Measuring the Total Number of US Job Seekers

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Christine Braun[1,*]

Abstract: I document a substantial rise in the proportion of job seekers who are classified as out of the labour force in the United States since 1980. I propose an adjusted unemployment rate to account for these searchers; the adjustment increases the unemployment rate by 5.2 percentage points, rids the unemployment rate of its downward trend, and decreases volatility by 50%. I also construct a measure of total search effort in the economy, including employed job seekers. Finally, estimates of the Phillips Curve using the adjusted unemployment rate or total searcher rate show no sign of a flattening output-inflation relationship in the post-2008 recession period.

Keywords: Unemployment, Labour Force Participation, Labour Market Volatility, Phillips Curve

Classification: J64, E24, E31

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I want to thank David Dorn, Nir Jaimovich, Tim Kehoe, Roland Rathelot, and Thijs van Rens, for invaluable input at early stages of the project. I also want to thank seminar participants at the University of California, Santa Barbara, University of Zurich, University of Warwick, University of Munich, University College London, Paris School of Economics, and the University of British Columbia. The paper has improved substantially with the help of anonymous referees and the editor. All remaining errors are my own.

1 Introduction

In 2019 in the United States, 50% of new hires were previously classified as out of the labour force, 31% came from a different job and only 19% of new hires were previously considered unemployed, that is, from the group considered to be actively searching. This startling statistic is not unique to 2019, Figure 1 shows that the proportion of hires coming from non-participation has increased by 50% since 1980. As a consequence, the unemployment rate is surprisingly abysmal at capturing the pool of potential hires.

In this paper, I show that accounting for non-participants who are actively searching for a job is vital for understanding the labour market. I construct an adjusted unemployment rate and total searcher rate (including employed job seekers) by estimating a latent monthly probability that an individual is searching for a job and classifying individuals as job seekers based on these probabilities rather than reported labour market status. The resulting adjusted unemployment rate is, on average, 5.2 percentage points higher and 50% less volatile. Accounting for all job seekers also has implications on the relationship between output and inflation; I show that there is no flattening of the Phillips Curve in the post-2008 era when using the adjusted unemployment rate or total searcher rate to estimate its slope.

Data on job search comes from the American Time Use Survey (ATUS). Time use diaries from the ATUS allow us to see search effort by all individuals, regardless of labour market status (employed, unemployed, or out of the labour force). Using the 2003-2019 ATUS diaries, I show that a significant number of people classified as out of the labour force are searching for a job, nearly 25% of prime age (25-55) people. Conditional on search for a job, people classified as out of the labour force, spend about 140 minutes per day searching, nearly as much as the unemployed (157 minutes) and more than the employed (121 minutes).

Next, I estimate the probability an individual is searching for a job based on observable characteristics. To estimate these probabilities, I use machine learning on the ATUS data to inform about which demographic characteristics are the strongest predictors of job search. With these estimates, I predict search effort for all individuals in the Current Population Survey and show that the predicted probabilities are correlated to different measures of labour force attachment. I classify the non-employed as job seekers probabilistically based on the estimated search probability, rather than deterministically based on reported labour market status. I classify the employed as job seekers in the same fashion. Using these classifications, I create an adjusted unemployment rate since 1980. The adjustment shows that the current method for measuring the number of unemployed captures less than 50% of non-employed job seekers on average each quarter. Therefore, the adjusted unemployment rate is on average 5.2 percentage points higher than the standard unemployment rate. The adjusted unemployment rate also does not display the same low-frequency downward trend observed in the standard unemployment rate. This difference in trends is attributed to the fact that the fraction of job seekers classified as non-participants has increased from 9.5% in 1980 to 13% in 2020.

The aggregate statistics presented here, contribute in several aspects to the understanding of how well standard search and matching models can capture labour market fluctuations. I show that considering all job seekers in the economy has a significant impact on the volatility of the unemployment rate and labour market tightness; both are between 25%-50% less volatile. It is a well-established fact that the search and matching model cannot generate the perceived labour market volatility in the standard statistics (Andolfatto, 1996; Shimer, 2005), and many have since adjusted the model in efforts to achieve more volatility.[1] I show that reconsidering the data, to include all job seekers, aids in bridging some of the gap.

Considering all job seekers has a significant impact on broader macroeconomic implications as well. Many papers have investigated the flattening of the output-inflation relationship (Phillips Curve) following the Great Recession, often using the unemployment gap (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 when using the adjusted unemployment rate or total searcher rate instead, there is little flattening in the post-2008 recession period and that pre-recession estimates are similar across all statistics.

The paper contributes to the literature exploring the effects of misclassification of individuals on both the level and volatility of the unemployment rate (Abowd and Zellner, 1985; Feng and Hu, 2013; Ahn and Hamilton, 2022; Jones and Riddell, 1999). The method used here differs from the existing studies by using data directly on job search to estimate misclassification probabilities for the non-employed, rather than re-interview surveys conducted in the 1980s. Similarly to Ahn and Hamilton (2022), I show that misclassification has increased over time due to demographic changes; which is consistent with Perry (1970); Flaim (1979); Shimer (2001); Barnichon and Mesters (2018) who suggest that demographic changes decreased the unemployment rate by 1-2 percentage points since 1980.

[1] See for example Hall and Milgrom (2008); Hagedorn and Manovskii (2008) and many thereafter.

This paper also adds to a growing literature focused on constructing a better measure of labour underutilization for the United States.[2] 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.* (2020) construct a measure of labour 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 labour slack with data on search effort from the ATUS, instead of ex-post transition probabilities, and constructing a total searchers rate that 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. The total searcher rate presented here is the first such measure constructed using search effort of the employed, rather than part-time/full-time status.

2 Data

The two main data sources are the basic monthly files from the Current Population Survey (CPS)[3] and the American Time Use Survey (ATUS)[4] . The CPS is the main source of data used for calculating aggregate statistics regarding the labour 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 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 each month's sample can

[2]Schweitzer (2003) and Jones *et al.* (2003) attempt similar exercises for the United Kingdom.
[3]NBER (2020)
[4]BLS (2019)

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 labour 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 labour force.[5]

This broad classification of labour force status is advantageous in many respects but, needless to say, not perfect. Misclassification of people across labour 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 labour force and later reclassified as unemployed. Similarly, Ahn and Hamilton (2022) show that two-thirds of people who were classified as out of the labour 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 labour 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 1980s, unemployment and out of the labour force are behaviorally distinct states.

Despite measurement issues, the CPS data have become, not only the standard source for labour market stocks but also the main source for estimating the flows across labour market states. The Bureau of labour Statistics publishes the flows across labour market states

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

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 that suggests the misclassification problem is large and that the unemployment rate itself is not a good measure of labour market slack. Then, using the ATUS I show how misclassification can be revisited in the time use diaries and used to estimate aggregate search statistics for the United States.

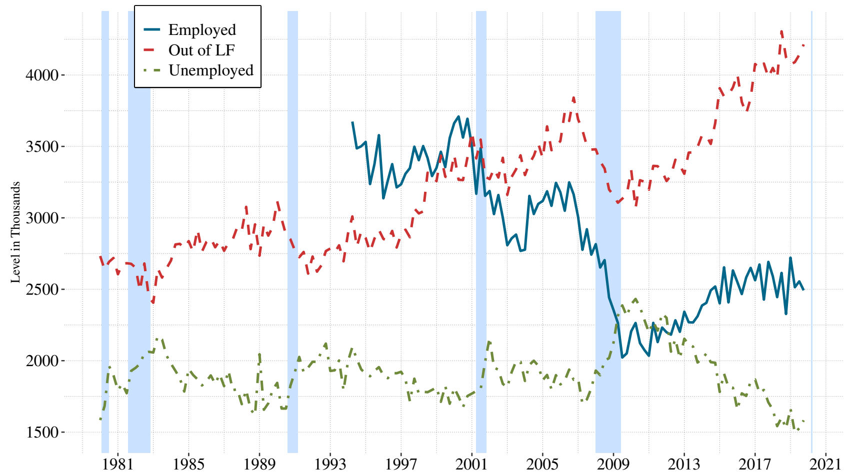
2.1 Hires by labour Force Status

Figure 1 plots the total number of new hires by previous labour force status, a description of how hires are calculated can be found in Appendix A.1. The figure shows that while total hires out of unemployment have remained stable at around 2 million per month since 1980, hires from out of the labour force have nearly doubled. In the 1980s, workers that were previously classified as out of the labour 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 labour force have also been increasing, in the 1990s hires from out of the labour force made up 36% of all hires, and 50% in 2019.[6] The figure shows that the pool of unemployed does not capture potential workers well in terms of hires.

Another striking fact that Figure 1 shows, although not the focus of this paper, is that the number of workers hired from employment decreased rapidly during the 2008 recession and

[6] 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.

Figure 1: *Total hires by labour market status*



Note: The figure plots the number of new hires from each labour market state in thousands. Details of how these values are calculated can be found in Appendix A.1.

did not recover fully afterward. Fujita *et al.* (2020) explore this phenomenon and conclude that a large part of the decline and subsequent lower level of employment to employment transitions can be accounted for by a change in the way the employment question was asked in 2007.

2.2 Job Search

The CPS also asks several questions about job search efforts; however, these questions are limited to people who are classified as unemployed. On 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 activity recorded is 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 labour 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 labour 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 labour force accordingly. Regardless of a person's labour market status, if they spent any time searching for a job on the interview day, the time will be recorded as a job search activity. Therefore, the ATUS data can be used to estimate the probability that any person is searching for a job.

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 calculated naively as $1-(1-p)^{30}$ where p is the daily probability, that

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

Table 1: *Search effort by labour force status: extensive margin*

	Age 16+		**Age 25-55**	
	Daily Probability	Monthly Probability	Daily Probability	Monthly Probability
Employed	0.598	16.480	0.542	15.047
At Work	0.569	15.734	0.514	14.328
Absent	1.299	32.443	1.247	31.363
Unemployed	17.464	99.684	23.374	99.966
At Work	6.021	84.477	5.912	83.928
Absent	18.685	99.798	25.815	99.987
Out of the labour force	0.401	11.349	0.930	24.449

Notes: Summary statistics calculated from the pooled 2003-2019 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. 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.*

is, the probability of no searching any day of the month where search is assumed to be independent across days. 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 (15.8) of searching for a job than those absent from work (32.4). Those classified as out of the labour 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 labour force is higher than the probability of observing an employed person, age 25-55, searching for a job (15.0).

