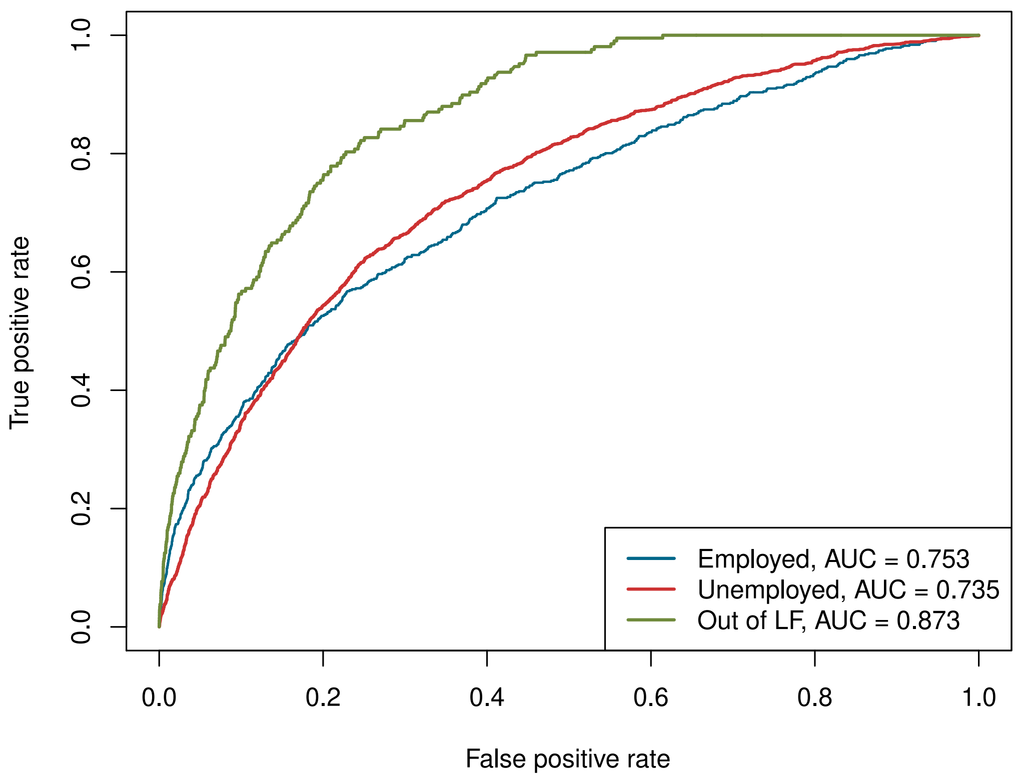


Figure 3: Fraction of Job Searchers

(a) Employed

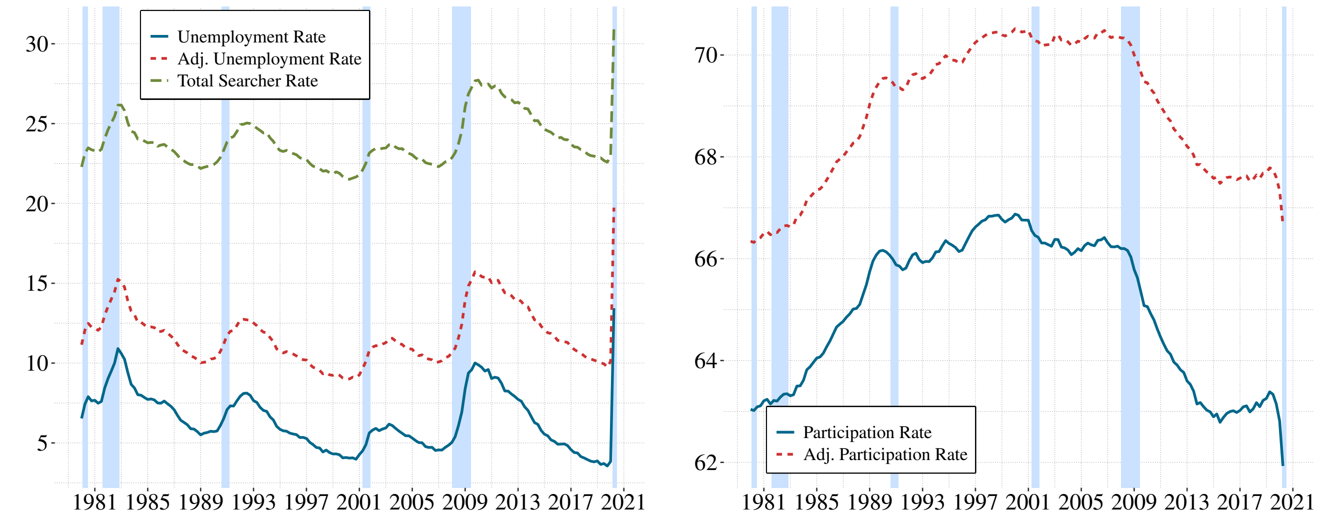
(b) Unemployed

(c) Out of the Labor Force

(d) Total Population

Note: The figure plots the quarterly fraction of job searchers among the employed, unemployed, out of the labor force and total population.