The intensive margin of search (minutes spent searching) is reported in Table 2. Both the unconditional average and conditional on positive search time are reported. First, across both samples, the unemployed have the highest unconditional search intensity, searching for

Table 2: *Search effort by labour force status: minutes per day*

	Age 16+		Age 25-55	
	Unconditional	Conditional	Unconditional	Conditional
Employed	0.696	116.285	0.696	116.285
At Work	0.609	107.079	0.609	107.079
Absent	2.757	212.265	2.757	212.265
Unemployed	26.028	149.034	26.028	155.992
At Work	8.047	133.652	8.047	142.144
Absent	27.945	149.562	27.945	156.435
Out of the labour force	0.527	131.546	0.527	138.474

Notes: Summary statistics calculated from the pooled 2003-2019 ATUS. Unconditional job search minutes and conditional and minutes conditional on positive search time.

an average of about 30 minutes per day. The unconditional average for the employed and out of the labour force is mostly below one minute across both samples, stemming from the fact that not even 1 percent of each group is searching for a job on the interview day. 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 labour 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.* (2022) who use data from the Survey of Consumer Expectations, 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 labour force. Table 3 reports the percent of time each group spends in three types of job search

Table 3: *Search effort by labour force status: percent of time by activity*

	Age 16+			**Age 25-55**		
	E	U	O	E	U	O
Active Job Search	81.5	90.8	85.0	81.2	92.3	90.3
Interviewing	14.2	6.9	10.9	13.6	5.1	5.3
Other	4.3	2.2	4.1	5.3	2.6	4.4

Notes: Summary statistics calculated from the pooled 2003-2019 ATUS. Conditional on searching, the table show the percent of time spent in Active Job Search (050481), Interviewing (050403), and Other (050404,050405,050499).

activities. The first activity labeled "Active Job Search" consists of ATUS category number 50401 which includes contacting employers, sending out resumes, etc. The second category is "Interviewing" and the third category "Other" consists of all other ATUS categories (50403,50405,50499) 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 labour market states and both samples, most time is spent doing active job search. Employed individuals spend about 14% of the time interviewing whereas unemployed individuals spend only about 7% of the time interviewing. This is consistent with Faberman *et al.* (2022), who show that the employed get more interviews than the unemployed. Those classified as out of the labour force also spend more time interviewing than the unemployed, nearly 11% of their time. The evidence presented in Table 2 and Table 3 suggest that people who are classified as out of the labour force but exert positive search effort, may not be behaving differently from those classified as unemployed.

2.2.1 Robustness - Independent Search Across Days

The main disadvantage of using the ATUS to study job search behavior is that people are only surveyed about one day in the month. Due to the cross-sectional nature of the ATUS, the probability that a person searches for a job can only be calculated as independent of job search history. To assess how important the correlation between job search on consecutive days is I supplement the with job search data from the Survey of Consumer Expectations (SCE) Job Search Supplement[8]. The survey asks people about the specifics of their job search behavior over longer periods of time. Although the survey does not explicitly ask how many days per week people search for jobs, it can be used in conjunction with the ATUS data to get an estimate of how persistent job search is.

The SCE is a monthly survey conducted by they New York Federal Reserve which contains a Job Search Supplement (JSS) 2013-2019 that interviews people about the specifics of their job search process. People in the JSS are classified as employed, unemployed, and out of the labour force in the main SCE survey.[9] Table 4 reports the summary statistics of search effort by labour force status from the JSS. The first row of the table reports the percentage of each group in the population.[10] The second and third row of Table 4 shows that people in each state search for jobs, nearly a quarter of the employed population searches for a job in a given month, and nearly 8 percent of those classified as out of the labour force. Comparing these values to the naive monthly probabilities calculated using the daily ATUS shows that the naive assumption of independent search overestimates the total fraction of out-of-the-labour

[8]FRBNY (2013-2020a) and FRBNY (2013-2020b)

[9]It is possible to classify workers into labour market states using the answers to the search questions and the definition of unemployment as Faberman *et al.* (2022) do. However, this eliminates any misclassification in the data.

[10]Comparing these percentages to those reported in the first row of Table A1 in Appendix Section A.2 shows that the fraction of people in each labour market state is similar across the ATUS and JSS samples.

Table 4: *Search effort from JSS*

	Employed	Unemployed	Out of LF
Percent of Population	0.692	0.045	0.264
Percent Searching Last 7 Days	0.198	0.644	0.067
Percent Searching Last 4 Weeks	0.224	0.689	0.076
Minutes Searching Last 7 Days			
Unconditional	73.645	410.299	25.474
Conditional	364.991	645.885	399.170
Applications Sent Last 7 Days			
Unconditional	2.198	6.843	0.488
Conditional	4.033	9.496	6.060
Job Offers			
Unconditional	0.267	0.753	0.263
Conditional	0.425	0.832	1.845
Implied Efficiency (offers/applications)			
Unconditional	0.122	0.110	0.538
Conditional	0.105	0.088	0.304
Relative to Unemp.	1.203	1.000	3.476

Source: Survey of Consumer Expectations, © 2013- 2020 Federal Reserve Bank of New York (FRBNY)

force and unemployed searchers. However, search effort of the employed is underestimated in the ATUS as a consequence of the fact that workers are only asked about their primary activity, which implies that job search amongst the employed is likely to be underreported if they conducted any job search while at work. Focusing on employed workers that did not go to work on the interview day in the ATUS shows that 0.013 percent search daily, implying 32% search monthly using the independence assumption and therefore again overestimating the fraction of searchers compared to the JSS.[11]

Row 4 and 5 of Table 4 report the minutes each group spent searching for a job in the last 7 days. While the unemployed spend nearly 11 hours per week searching for a job the employed and out of the labour force spend about 6 and 6.6 hours per week searching.

[11] See number reported in the second column of Table A1 in Appendix Section A.2.

Table 5: *Steady searchers and expected days per week*

	Employed NAW	Unemployed	Out of Labor Force
Percent Steady Searchers	0.205	0.868	0.381
Days Per week	1.837	3.823	2.335
Expected Days Per Week	1.217	4.370	2.055

Combining these weekly minutes spent searching with the ATUS information about minutes per day (reported in Table A1) implies that the employed spend on average 1.8 days per week searching for jobs, the unemployed spend 3.8 days per week, and the out of the labour force spend 2.3 days per week.

Rows 6-9 of Table 4 report the number of applications sent in the last 7 days and the number of job offers received. The unemployed spend more applications than the employed and out of the labour force and receive more job offers than the employed but fewer than the out of the labour force. The final row the the table shows the search efficiency of each group, defined as offers per application, relative to the unemployed. Both the employed and out of the labour force are more efficient in their job search than the unemployed. The employed are 20 percent more efficient while those classified as out of the labour force are nearly 3.5 times more efficient.[12]

Using the time-use survey from the United Kingdom which interviews people over two days, Faberman *et al.* (2022) show that 16% of the employed that search for a job on the first day also search for a job on the second day. For the unemployed in the UK, the fraction of continued searchers is 35%. Following Faberman *et al.* (2022) I calculate the fraction of "steady" and "intermittent" searchers that are needed in each group such that the daily

[12]The latter fact contrasts what Faberman *et al.* (2022) find, however, this is due to the fact that they use the job search questions to define unemployment, thus eliminating the misclassification problems.

probabilities from the ATUS match the weekly probabilities for the JSS, where "steady" searchers are assumed to search 5 days per week each month and "intermittent" searchers are assumed to search only one day per month. All job seekers are assumed to be either steady or intermittent searchers.

Let π_j^{day} be the daily search probability from labour market state j calculated from the ATUS and let π_j^{month} be the monthly probability calculated from the JSS. Let μ_j as the fraction of steady searchers, and $1 - \mu_j$ as the fraction of intermittent searchers. Then for each labour market state we can solve for the fraction of steady searchers as follows

$$\pi_j^{month} = \mu_j \pi_j^{day} + 20.85 \times (1 - \mu_j)\pi_j^{day}. \quad (1)$$

Where 20.85 is the total number of days that can be searched if you search 5 says per week and there are 4.17 weeks per month on average.

The first row of Table 5 reports the implied steady searchers in each labour market state. For the unemployed, it must be that 87% are steady searchers, while for the employed 21% must be steady searchers and the out of the labour force 38% must be steady searchers for the ATUS daily search probability estimates to aggregate to the JSS weekly search probability estimates.

The second row of Table 5 reports the implied days per week that each group must be searching from the daily intensive margin calculated from the ATUS and the weekly intensive margin calculated from the JSS. Finally using the estimated steady search fraction it is possible to calculate the expected number of days searching that can be compared with these numbers as a type of "external" moment. The expected number of days per week is calculated as follows

$$\mathbb{E}[days_j] = \frac{20.85 \times \mu_j + 1 \times (1 - \mu_j)}{4.17}, \tag{2}$$

and is reported in the last row of Table 5. The expected days per week are close to the estimated days per week for each labour market state. This implies that, although we can not observe the persistence of job search across days, a simple structure where a fraction of workers search every day can align the daily probabilities from the ATUS to the monthly probabilities from the JSS and replicate the average days per week well. In what follows, I show how to estimate the fraction of searchers in each group for the US since 1980, using both the naive assumption of independent search across days and an alternative where it is assumed that a fraction of searchers are steady searchers.

3 Estimation and Prediction

The previous section documented that about 11% in the ATUS and 8% in the JSS of those classified as out of the labour force are searching for a job during the month, suggesting that the CPS definition of unemployment does not capture labour underutilization well. The probability that an individual searches for a job while being classified as out of the labour force differs across gender, age, and education; demographic characteristics along which individuals who are classified as out of the labour force have changed substantially since 1980.

In this section, I estimate search effort among ATUS respondents based on labour 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.[13] The total number of potential covariates for the employed group is 58 and for the unemployed and out of the labour force groups is 52. 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 labour market state, employed, unemployed, out of the labour force, and the employed NAW. Estimating search probabilities that depend on demographic characteristics for the unemployed ensures that the adjusted unemployment rate is not biased by changes in the demographic composition of the unemployed.

[13]Search effort at the intensive margin may vary over the business cycle, I do not include any covariates that capture business cycle fluctuations to keep the adjusted unemployment rate comparable to the standard unemployment rate, which also does not account for changes in the intensive margin of search. Although cyclical fluctuations in the intensive margin may be interesting, they are out of the scope of this paper.

This also allows for misclassification error among the U-O margin, that is, workers classified as unemployed who should be classified as out of the labour force.

For each CPS-defined labour market status, I run a net-elastic logistic regression, where the dependent variable is an indicator of whether 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 a 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. 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.[14] 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.

[14]The details of this estimation procedure are outlined in Appendix A.4.

Table A2 shows the selected covariates and resulting parameter estimates for each labour force status. For the employed group, 5 of the interaction terms are included in the estimation. For the unemployed and out-of-the-labour force groups 17 and 8 interaction terms are included. Figure A1 plots the receiver operating characteristic curve for each group. The out-of-the-labour force group has the best fit with an area under the curve (AUC) of 0.873, the employed AUC is 0.753, the employed NAW AUC is 0.749, and the unemployed AUC is 0.735.

Appendix section A.5 shows how the estimates and resulting series described in the remaining part of this section change when using a neural network instead of a net elastic logit to estimate search effort.

3.2 Predicting Search Effort

The CPS contains all the same demographic information as the ATUS, and labour market status is determined equivalently in both samples. Therefore, although the ATUS sample began 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.

Table 6: *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

3.2.1 Baseline

In the Baseline specification, the daily probabilities are aggregated under the assumption search effort is independent across days. As shown in the previous section, this may underestimates the search effort of the employed and over estimate the search effort of those classified as out of the labour force. Under the independence assumption , the weekly probability that a person is searching for a job is 1 minus the probability they do not search any day during the week, i.e.

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

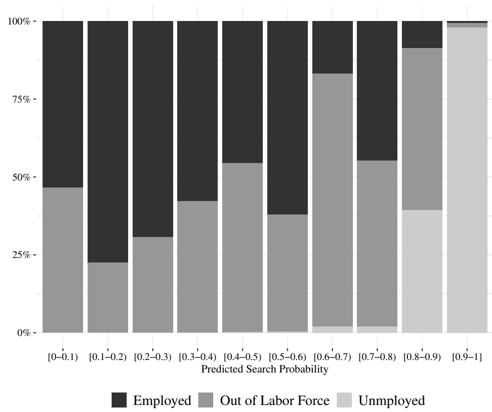
The monthly probability that they searche for a job is constructed analogously, i.e.

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

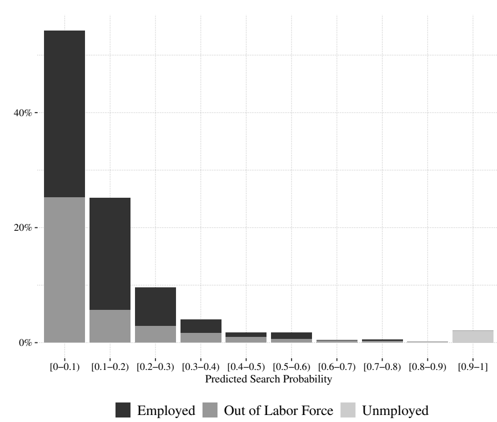
with 4.17 weeks per month. Equation 7 is one minus the cumulative product of not searching each week in the month, that is, it is the probability that person i searched at least once during the month. The probability is in line with the CPS definition of unemployment of having at least one active search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

Table 6 reports percentiles of the predicted search probabilities for each labour 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 labour force group, in fact, the 25th percentile is at 0.04. However, the out of the labour 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 labour force group is 0.44 and 0.35 for the employed group. For the estimated probabilities to be useful in constructing an adjusted unemployment rate, they should be an indicator of labour force attachment. In subsection 3.4 I show that the estimated search probability is positively correlated with job finding rates and subsequent hours worked, implying these probabilities are indeed a good proxy for labour force attachment.

Figure 2: *Distribution of predicted probabilities in 2019*



(a) Overall Composition



(b) Composition within Bins

Note: Panel (a) plots the histogram of predicted probabilities in 2019. Panel (b) shows the percent of each labour market group in each bin.

Table 6 does not show the distribution of overall predicted probabilities or how these are distributed across workers of different classifications. Figure 2 plot the predicted probabilities for 2019. Panel (a) plots the overall composition and shows that half of all predicted probabilities are between 0 and 0.1. These probabilities are nearly equally distributed among employed workers and people classified as out of the labour force, as shown in Panel (b). Nearly all unemployed workers have predicted probabilities between 0.8 and 1. The probabilities between 0.8 and 0.9 are nearly evenly distributed among the unemployed and out of the labour force.

3.2.2 Robustness - Independent Search Across Days

In this section I aggregate the daily probabilities under the alternative assumption proposed by Faberman *et al.* (2022) and discussed in detail in section 2, where there exists a fraction of steady searchers that search 5 days per week each week of the month, and the rest search only one day per month. I call this aggregations method FMST. Using the estimated fraction of steady searchers from section 2 (reported in Table 5) and the predicted daily search probabilities, the predicted monthly search probability for each worker is,

$$\hat{P}_i^{FMST} = \hat{\mu}_{j(i)} \times \bar{\hat{p}}_i^d + 20.85 \times \bar{\hat{p}}_i^d \tag{8}$$

where $\bar{\hat{p}}^{d_i}$ is the average predicted daily probability, and $\hat{\mu}_{j(i)}$ is the estimated fraction of steady searchers for the state which i is classified as[15].

[15] The predicted search probabilities for the employed are calculated using the parameters from the employed NAW estimation.

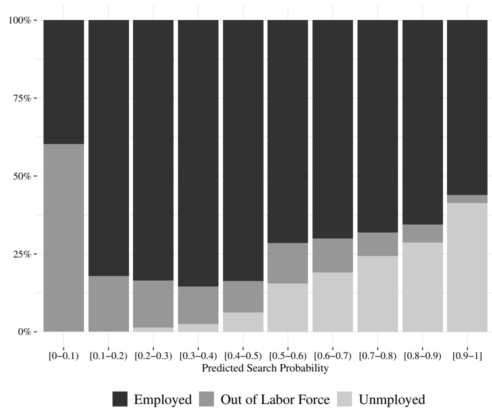
Table 7: *Percentiles of predicted search effort: FMST approach*

	Employed	Unemployed	Out of the Labor Force
5th Percentile	0.0378	0.2404	0.0001
10th Percentile	0.0516	0.2993	0.0003
25th Percentile	0.0829	0.4431	0.0020
50th Percentile	0.1538	0.6500	0.0207
75th Percentile	0.2652	0.9063	0.0768
90th Percentile	0.4160	1.0000	0.1661
95th Percentile	0.5646	1.0000	0.2616

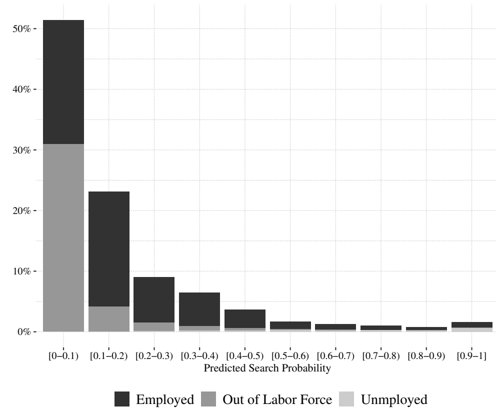
Table 7 reports percentiles of the predicted monthly search probability for each labour market state using the FMST approach to aggregate. There are several noticeable differences when comparing to the baseline. First, the 5th percentile of the unemployed group is only 0.24 compared to the baseline of 0.86. Second, all the percentiles of the employed are higher, with the 95th percentile increasing from only 0.35 to 0.56. This increase reflects the fact that the baseline underestimate search effort of the employed. Third, the percentiles of the out of the labour force are slightly lower. For example, the 95th percentile drops from 0.44 to 0.26, reflecting the fact that the baseline overestimates search effort of those classified as out of the labour force.

Figure 3 plots the distribution of predicted probabilities for the FMST approach for 2019. The overall composition is similar to the baselines probabilities, nearly half of the estimated probabilities are between 0 and 0.1 and the contribution to this bin from the out of the labour force is about 55%. The main difference between the baseline and FMST distributions is in the composition of the higher end of the predicated probabilities. Panel (b) shows that using the FMST approach, the predicted probabilities between 0.9 and 1 is composed of more than 50% employed workers, and the rest of unemployed workers.

Figure 3: *Distribution of predicted probabilities in 2019: FMST approach*



(a) Overall Composition



(b) Composition within Bins

Note: Panel (a) plots the histogram of predicted probabilities in 2019. Panel (b) shows the percent of each labour market group in each bin.

3.3 Aggregate Unemployment

Using the monthly predicted probability of search effort for each person, the estimated number of searchers within each CPS defined labour market state, unemployed U^s, employed E^s, and out of the labour 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 labour 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 4 plots the predicted fraction of people searching in each labour 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 countercyclical pattern, except 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 percentage varying between 95% and 98%. The fraction of people searching for a job who are classified as out of the labour force has risen by nearly 4 percentage points since 1980, which corresponds to nearly 7 million extra job seekers. The final panel of Figure 4 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 labour force groups in Figure 4 display a clearly countercyclical pattern, 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 the search effort of the unemployed is countercyclical in the US, such as Shimer (2004), Faberman and Kudlyak (2019) 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 procyclical search effort. While the fraction of people searching among

Figure 4: *Fraction of job searchers*

(a) Employed

(b) Unemployed

(c) Out of the labour Force

(d) Total Population

Note: The figure plots the quarterly fraction of job searchers among the employed, unemployed, out of the labour force and total population. The baseline uses the independent search across days assumptions and the FMST uses the fraction of steady searchers assumption.

people classified as out of the labour force has risen by one-third since 1980, the rise is also counter-cyclical, 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,

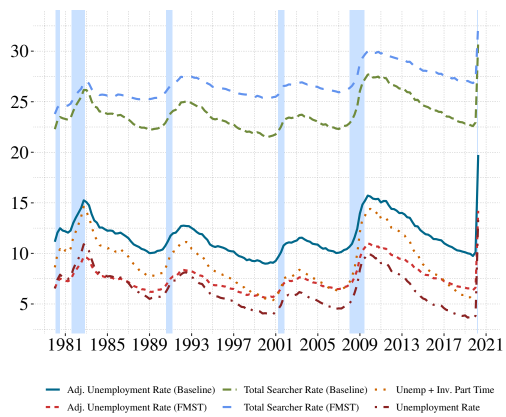
$$S_t = \frac{U_t^s + O_t^s + E_t^s}{U_t^s + O_t^s + E_t}. \tag{13}$$

The total searcher rate is in spirit most similar to the Bureau of labour Statistic's most inclusive measure of labour 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 labour underutilization since it weights individuals by their propensity to begin new employment. Finally, an adjusted measure of labour force participation is constructed by taking the ratio of the weighted average of all non-employed plus all employed to the total population,

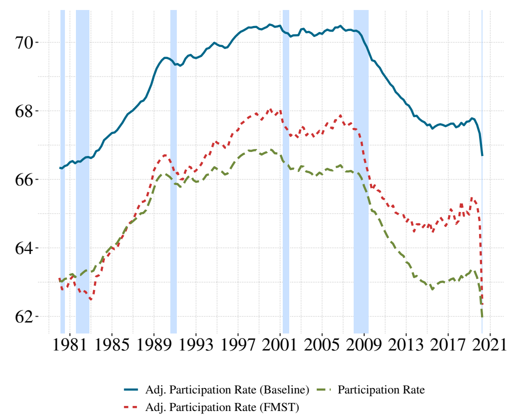
$$\tilde{PR}_t = \frac{U_t^s + O_t^s + E_t}{U_t + O_t + E_t}. \tag{14}$$

Although the adjusted unemployment rate and total searcher rate weight workers based on their job search probabilities, it may also be important to consider search efficiencies when constructing aggregate labour market statistics, since these will affect workers outside options and their wages through bargaining. Appendix section A.7 shows how weighting the different labour market states using the estimated search efficiency (offers/application) reported in Table 4 affects the levels of the unemployment and total searcher rate. Appendix section A.6 tests robustness to the assumption that the covariates are time invariant.

Figure 5: *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. The baseline uses the independent search across days assumptions and the FMST uses the fraction of steady searchers assumption.

Panel (a) of Figure 5 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. Also plotted is the unemployed plus involuntarily part-time employed[16] workers constructed by Borowczyk-Martins and Lalé (2020). The involuntarily part-time employed are often used as another measure of total slack in the labour market. Adding the involuntarily

[16]Lale (2020)

part-time employed does not increase the level of total labour slack when compared to the total searcher series, but does increase the cyclicality.

Panel (b) of Figure 5 plots the standard and adjusted labour force participation rates. The average adjusted participation rate is 3.9 percentage points higher than the standard participation rate. The standard labour force participation rate drops by 4 percentage points from 2000 to 2015. The adjusted participation rate decreases 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.

3.4 Search Effort and Labour Force Attachment

For the adjusted unemployment rate to be a useful measure of labour underutilization, it should weight non-employed people with a higher labour force attachment more than those with a lower labour force attachment. To test if the predicted search probabilities are indeed a good measure of labour market slack, three statistics measuring labour force attachment 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 labour 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 labour force attachment. Third, for the subset of employed individuals who switched jobs, the change in their usual hours worked is used as a measure of labour force attachment. If the estimated job search probability is a useful measure of labour force attachment, it should be positively correlated with all three statistics.

To estimate the correlation between the predicted job search probability and the three measures of labour force attachment, I run the following regression:

$$y_{it} = \beta \hat{P}_{it-1} + \delta_t + \varepsilon_{it} \tag{15}$$

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 correlations 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 labour force attachment.