Figure 4: Unemployment, Total Searcher and Participation Rate

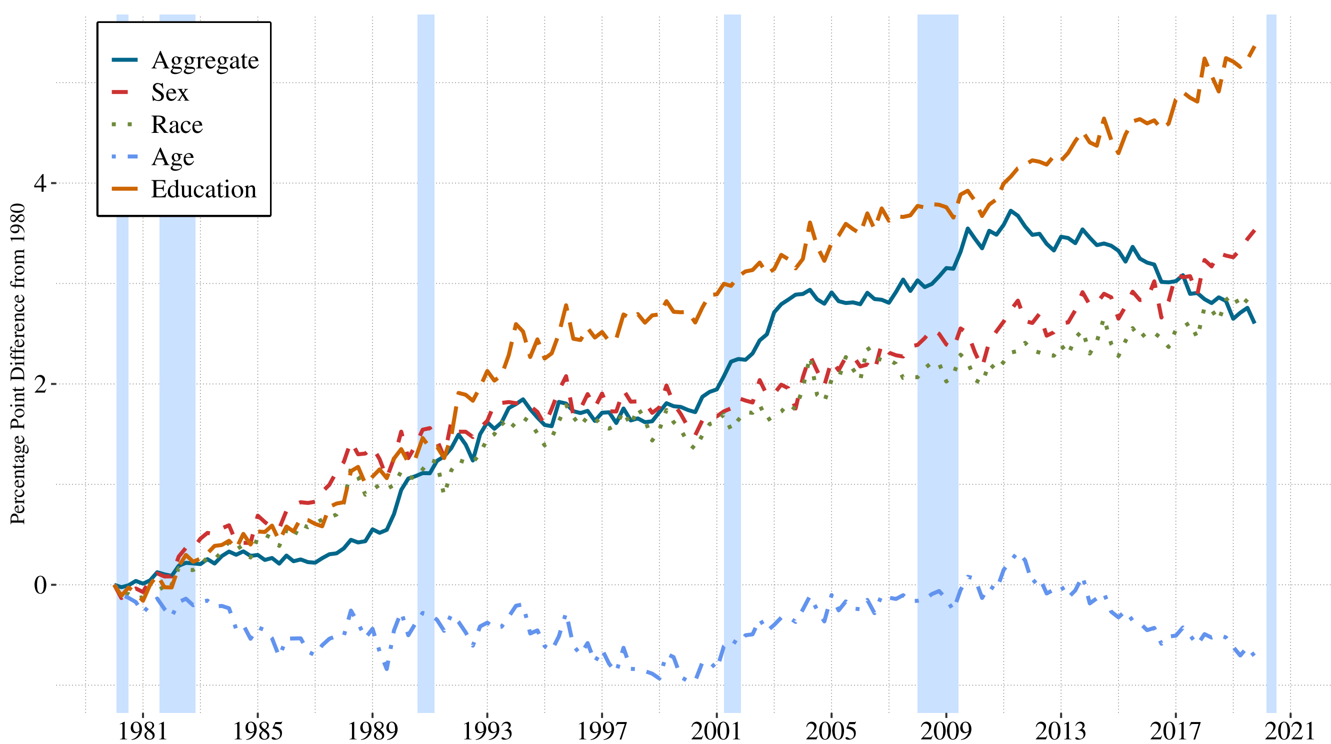


(a) Unemployment and Total Searcher Rate

(b) Participation Rate

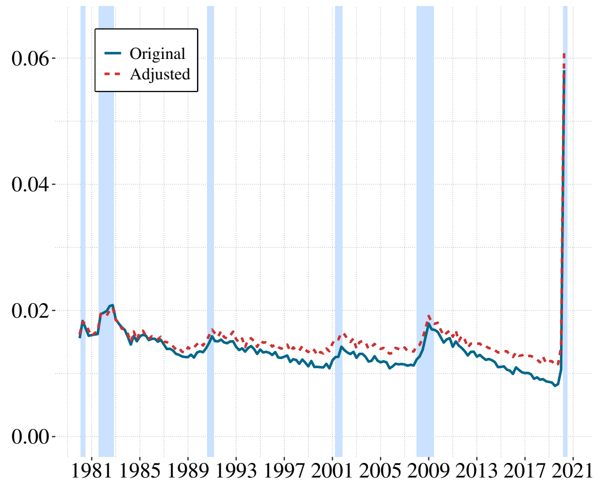
Note: The figure plots the quarterly original and adjusted unemployment rate and participation rate.

Figure 5: Decomposition of Out of the Labor Force Searching for a Job

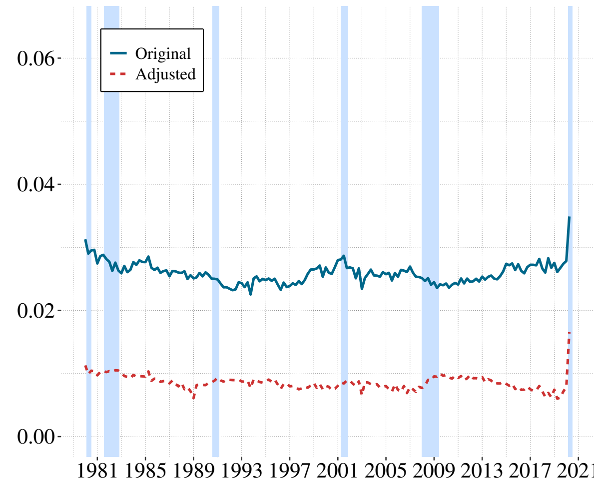


Note: The figure plots the fraction of out of the labor force that is searching for a job ("Aggregate") along with the four counter factual series if the fraction of each demographic group remained at its 1980's values. Each series is graphed as a percentage point difference from the 1980 value.

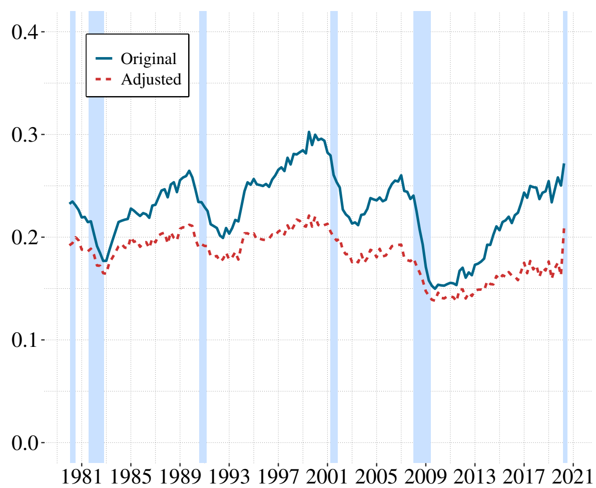
Figure 6: Labor Market Flows



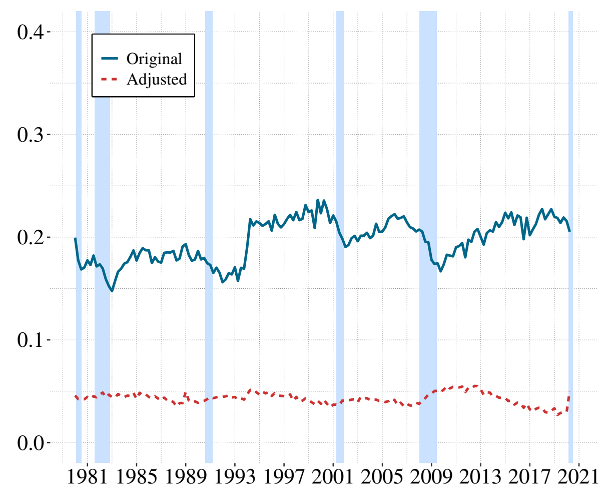
(a) Employed to Unemployed



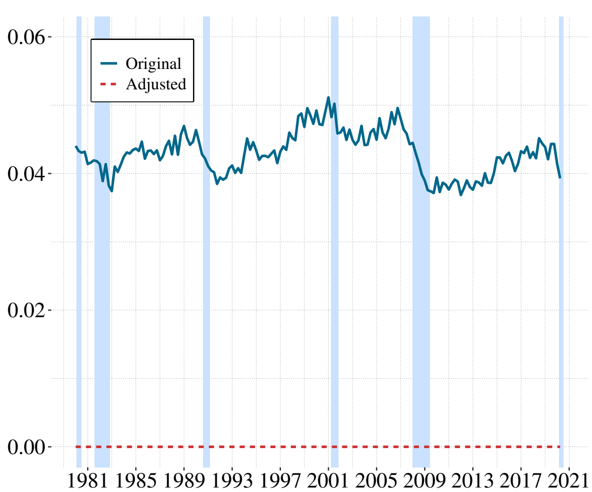
(b) Employed to Out of the Labor Force



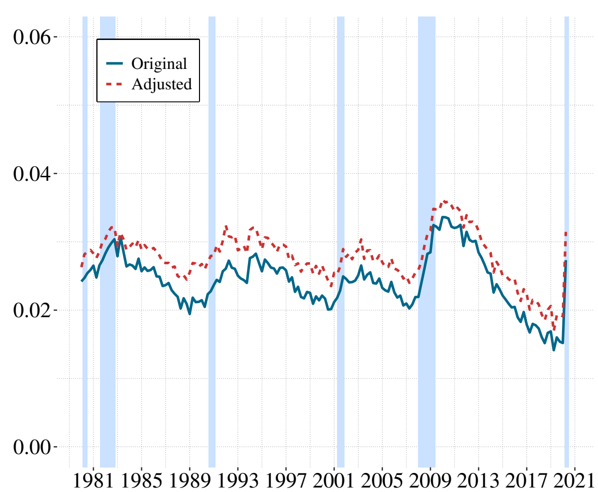
(c) Unemployed to Employed



(d) Unemployed to Out of the Labor Force



(e) Out of the Labor Force to Employed



(f) Out of the Labor Force to Unemployed

Note: The figure plots the seasonally adjusted quarterly original and adjusted flows across labor market states.

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A Appendix

A.1 CPS Data Cleaning and Aggregate Series Creation

The main data used to calculate the number of individuals and flows across the labor market come from the basic monthly files of the Current Population Survey from January 1979 to December 2018. Over this period several changes to the demographic variables used to predict the search probability occurred. First, whether or not a child was present in the home was not asked prior to 1984 and between January 1994 to October 1999. For the years prior to 1984, the indicator for if a child was present is replaced with the sample mean in 1984. During the months between January 1994 and October 1999, the indicator is replace with the average of the sample average in 1993 and 2000. Second, the education variable changed from a continuous measure to a discrete degree based measure in 1992. The education variable is made consistent using the method described in Jaeger (1997).

After predicting and aggregating the series of total employed and out of the labor force that are searching for a job, each series has a small discrete jump at different dates. The employed searchers series as a discrete jump in January 1989. The jump is removed from the series by adding a constant term to the series pre January 1989 by a constant factor such that the ratio of January 1989 to December 1988 is equal to the average January/December ratio over the whole sample. Similarly the out of the labor force series is adjusted in January 2003 and January 1989. The OLF search series is adjusted in December 1999, January 1994, February 1994, February and January 1989. Each series is then seasonally adjusted using the X-13ARIMA-SEATS seasonal adjustment program provided by the Census Bureau, available at: `https://www.census.gov/srd/www/x13as/`.

Flows of the labor market are calculated using the matched basic monthly files of the Current Population Survey. The matching and flow calculation files are taken from Robert Shimer and modified; the original programs are available at: `https://sites.google.com/site/robertshimer/research/flows`. The flows are first seasonally adjusted using X-13. Next the flows are corrected for margin error similar to Elsby et al. (2015) (described in detail below) and finally the flows are adjusted for time aggregation as proposed by Shimer (2012).