3.5 Decomposition

The previous section shows that there has been a large increase in the number of job seeks in all three labour market states. Simultaneously, there have been many demographic changes

Table 8: *Correlation between search effort and labour force attachment: 1994-2019*

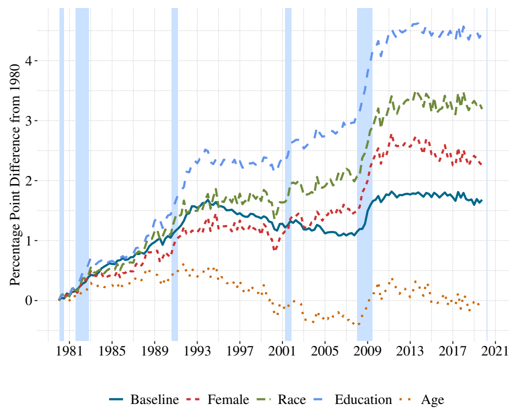
	Job Finding Prob.		Hours Worked		Change in Hours	
Search Probability	0.190	0.191	7.728	7.838	22.335	22.275
	(0.000)	(0.000)	(0.067)	(0.067)	(0.250)	(0.249)
Mean	0.037	0.037	30.33	30.33	0.33	0.33
Month × Year FE		✓		✓		✓
Observations	17608693	17608693	345967	345967	188130	188130
Sample	Full	Full	Nonemployed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

including an increase in educational attainment, an increase in women's labour force attachment, and aging of the population. In this section, I decompose the changes in job seekers to analyze how these demographic changes have affected the number of job seekers. To do so, each series is re-estimated holding fixed the fraction of each demographic observable, i.e. sex, age, race, and education.[17] The resulting series is a counterfactual series showing how the number of job seekers would have evolved if the demographic composition had not changed since 1980.

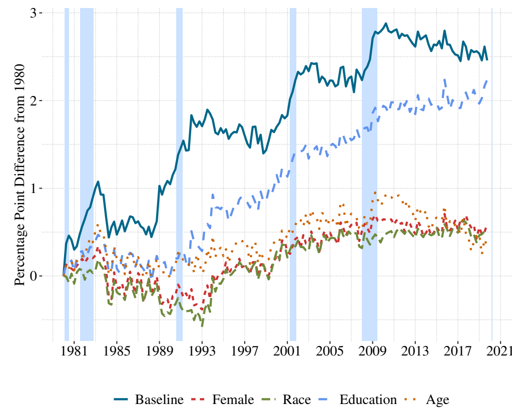
Figure 6 plots the resulting counterfactual searcher series. The dark blue line in Panel (a) shows that the baseline estimation of employed job seekers increased by nearly 2 percentage points since 1980. The line labeled "Female" can be interpreted as the counterfactual number of job seekers that would have existed if the fraction of employed women had remained fixed since 1980. The remaining lines are interpreted analogously. Panel (a) shows that the aging of the employed population played the largest role in increasing the search effort of the group. The line labeled "Age" shows that if the age composition of the employed had remained fixed at its 1980 level, there would have been no increase in the fraction of employed searchers. Changed in education, race, and gender composition, on the other hand, decreased search

[17] Details of how each series is constructed can be found in Appendix A.8.

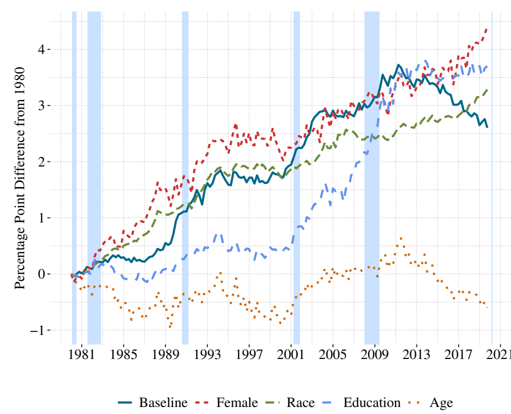
Figure 6: *Decomposition of searchers*



(a) Employed



(b) Unemployed



(c) Out of labour Force

Note: The figure plots the percentage point difference from 1980 in the fraction of estimated job seekers in each labour market states holding fixed the specified demographic variables. Details of the decomposition can be found in Appendix section A.8.

effort of the employed. This can be seen by the fact that each of the counterfactual series where the demographic composition is held fixed increased by more than the baseline.

Panel (b) of Figure 6 plots the counterfactual fraction of searcher in the pool of unemployed. For the unemployed, in increase in searchers can be attributed to changed along all four demographic variables, but to a lesser extent the composition of education. Panel (c) plots the counterfactual series for the group of out of the labour force searchers. The composition of gender and race played little role in the increase in the fraction of job seekers among the group classified as out of the labour force. The educational composition played a large role in the increase until 2001, and the age composition of those classified as out of the labour force contributed to much of the increase since 1980.

Overall, the figure shows that changed in the age and educational composition of each group played the largest roles in the changing number of estimated job seekers. Although the quadratic in age is estimated as an inverted parabola (Table A2), implying that search effort declines with age, the estimates imply that this decline occurs late in life, around age 70 for the employed and unemployed, and age 61 for the out of the labour force. So while the US population has aged from 30 (median) in 1980 to 38.5 in 2020, this age still remains well below the point at which search effort is predicted to decline. Similarly, educational attainment of the US population has substantially increases over this period and the estimated correlation between the probability of job search is increasing in education (Table A2) implying that as education increased, so did the propensity of job search.

Although the receipt of unemployment insurance (UI) should not play a role in the classification of individuals into the labour market groups in the CPS. It would affect misclassification of workers receiving UI are more truthfully reporting that they have looked for a job in the past 4 weeks. Unemployment insurance (UI) eligibility rules have changed many times across states and at the federal level since the 1980s, and there is substantial heterogeneity in eligibility and uptake cross workers.[18] Birinci and See (2023) show that

[18] An archive of UI eligibility rules can be found at `https://oui.doleta.gov/unemploy/statelaws.asp`.

workers who are better able to self-insure against job loss are less likely to take up UI, they show that there is a positive correlation between education and self insurance. This may be one behavioral explanation for why educational attainment plays an important role in the misclassification of non-employed individuals.

4 Implications

In this section, I show the misclassification of workers has significantly impacted three well studied aspects of the macroeconomy. First, it is well-known that the work-horse search and matching model cannot match the volatility in labour market tightness, when using only the standard pool of unemployed, through reasonable productivity shocks (Shimer, 2005).[19] I show that labour market tightness, constructed using the adjusted unemployment rate or total searchers rate, is 24%-38% less volatile. In fact, the labour market is less volatile in several dimensions than previously thought. Second, calculate new measures of efficient unemployment and show that these measures have been increasing in the post 2008 recession period. Third, I show that the much-debated flattening of the Phillips Curve is significantly less, and in some specifications absent, when using the adjusted unemployment rate, or total searcher rate, as a measure of the output gap.

[19] In Shimer (2005) he firsts estimates the elasticity of the matching function using the standard pool of unemployed, total vacancies, and job finding rates. Then he shows that a calibrated version of the simple search and matching model, given his estimate of the matching function elasticity (0.72) can not replicate the observed volatility in labour market tightness. Barnichon and Figura (2015) re-estimate a matching function that includes out of the labour force searchers and found a matching function elasticity that is significantly smaller at 0.18. Shimer (2005) shows in section F III that as long as unemployment and vacancies are imperfect complements in the matching function, the impact of productivity shocks on fluctuations in tightness will be muted. To fully understand how much more muted these fluctuations are to the series constructed here, the model proposed by Shimer (2005) would need to be recalibrated.

Table 9: *Standard deviations of logged statistics 1980-2020*

	Job Seekers	Vacancy Rate	Tightness
Unemployment Rate	0.279	0.248	0.460
Adj. Uempoyment Rate			
Baseline	0.146	0.250	0.358
FMST	0.167	0.248	0.380
Total Searcher Rate			
Baseline	0.065		0.297
FMST	0.052		0.285

4.1 Volatility of labour Market

In assessing the volatility of the labour market, I look at three statistics: job seeker rates, vacancy rates, and labour market tightness. The three job seeker rates I compare are the standard unemployment rate, adjusted unemployment rate, and total searcher rate. The vacancy rates I compare are vacancies per labour market participant. Total vacancies[20] are constructed using the Help Wanted Index taken from Barnichon (2010b) from 1980 to November 2000, and total job openings from the Job Openings and labour Turnover Survey from December 2000 to July 2020. The standard vacancy rate is calculated as total vacancies per standard number of unemployed and employed. The adjusted vacancy rate is calculated as total vacancies per adjusted number of unemployed and employed.

Table 9 reports the volatility of each series. First, the volatility of the standard and adjusted vacancy series are nearly identical. The volatility of the job seeker rates differs substantially. The standard deviation (in log points) of the standard unemployment rate is 0.28 while the standard deviation of the adjusted unemployment rate is 0.15 for the baseline and 0.17 for the FMST, implying the adjusted unemployment rate is nearly half as volatile. When considering all searchers in the economy, the volatility drops to 0.07 for the baseline

[20] Barnichon (2010a)

and 0.05 for the FMST. This decrease in volatility is also reflected in labour market tightness. The volatility of standard labour market tightness is 0.46; the volatility of adjusted labour market tightness is 0.36 for the baseline and 0.38 for the FMST. The volatility of the total searcher labour market tightness is the lowest, 0.3 for the baseline and 0.29 for the FMST.

The changes in the volatility when correcting for the misclassification of non-employed individuals and when taking employed job seekers into account are large and significant when considering that the standard search and matching model cannot generate large movements in these key labour market statistics.

4.1.1 Labour market flows

Elsby *et al.* (2015) show that transitions into and out of the labour force account for nearly one third of the volatility of the unemployment rate. This has led to the inclusion of a labour supply margin to standard search and matching models, see Krusell *et al.* (2017) for example. These models attempt to match flows across the three labour market states that are calculated by matching individuals across consecutive months to calculate transition probabilities. The main difficulty of these models is to match the large and volatile flows into and out of the labour force.

Appendix section A.10 shows how the adjusted flows are calculated and plots these flows for the baseline search probabilities. The adjusted labour market flows are substantially different than the standard flows calculated from the matched Current Population Survey (CPS).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 0.05, implying that unemployment is a more persistent state.

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-labour-force margin; however, their adjustments decrease the flow from unemployment to out of the labour force by half and it remains 50% higher than the flow constructed here. Similarly, Elsby *et al.* (2015) correct labour 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 labour force is through relatively large transitory shocks to the disutility of search effort.[21] Using the adjusted flows significantly decreases the movements into and out the labour force that would need to be matched in a labour market model that includes a labour supply margin.

4.2 Efficient Unemployment

The unemployment rate is typically used as a measure for understanding the health of the labour market. When interpreting its level, a benchmark is needed to compare to. One standard measure used to compare the unemployment rate, it is the non-accelerating-inflation

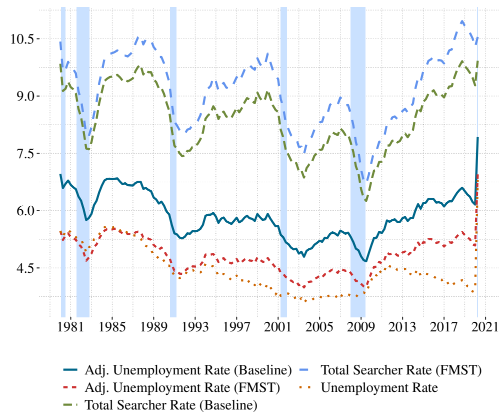
[21] See Krusell *et al.* (2008, 2010, 2011) for a complete explanation of how aggregate and idiosyncratic shocks affect labour market flows.

rate of unemployment (NAIRU). As an alternative, Michaillat and Saez (2021) suggest an efficient level of unemployment derived from the standard search and matching model. In this section, I revisit the efficient unemployment and total searcher rate. Michaillat and Saez (2023) show that the efficient unemployment rate can be estimated as $u^* = \sqrt{uv}$, where v is the vacancy rate.

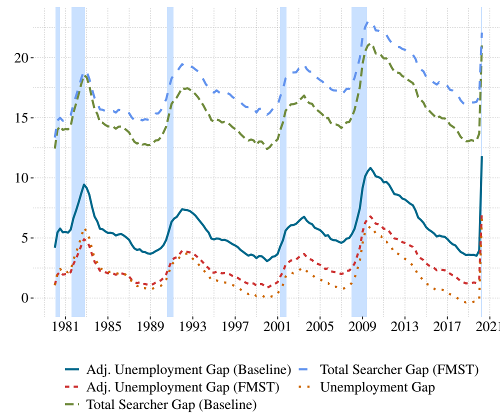
Using the vacancy rates as defined and constructed in the previous section, I calculate the efficient level of labour market slack for both the unemployment rate and total searcher. Panel (a) of Figure 7 plots the resulting levels of efficient labour market slack. First, the level series is higher than the level of efficient unemployment when using the standard unemployment rate. Second, each series is more cyclical than the standard efficient unemployment rate. While the standard efficient unemployment displays slight pro-cyclicality in the 1980s and 1990 recession, it is nearly flat through the 2000 and 2008 recessions. The adjusted efficient unemployment series (baseline and FMST) are more procyclical and fall during both the 2000 and 2008 recession. The cyclical movements of the efficient total searcher series are even more pronounced. Finally, while the standard efficient unemployment rate falls after the 2008 recession, all adjusted series rise, reaching some of their highest levels in the sample.

Panel (b) of Figure 7 plots the labour market gaps, calculated as the difference for each series from its corresponding efficient level. The first thing to note is that all series are mostly positive, implying the labour market is nearly never close to efficiency. However, it is worth noting that there is evidence that vacancies may be underreported due to time aggregation (Davis *et al.*, 2013), a higher level of vacancies would increase the level of efficient slack and decrease the gaps. Second, while the gap that comes from the standard unemployment rate

Figure 7: *Efficient labour market slack*



(a) Efficient Slack



(b) Gaps

Note: Panel (a) plot the efficient level of labour market slack defined as $x^* = \sqrt{xv_x}$ *where* x *is the labour market measure and* v_x *is its corresponding vacancy rate. Panel (b) plots the difference of the measure and its efficient level for each statistic. The baseline uses the independent search across days assumptions and the FMST uses the fraction of steady searchers assumption.*

falls slightly below zero, and to its minimum by 2019, all adjusted series are still positive and remain above their minimum level in the sample.

4.3 Phillips Curve

The unemployment rate, or unemployment gap, is often used as a measure of labour 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 positive 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 (2020) for a recent review.

More recent developments in understanding the dynamics of inflation and output have used regional variation in prices to overcome the simultaneity issues faced when using aggregate time series. Hazell *et al.* (2022) and Fitzgerald *et al.* (2020) for example, find that there has been little flattening of the Phillips curve when using regional US data, arguing that it was an anchoring of inflation expectations since the 1980s confound estimates of the slope of the Phillips curve when using aggregate time series data. An analogous argument is presented by Jorgensen and Lansing (2019). Beraja *et al.* (2019) uses regional variation and shows similar results when estimating the wage Phillips Curve. In what follows, I estimate the wage Phillips curve at the aggregate level with the adjusted measure of labour slack and echo the results of these regional studies: little to no flattening of the slope of the Phillips Curve.

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,

$$\pi_t = \phi(x_t - x_t^*) + \gamma E_t[\pi_{t+1}] \tag{16}$$

where π_t is the inflation rate at time t, x_t is a measure of labour 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,

$$E_t[\pi_{t+1}] \equiv \bar{\pi}_t = \frac{1}{4}(\pi_{t-1} + \pi_{t-2} + \pi_{t-3} + \pi_{t-4}). \tag{17}$$

Similar specifications have been used recently by Stock and Watson (2020),Galí and Gambetti (2020) and Ball and Mazumder (2011).

I estimate a wage Phillips curve, similar to Galí and Gambetti (2020), 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

$$\Delta w_t = \phi(x_t - x_t^*) + \gamma E_t[\pi_{t+1}] \tag{18}$$

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 labour 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 (2020) argue that the disappearance of the Phillips curve is robust to whichever measure one chooses. Therefore, the output gap measured using the standard unemployment rate is estimated as the difference between the standard unemployment rate and the Congressional Budget Office's natural rate of unemployment (NROU).[22] Since the adjusted unemployment rate and the total searcher rate are adjusted for demographic changes in the labour 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 (2020), that is:

$$\Delta w_t = \alpha + \phi_1(u_t - u_t^{NAIRU}) + \gamma_1 E_t[\pi_{t+1}] + \phi_2(u_t - u_t^{NAIRU}) \times Post_t + \varepsilon_t \qquad (19)$$

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, I first assume that the natural rate of unemployment is constant over the period. This assumption is rooted in the fact that the adjusted series no longer have a long run downward trend; in the following subsection, I include an adjusted natural rate as robustness.

$$\Delta w_t = \tilde{\alpha} + \phi_1 x_t + +\gamma_1 E_t[\pi_{t+1}] + \phi_2 x_t \times Post_t + +\varepsilon_t \qquad (20)$$

Again, ϕ_2 estimates the change in the Phillips curve.

[22] `https://fred.stlouisfed.org/series/NROU`

Table 10: *Correlations with nominal wage growth*

	1980Q1 - 2019Q4				
	Unempoyment Rate	Adj. Unemp. Rate		Tot. Searcher Rate	
		Baseline	FMST	Baseline	FMST
	(1)	(2)	(3)	(4)	(5)
U-Gap	-0.080				
	(0.023)				
U-Gap $\times$ Post	0.062				
	(0.024)				
$\tilde{U}$		-0.065	-0.095		
		(0.015)	(0.020)		
$\tilde{U}\times$ Post		0.018	0.031		
		(0.004)	(0.006)		
S				-0.076	-0.085
				(0.014)	(0.025)
$S\times$ Post				0.011	0.011
				(0.002)	(0.002)
$\bar{\pi}_{t-1}^{PCE}$	0.050	0.061	0.051	0.042	0.014
	(0.027)	(0.029)	(0.026)	(0.024)	(0.026)
Intercept	0.004	0.010	0.010	0.021	0.026
	(0.001)	(0.002)	(0.001)	(0.003)	(0.007)

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. *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).* $\bar{\pi}_{t-1}^{PCE}$ *is the four quarter average of the year-over-year inflation rate measured by the Personal Consumption Expenditure Index. Post is an indicator variable that takes on the value 1 after 2007Q2. The baseline uses the independent search across days assumptions and the FMST uses the fraction of steady searchers assumption.*

The sample period is 1980Q1 to 2019Q4. Δw_t is the annualized growth rate of average hourly earning of Production and Nonsupervisory Employees[23] 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).

Table 10 reports the results from the regressions. 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 decreasing by 78% (to -0.017) post-2007, similar to what Galí and Gambetti (2020) find. Columns (2) and (3) report the estimated parameters when using the adjusted unemployment rate (baseline and FMST) as a measure of the output

[23] `https://fred.stlouisfed.org/series/AHETPI`

gap. First, the estimated correlation pre-2007 is slightly lower for the baseline and slightly larger for the FMST. Second, both series still show some flattening but significantly less. For the baseline, the slope in the post-2007 period increases by 0.018 (28%), similarly for the FMST the slope increases by 0.031 (41%). Columns (4) and (5) report the results when using the total searcher rate as the output gap. Again, the pre-2007 correlations are similar to the unemployment rate but the change in the slope after 2007 is significantly smaller, 14% for the baseline and 13% for the FMST.

4.3.1 Robustness to Including an Adjusted NROU

In the analysis this far, I have assumed that the natural rate of unemployment (and total searchers) was constant over time for the estimation of the Phillips curve using the adjusted series. I test the robustness of the results to this assumption by calculating an adjusted natural rate of unemployment (and total searchers) and re-estimating the Phillips curve for each new measure using the gap, rather than levels.

To construct the adjusted natural rate for each statistic, I assume that the difference in the long run trends between the standard unemployment rate and the adjusted series are driven by differences in their natural rates. That is, only the cyclical difference are driven by the effects of the macroeconomy. First, for each adjusted series I estimate the following regression

$$u_t - x_t = \delta_0 + \delta_1^x t + \epsilon_t \tag{21}$$

where u_t is the standard unemployment rate, x_y is the adjusted series, and t is a continuous time variables. δ_1^x estimates a linear trend difference for each series. Second, construct a natural rate for each series as

$$NR_t(x) = NROU_t + \hat{\delta}_1^x t. \tag{22}$$

The resulting natural rates have substantial level differences from the adjusted series, but these differences will be absorbed in the constant of the Phillips curve regression. Table A5 in Appendix section A.9 reports the coefficients from the linear trend of the differences of the standard unemployment rate and the adjusted series and Figure A6 plots the resulting adjusted natural rates.

Table 11 reports the results from the Phillips Curve estimation using the gap measures instead of levels for each of the adjusted series. Columns (1) and (2) show the results for the adjusted unemployment rate, compared to the results in the previous section, the pre-2007 correlations are slightly large for both the baseline and FMST series. The flattening of the Phillips curve is larger for both the adjusted unemployment rate series 49% for the baseline and 74% for the FMST, however still less than 78% when using the standard unemployment rate. The slope of the Phillips curve after 2008 for both adjusted series is large (-0.03 for the baseline and -0.026) is larger than the slope when using the standard unemployment rate (-0.017). While the magnitudes of the decrease in the flattening of the Phillips curve depend on whether it is estimated with levels rather than gaps, the finding that the flattening is less dramatic with the adjusted measure is robust to specification.

Columns (3) and (4) of Table 11 report the results for the total searcher gap measures. As with the adjusted unemployment rate gap measures, the pre-2008 correlations are larger than when using levels. The post 2008 coefficients are still positive and significant by much

Table 11: *Correlations with nominal wage growth: robustness*

	1980Q1 - 2019Q4			
	Adj. Unemp. Rate		Tot. Searcher Rate	
	Baseline	FMST	Baseline	FMST
	(1)	(2)	(3)	(4)
$\tilde{U}$-Gap	-0.071	-0.103		
	(0.017)	(0.027)		
$\tilde{U}$-Gap$\times$ Post	0.034	0.075		
	(0.009)	(0.031)		
S-Gap			-0.072	-0.103
			(0.014)	(0.016)
S-Gap$\times$ Post			0.012	0.009
			(0.002)	(0.002)
$\bar{\pi}^{PCE}_{t-1}$	0.064	0.049	0.050	0.033
	(0.029)	(0.027)	(0.026)	(0.020)
Intercept	0.006	0.004	0.015	0.022
	(0.001)	(0.001)	(0.002)	(0.003)

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. *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).* $\bar{\pi}^{PCE}_{t-1}$ *is the four quarter average of the year-over-year inflation rate measured by the Personal Consumption Expenditure Index. Post is an indicator variable that takes on the value 1 after 2007Q2. The baseline uses the independent search across days assumptions and the FMST uses the fraction of steady searchers assumption.*

smaller and nearly identical to the post coefficients when using levels rather than gap. The decrease in the flattening of the Phillips curve when using the gap measures for total searchers is robust to specification.

5 Conclusion

I document a rise in hires from out of the labour force and, using the American Time Use Survey, a large proportion of individuals searching actively while being classified as out of the labour force, and argue that the standard unemployment rate, therefore, does a poor job capturing the churning of the labour 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 labour market flows since 1980. There has been a substantial increase in the proportion of people classified as out of the labour force that are predicted to be actively seeking employment. Adding these job seekers into the unemployment rate nearly doubles its level, rids the unemployment rate of the low-frequency downward trend, and significantly decreases overall labour market volatility.