A.2 Margin Error Adjustment

The margin error adjustment is similar to Elsby et al. (2015). First define new stocks of unemployed and out of the labor force as:

$$\tilde{U}_t = U_t^S + O_t^S$$

$$\tilde{O}_t = O_t - O_t^S$$

. Then let $S_t = [E_t \ \tilde{U}_t]$ be the vector containing the number of employed in unemployed and let $\Delta S_t = [E_t \ \tilde{U}_t]' - [E_{t-1} \ \tilde{U}_{t-1}]'$ be the change in the current state vector. The change in the current state vector can be written as:

$$\Delta \mathbf{S}_t = \begin{bmatrix} -E_{t-1} & -E_{t-1} & \tilde{U}_{t-1} & 0 & 0 \\ E_{t-1} & 0 & -\tilde{U}_{t-1} & -\tilde{U}_{t-1} & \tilde{O}_{t-1} \end{bmatrix} \times \begin{bmatrix} p_{E\tilde{U}} \\ p_{E\tilde{O}} \\ p_{\tilde{U}E} \\ p_{\tilde{U}\tilde{O}} \\ p_{\tilde{O}\tilde{U}} \end{bmatrix}$$

$$\Delta \mathbf{S}_t = \mathbf{X}_{t-1}\mathbf{p}$$

Where p_{jk} is probability that an individual transitions from labor market state j to k. Notice that here, individuals can not directly transition from out of the labor force to employment. The estimated vector of transition probabilities, denoted $\hat{\mathbf{p}}$, has a covariance matrix proportional to the matrix that is consistently estimated using:

$$\mathbf{W} = \begin{bmatrix} \frac{\hat{p}_{E\tilde{U}}(1-\hat{p}_{E\tilde{U}})}{E_{t-1}} & -\frac{\hat{p}_{E\tilde{U}}\hat{p}_{E\tilde{O}}}{E_{t-1}} & 0 & 0 & 0 \\ -\frac{\hat{p}_{E\tilde{U}}\hat{p}_{E\tilde{O}}}{E_{t-1}} & \frac{\hat{p}_{E\tilde{O}}(1-\hat{p}_{E\tilde{O}})}{E_{t-1}} & 0 & 0 & 0 \\ 0 & 0 & \frac{\hat{p}_{\tilde{U}E}(1-\hat{p}_{\tilde{U}E})}{\tilde{U}_{t-1}} & -\frac{\hat{p}_{\tilde{U}E}\hat{p}_{\tilde{U}\tilde{O}}}{\tilde{U}_{t-1}} & 0 \\ 0 & 0 & -\frac{\hat{p}_{\tilde{U}E}\hat{p}_{\tilde{U}\tilde{O}}}{\tilde{U}_{t-1}} & \frac{\hat{p}_{\tilde{U}\tilde{O}}(1-\hat{p}_{\tilde{U}\tilde{O}})}{\tilde{U}_{t-1}} & 0 \\ 0 & 0 & 0 & 0 & \frac{\hat{p}_{\tilde{O}\tilde{U}}(1-\hat{p}_{\tilde{O}\tilde{U}})}{\tilde{O}_{t-1}} \end{bmatrix}$$

The vector of transition probabilities, $\mathbf{p}$, is chosen to minimize the weighted least square to the estimated transition probabilities and restricted to match the observed changes in labor market states. That is:

$$\mathbf{p} = \text{argmin } (\mathbf{p} - \hat{\mathbf{p}})'\mathbf{W}^{-1}(\mathbf{p} - \hat{\mathbf{p}}) \quad \text{s.t. } \Delta \mathbf{S}_t = \mathbf{X}_{t-1}\mathbf{p}$$

The Lagrangian is

$$\mathcal{L} = (\mathbf{p} - \hat{\mathbf{p}})'\mathbf{W}^{-1}(\mathbf{p} - \hat{\mathbf{p}}) - 2\mu[\Delta\mathbf{S}_t - \mathbf{X}_{t-1}\mathbf{p}]$$

where μ is the vector of Lagrange multiplies. The solution is,

$$\begin{bmatrix} \mathbf{p} \\ \mu \end{bmatrix} = \begin{bmatrix} \mathbf{W} & \mathbf{X}'_{t-1} \\ \mathbf{X}_{t-1} & 0 \end{bmatrix}^{-1} \times \begin{bmatrix} \mathbf{W}\hat{\mathbf{p}} \\ \Delta\mathbf{S}_t \end{bmatrix}.$$

Since all objects on the right-hand side are known, the above equation gives the solution to the margin error adjusted probabilities **p**.