The unemployment rate is the most used indicator of the labour market and often used when determining policy, therefore having an accurate measure of it is important. An application of 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 little post-2008 flattening. This result suggests that policies, such as unemployment insurance, should have similar effects on aggregate wage inflation pre and post 2008. Understanding if and how this channel has changed is important for the understanding of feedback channels of monetary policy.

A Appendix

A.1 Data Cleaning and Aggregation

A.1.1 CPS Demographic Data

The main data used to calculate the number of individuals and flows across the labour 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 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 was replaced with the sample mean in 1984. During the months between January 1994 and October 1999, the indicator is replaced 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).

A.1.2 Aggregation

After predicting and aggregating, several of the series have a small, discrete jump at different dates. The employed searcher series as a discrete jump in January 1989 and January 1994. The jump is removed from the series by multiplying a constant term to the series pre January 1994 and pre January 1989 such that the ratio of January 1989 to December 1988 and January 1994 to December 1993 are equal to the average January/December ratio over the whole sample. The unemployment and search unemployment series are adjusted from December 1983 to January 1984 and March to May 1995 in the same fashion. The out of the labour force series is adjusted from December 1988 to January 1989 and December 2002 to January 2003. The out of the labour force search series is adjusted from January to February 1984, December 1988 to January 1989, January to February 1989, December 1991 to January 1992, December 1993 to January 1994, and November to December 1999. All series are seasonally adjusted using the X-13ARIMA-SEATS seasonal adjustment program provided by the Census Bureau, available at `https://www.census.gov/srd/www/x13as/`.

A.1.3 Flows and Hires

Flows of the labour 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, and then corrected for margin error similar to Elsby *et al.* (2015) (described in detail below).

Hires plotted in Figure 1 are calculated using the match basic monthly files and calculating the total number of hires by previous labour force status (including employed at a different employer starting in 1994) per total population of the matched monthly files. That fraction is then multiplied by the total population of the basic monthly files. The series are seasonally adjusted using X-13ARIMA and averaged to quarterly values.

A.2 ATUS 2013-2019 Subsample

Table A1 reports summary statistics by labour force status in the ATUS from 2013 to 2019 for comparison to the JSS. The second column of the table labeled "Employed NAW" is a subsample of the employed people who were interviewed on a weekday and did not go to work on the interview day. In the ATUS workers are only asked about their primary activity and no secondary activity is included, which implies that job search amongst the employed is likely to be underreported if they conducted any job search while at work. This is evident from the fact that the percent of workers searching in the full pool of employed workers is 0.006, while for the subsample that did not go to work on the interview day, the fraction doubles to 0.013. Similarly, workers not a work spend nearly an hour longer per day searching for a job. In what follows, the subsample of workers not at work on the interview way will be used as a comparison group to the employed workers in the JSS.

Table A1: *ATUS 2013-2019 summary statistics*

	Employed	Employed NAW	Unemployed	Out of Labor Force
Percent of Population	0.713	–	0.045	0.242
Percent Searching	0.006	0.013	0.190	0.006
Minutes Searching Per Day				
Unconditional	0.884	2.654	32.070	0.980
Conditional	152.031	198.673	168.934	170.987

A.3 Estimation Results

Table A2 shows the estimated parameters for each labour market state. For the unemployed and out of the labour force groups, the full time dummy and its interactions with education are not included. The interactions that do not display a point estimate were not chosen by the net-elastic logit estimation.

Figure A1 plots the receiver operating curve for each estimation. The area under the curve reports the goodness of fit. The best fit is for those classified as out of the labour force, with an area under the curve of 0.873. The goodness of fit for the employed and unemployed is similar, with an area under the curve of 0.753 and 0.735.

A.4 Details of the Estimation Procedure

The log-likelihood function that is maximized is as follows,

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

If $\alpha = 1$ the likelihood function reduces to the Least Absolute Shrinkage and Selection Operator (LASSO) Logit and if $\alpha = 0$ it reduces to the Ridge Logit. The goal of both the Ridge and LASSO estimators is to include a trade-off between overfitting and under

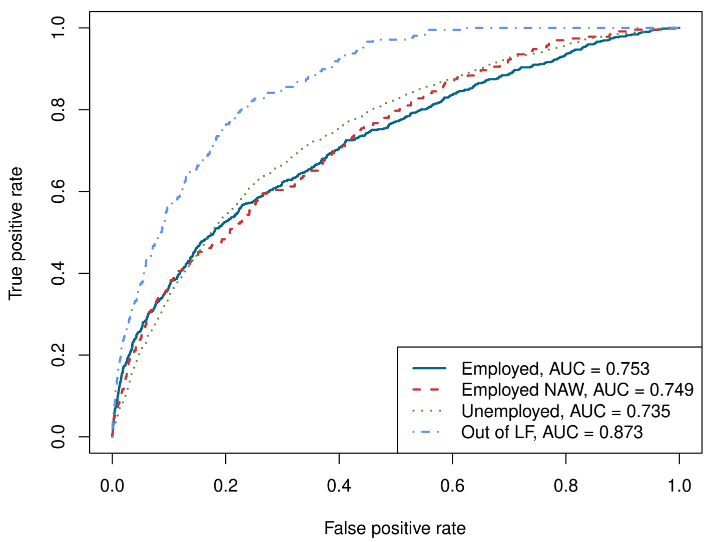
Table A2: *Logit parameters*

Parameter	Employed	Employed NAW	Unemployed	Out of the Labor Force	Parameter	Employed	Employed NAW	Unemployed	Out of the Labor Force
Monday	0.351	0.275	0.515	0.524	College × Age				
Thursday	0.340	0.430	0.301	0.605	High School × Age				
Tuesday	0.272	0.614	0.411	0.628	Less than HS × Age				
Wednesday	0.241	0.539	0.654	1.027	Some College × Age				
Saturday	-0.563	Not Included	-0.864	-0.415	College × Age^2				
Sunday	-0.549	Not Included	-0.672	-0.249	High School × Age^2			-0.000	
Female	-0.699	-0.684	-0.352	-0.337	Less than HS × Age^2				
Age	0.076	0.144	0.169	0.184	Some College × Age^2				
Age^2	-0.001	-0.002	-0.002	-0.003	College × Married				0.022
College	-0.158	-0.530	-0.229	-0.398	High School × Married				
High School	-0.792	-0.812	-0.761	-1.132	Less than HS × Married		0.174		
Less than HS	-1.060	-0.764	-1.298	-1.009	Some College × Married			0.292	-0.006
Some College	-0.624	-0.498	-1.121	-0.276	College × Child				
Married	-0.619	-0.800	-0.220	0.462	High School × Child				0.239
Child	0.009	-0.113	-0.210	-0.567	Less than HS × Child				
Race - Other	-0.611	-0.296	0.101	-0.117	Some College × Child	0.201		0.098	0.202
Race - White	-0.595	-0.672	-0.033	-0.691	College × Race - Other	-0.741		-0.527	
Full Time	-1.603	-1.025	Not Included	Not Included	High School × Race - Other			-0.432	
Female × Age		-0.018			Less than HS × Race - Other				-1.668
Female × Age^2					Some College × Race - Other	-0.006		-0.295	-2.040
Female × College					College × Race - White				
Female × High School					High School × Race - White				
Female × Less than HS					Less than HS × Race - White				
Female × Some College			0.241		Some College × Race - White				
Female × Married			-0.334	-1.148	College × Full Time			Not Included	Not Included
Female × Child	-0.211		-0.041		High School × Full Time			Not Included	Not Included
Female × Race - Other			0.125	0.164	Less than HS × Full Time			Not Included	Not Included
Female × Race - White				-0.348	Some College × Full Time	0.146		Not Included	Not Included
Female × Full Time	0.503		Not Included	Not Included	Constant	-3.467	-4.296	-3.474	-5.816

Note: A total of 58 parameters we included in the Logit estimation for the Employed group and 52 for the Unemployed and Out of the labour 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. For the employed not at work (NAW), Saturday and Sunday are not included because the sample does not include workers interviewed on the weekend.

fitting the data that is used to train the model. Under fitting results in a high bias, which overfitting leads to a high variance, therefore the estimators face a tradeoff between bias and variance in the test data (in this case the ATUS data). The main difference between the Ridge and LASSO specifications is that Ridge does not set coefficients to zero, making it a poor model for feature reduction, while LASSO does set coefficients to zero (Zou and Hastie, 2005). If the number of potential regressors (p) is larger than the number of observations (n), LASSO will include at most n regressors. However, this is not the case in the ATUS data. When $\alpha \in (0, 1)$ the estimator is a Net-Elastic Logit which combines the Ridge and LASSO into one. Since the number of potential regressors is significantly less than the number of

Figure A1: *Receiver operating characteristic curve*



observations in the ATUS data, I choose $\alpha = 0.95$, putting more weight on the LASSO penalty rather than the Ridge. 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.

The λ parameter is the tuning parameter or regularization penalty. If $\lambda = 0$ then the estimator reduces to the standard Logit estimator. λ is chosen through 10-fold cross validation by minimizing the test Mean Squared Error (MSE). That is, the ATUS data is split randomly into 10 datasets "folds" and the model is estimated 10 times, each time leaving one fold out. The estimated model is then used to predict the job search probability of the left out fold, and the MSE is calculated for each estimation. Finally, λ is chosen to minimize the average MSE across the 10 estimations.

Table A3: *Percentiles of predicted search effort: neural network*

	Employed	Unemployed	Out of the Labor Force
5th Percentile	0.0134	0.7401	0.0000
10th Percentile	0.0134	0.8879	0.0000
25th Percentile	0.0227	0.9829	0.0000
50th Percentile	0.0669	0.9963	0.0000
75th Percentile	0.0843	0.9999	0.0278
90th Percentile	0.2191	1.0000	0.2826
95th Percentile	0.2980	1.0000	0.4323

A.5 Estimation using a neural network

In the baseline estimation, a net-elastic logit approach is used to estimate whether a person is searching for a job. Alternatively, a neural network can be estimated on the data to classify people to be either searchers or non-searchers. As a robustness to the baseline estimation, I estimate a neural network consisting of one hidden layer with 5 nodes for the employed and 4 nodes for the unemployed and out of the labour force. All the same covariates are used as the main specification. Then classification probabilities are estimated for all workers in the CPS samples and search probabilities are calculated identically as described in subsubsection 3.2.1.

Table A3 reports the percentiles of the predicted search probabilities for each labour market state. The percentiles are similar for the unemployed group when comparing to the baseline estimation, the 50% percentile are both over 0.99. For the employed group, the percentiles are slightly smaller for the neural network but still similar. The 5th percentile of search effort of the employed using the neural network is 0.013 and 0.028 in the baseline. The 95th percentiles are 0.29 and 0.35 respectively. For the out of the labour force group, the 50th percentile and below remain at 0 for the neural network estimation, but the 90th and 95th percentiles for both the neural network and baseline estimation are similar. The

90th percentile for the neural network estimation is 0.28 and 0.30 for the baseline estimation. The 95th percentiles are 0.43 and 0.44 respectively.

Figure A2: *Fraction of job searchers: neural network*

(a) Employed

(b) Unemployed

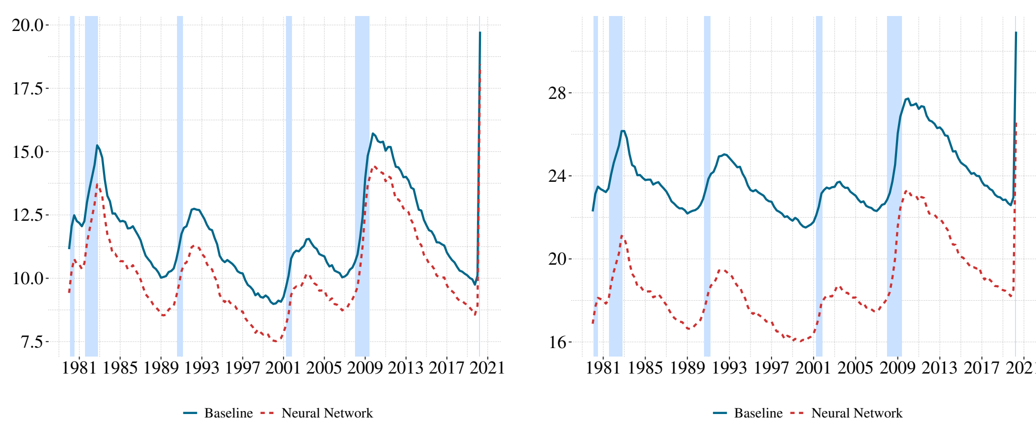
(c) Out of the labour Force

(d) Total Population

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

Figure A2 plots the baseline and neural network estimated fraction of workers that are searching in each labour market state and the total fraction of searchers. Each panel shows a level shift downwards in the fraction of searchers in each labour market state, however the trends are similar in the baseline and neural network estimation. The largest level difference is amongst the employed. The average level difference in the fraction of workers searching for a job between the baseline and neural network estimation is 4 percentage points. The average level difference between the baseline and neural network estimation is 1 percentage point for the unemployed and 3 percentage points for the out of the labour force group. Panel (d) of the figure shows the fraction of searchers out of the total population, the average level difference between the baseline and the neural network estimation for the total population is 3.7 percentage points.

Figure A3: *Unemployment and total searcher rates*



(a) Unemployment Rate (b) Total Searcher Rate

Note: The figure plots the quarterly baseline and neural network unemployment rate and total searcher rate.

Although there are level difference in the fraction of searchers in each state, when comparing the baseline and neural network estimation unemployment rate, shown in panel (a) of Figure A3, there are small differences. The average difference between the two series is 1.4

percentage points. Importantly, the two series have similar trends and neither display the downward trend that is present in the standard unemployment rate. Panel (b) of Figure A3 plot the total searchers rate for the baseline and neural network estimation, here the level difference is large, averaging 5 percentage points over the sample. The baseline total searcher rate does not display a trend, however the total searcher rate when using the neural network estimation shows a positive trend since the 2000s.

Overall, the main findings from the net-elastic estimation strategy align with the findings when using other forms of machine learning procedures. That is, there is an upward trend in the fraction of employed workers searching for a job since the 1980s and there has been an increase in misclassification between the unemployed and out of the labour force. This misclassification problem has contributed to the downward trend of the unemployment rate, and the result that the trend of the adjusted unemployment rate has been steady since the 1980s is robust to choice in machine learning algorithms.

A.6 Time Varying Predictors

In the main estimation, the covariates in the Logit are time invariant. This implies that the effect of the demographic characteristics on the misclassification probability has not changed. The assumption is necessary to be able to use the estimates from the ATUS to predict misclassification in the CPS back to 1980. If the propensity with which demographic characteristics can predict misclassification has changed over time, this assumption may over or underpredict the amount of job seekers.

Although it is not possible to test if there have been changes since 1980, it is possible to analyze how much time varying coefficients matter for the sample period of the ATUS (2003-2019). To test the robustness of the results to this assumption, I re-estimate Equation 4 and allow for each covariate and all interaction to have a linear trend. The estimation now includes a possible 107 covariates for the employed, and 96 for the unemployed and out of the labour force. The ML algorithm picks up 6 time varying covariates[24] for the employed, 6 time varying covariates[25] for the unemployed, and 10[26] for the out of the labour force.

Next, I construct two predicted search series for each labour market group. First, I predict the probability that a person is searching for each person in the CPS from 2003 onward using the new model with time varying coefficients. Second, I predict the probability each person is searching but hold the year constant at 2003. Comparing the first "Time varying" series to the baseline shows how much including time varying coefficients changes the predicted fraction of searchers in each group since 2003. Comparing the "Constant 2003" series to the "Time varying" series shows how much the time varying coefficients that the ML algorithm picks up affects each series.

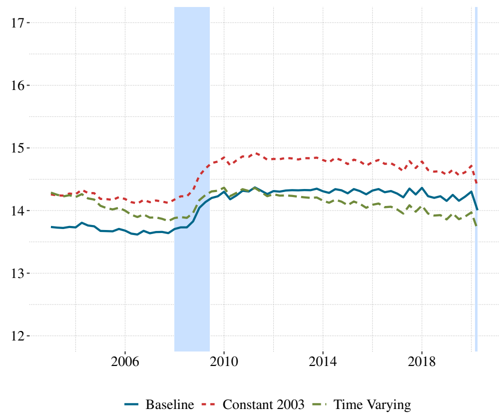
Figure A4 plots the resulting two series and the baseline for each labour market group and the total fraction of searchers since 2003. For all three groups and the total, including the time varying coefficients, has little effect on the level of searchers. For the employed and unemployed, including time varying coefficients makes both series slightly more cyclical, both have larger declines after the end of the 2008 recession. For the unemployed, the

[24] White, Female × child, Female × Other race, Female × full time, High School × white, and Some college × fulltime

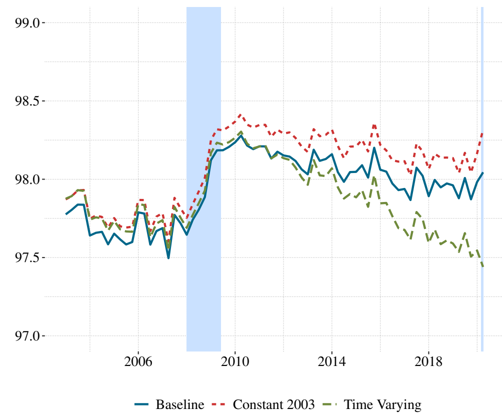
[25] Some college, Female × some college, Age squared × High school, High school × other race, Some college × other race

[26] Less than HS, Other race, Female × white, age × college, College × married, Less than HS × married, College × child, Some college × other race, Less than HS × white, Some college × white

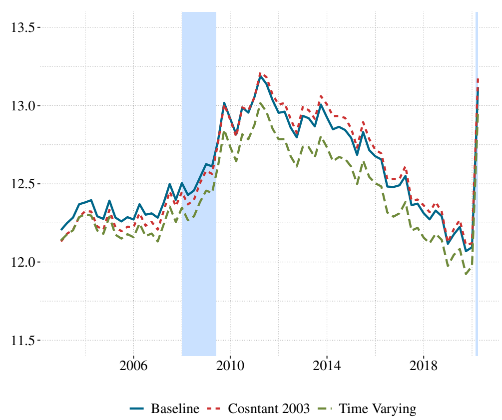
Figure A4: *Fraction of job searchers*



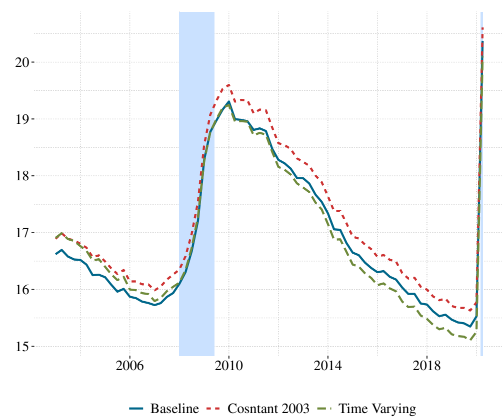
(a) Employed



(b) Unemployed



(c) Out of the labour Force



(d) Total Population

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

fraction of searchers drops back to its pre-recession level when including time varying coefficients. The fraction of searchers in the out of the labour force group and the total fraction of searchers is nearly unchanged when including time varying coefficients, and the cyclical swings through the 2008 recession are nearly identical. Overall, the figure shows that while the ML algorithm does identify that some demographic characteristics have changed in importance for identifying misclassification, these characteristics do not affect the aggregate fraction of predicted searchers to a large extent.

A.7 Search Efficiency

One important aspect that is not taking into consideration in the main text when aggregating job seekers is their relative search efficiencies. Having a statistics that include relative search efficiencies may be important for understanding how outside options of workers evolve and this how wages or bargaining powers are determined. Estimating search efficiencies of each group is complicated by the fact that the outcomes we observe, such as job offers, number of applications or time spent interviewing are all endogenous objects which depend on some form of "innate" search efficiency of each group and the composition of each group in the pool of total job seekers.

In this section, I try to understand how search efficiency impacts the adjusted series by using an estimate of efficiency from the JSS. The efficiency weights I construct are time invariant and estimated over several years of data for the JSS. This will address some of the issues mentioned, but to get a more accurate measure, a general equilibrium model may be necessary.

The final panel of Table 4 showed that search efficiency, defined as number of job offers to number of applications sent, differed across the three labour market groups. The employed and unemployed had similar efficiencies, 0.12 and 0.11, respectively. Perhaps surprisingly, those classified as out of the labour force but searching for a job had the highest efficiency, receiving an offer on every second application (0.53). Higher search efficiency by the OLF

Table A4: *Standard deviations of logged statistics 1980-2020: efficiency weighted*

	Job Seekers	Vacancy Rate	Tightness
Unemployment Rate	0.279	0.248	0.460
Adj. Uempoyment Rate			
Baseline	0.095	0.255	0.322
FMST	0.119	0.252	0.339
Total Searcher Rate			
Baseline	0.060		0.297
FMST	0.057		0.288

group, however, does align with the fact that they make up 60% of hires but only 24% of estimated total searchers.

Figure A5 plots the standard unemployment rate, baseline and efficiency adjusted unemployment rate, and the baseline and efficiency weighted total searcher rate. The efficiency weighted unemployment rate and total searcher rate are defined as:

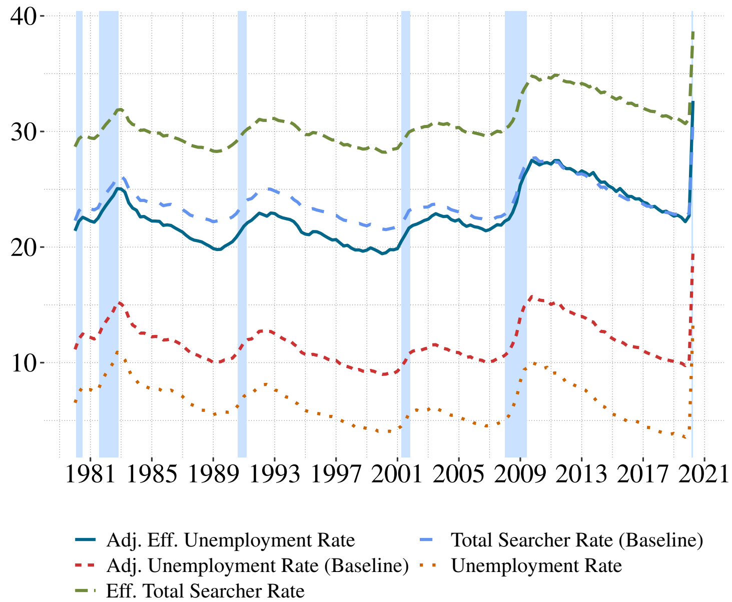
$$\tilde{U}_t^e = \frac{U_t^s + e^O O_t^s}{U_t^s + e^O O_t^s + e^E E_t^s + (E_t - E_t^S)} \tag{A.2}$$

$$\tilde{S}_t^e = \frac{U_t^s + e^O O_t^s + e^E E_t^s}{U_t^s + e^O O_t^s + e^E E_t^s + (E_t - E_t^S)} \tag{A.3}$$

where $e^O = 3.476$ is the efficiency (offers/applications) of the OLF group relative to the unemployed reported in Table 4, and $e^E = 1.203$ is the relative efficiency of the employed.

Table A4 reports the standard Deviation of the logged measures. The main difference between the volatility of the efficiency weighted statistics and the unweighted is in the adjusted unemployment rates. The efficiency weighted statistics are less volatile since they put more weight on the out of the labour force group. This group is large and relatively less volatile than the unemployed group. The volatility of total searcher statistics is relatively

Figure A5: *Unemployment and total searcher rate: efficiency weighted*



Note: The figure plots the standard unemployment rate, the baseline adjusted unemployment and total searcher rates, and the efficiency weighted adjusted unemployment and total searcher rates. The estimate of efficiency used to weight workers is from Table 4.

close to the unweighted because the employed group dominates and has lower volatility than both the unemployed and out of the labour force.

A.8 Demographic Decomposition Details

To decompose the fraction of searcher in each labour market state into changes in the demographic composition, the search probabilities are calculated in re-sampled CPS basic monthly samples. To construct the series labeled ”Female” in Figure 6 each monthly CPS sample from 1980 onwards is resampled 1,000 times with counterfactual weights such that the fraction of women in each labour market state is held constant at its 1980 level. For example, the counterfactual probabilities that are used to resample the employed in the monthly CPS in February 1980 (198002) are constructed as follows:

$$SP_i^e(198002) = \frac{Prob_{198001}}{Prob_{198002}} \frac{w_i^e(198002)}{\sum_i w_i(198002)} \tag{A.4}$$

where,

$$Prob_{198001} = \frac{\sum_{i \in FE} w^e_{i(198001)}}{\sum_i w^e_{i(198001)}} \tag{A.5}$$

$$Prob_{198002} = \frac{\sum_{i \in FE} w^e_{i(198002)}}{\sum_i w^e_{i(198002)}}, \tag{A.6}$$

and $w_i^e(t)$ is the CPS sampling weight of worker i in the group of employed workers in year t. First, these probabilities are used to resample each monthly CPS file 1,000 times. Second, the fraction of searchers in each labour market state is aggregates as described in the main text. Finally, the mean of each set of resamples is plotted in Figure 6 as a difference from its value in 198001. The counterfactual series for fixed race and education shares are constructed analogously. The counterfactual series for age, hold fixed the share of workers in six age categories: 16-20, 21-34, 35-44, 45-54, 55-64, and 65+.

A.9 Phillips Curve Robustness

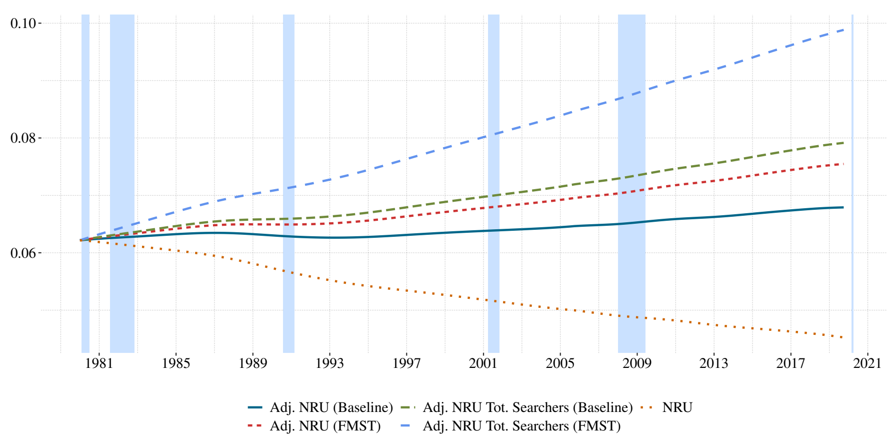
A.10 labour Market Flows

The standard method used to calculated flows between labour 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

Table A5: *Linear trends in difference between standard unemployment rate and adjusted series*

	Adj. Unemp. Rate		Tot. Searcher Rate	
	Baseline	FMST	Baseline	FMST
intrecept	0.0412	-0.0037	0.1574	0.1766
	(0.0003)	(0.0006)	(0.0005)	(0.0013)
linear trend	0.0006	0.0008	0.0009	0.0013
	(0.0000)	(0.0000)	(0.0000)	(0.0001)

Figure A6: *Adjusted natural rates*



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 labour 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:

$$f_{EU} = \frac{\sum_{i \in E_1 N_2} wgt_i \times \hat{P}_{i2}}{\sum_{i \in E_1} wgt_i} \tag{A.7}$$

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 labour 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 labour force is calculated as:

$$f_{EO} = \frac{\sum_{i \in E_1 N_2} wgt_i \times (1 - \hat{P}_{i2})}{\sum_{i \in E_1} wgt_i} \tag{A.8}$$

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,

$$f_{UE} = \frac{\sum_{i \in N_1 E_2} wgt_i \times \hat{P}_{i1}}{\sum_{i \in N_1} wgt_i}. \tag{A.9}$$

The transition probabilities between unemployment and out of the labour 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 labour 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 labour force to unemployment by only change in his estimated search probability, that is, with weight 0.2. Therefore, the flow from out of the labour force to unemployment is calculate as

$$f_{OU} = \frac{\sum_{i \in N_1 N_2} wgt_i \times max\{\hat{P}_{i2} - \hat{P}_{i1}, 0\}}{\sum_{i \in N_1} wgt_i}. \tag{A.10}$$

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

$$f_{UO} = \frac{\sum_{i \in N_1 N_2} wgt_i \times |min\{\hat{P}_{i2} - \hat{P}_{i1}, 0\}|}{\sum_{i \in N_1} wgt_i}. \tag{A.11}$$

By construction the flow from out of the labour 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 labour market states to be consistent with the evolution of the labour market stocks. In the standard labour 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 and decreases the estimated flow from unemployment to out of the labour force by 43%.

Figure A7 plots the standard and adjusted labour market flows using the baseline probabilities across labour market states for the full sample. The most notable changes occur along the participation margin. The average flow from out of the labour force to unemployment increases slightly from of 0.027 to 0.030 and the average flow from unemployment to out of the labour force decrease from and average of 0.21 to 0.05. The average flow from unemployment to employment decrease slightly from an average of 0.25 to 0.20. The average flow from employment to out of the labour force decreases by more half from 0.028 to 0.01. The standard flow from employment to out of the labour force is nearly twice as high as the standard flow from employment to unemployment; the continuous flow from employment to out of the labour force is less than the continuous flow from employment to unemployment.

Much of the previous work on labour 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. They show that misclassification happens along all margins, however the largest error occurs among individuals that are at first classified as out of the labour force and later reclassified as unemployed. However, the methods they propose continue to treat unemployment simply as an extensive margin. The benefit of the method proposed here is again, that all individuals, regardless of their labour market state when not employed contribute to each flow, so misclassification is not an issue.

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 labour 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 labour force for the entire period. Indeed, this correction ("deNUNification") decreases the flow between unemployment and out of the labour force but it does not address the issue of movements from out of the labour force directly to employment and vice versa. For example, an individual who is observed as unemployed in the first month, out of the labour 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 labour force as well as the flow from out of the labour force to employment.

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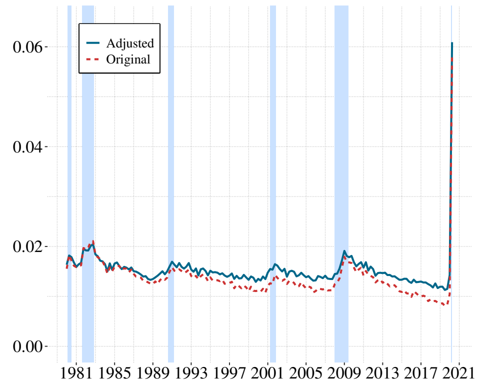
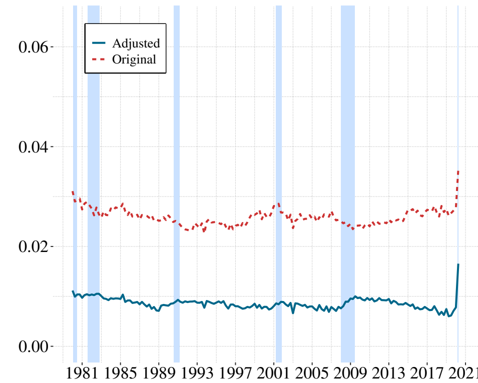
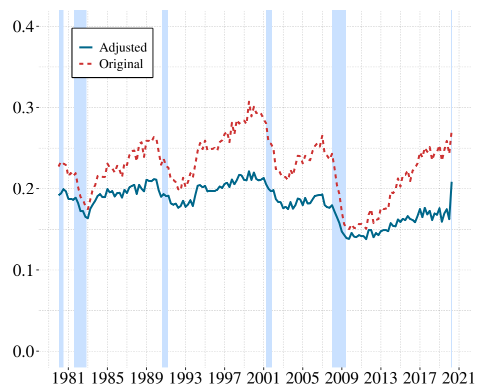
Figure A7: *labour market flows*



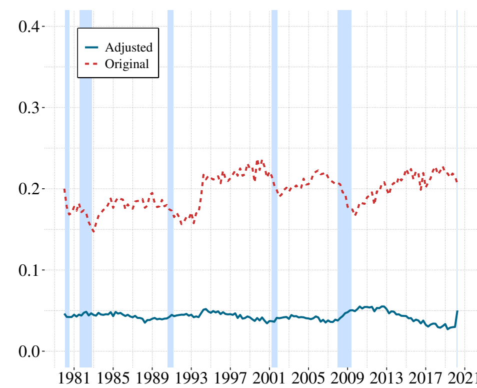
(a) Employed to Unemployed



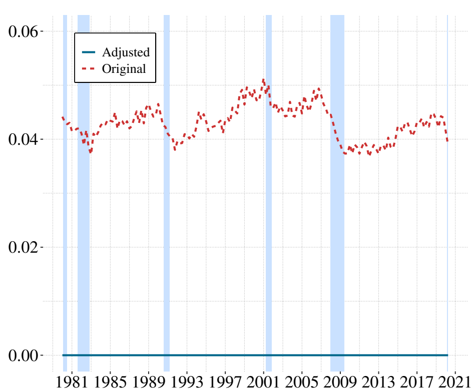
(b) Employed to Out of the labour Force



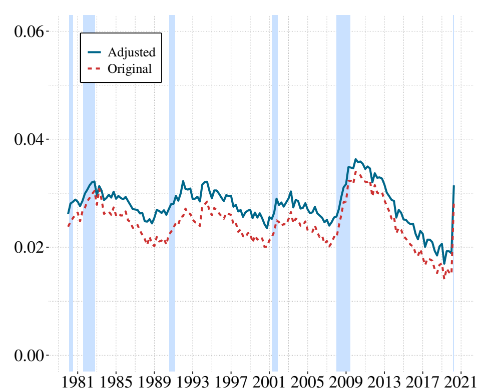
(c) Unemployed to Employed



(d) Unemployed to Out of the labour Force



(e) Out of the labour Force to Employed



(f) Out of the labour Force to Unemployed

Note: The figure plots the seasonally adjusted quarterly standard and continuous flows across labour market states.

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