Explaining Demographic Heterogeneity in Cyclical Unemployment

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Abstract

In the United States, there is substantial heterogeneity in labor market outcomes across demographic groups. Not only do young workers, non-white workers, and those without any college education have persistently higher unemployment rates than other demographic groups, but these disadvantaged workers also experience substantially larger increases in unemployment rates during recessions. In this paper, we analyze the sources of these disparities by decomposing the unemployment rate for each demographic group into the transition flows between labor market states. We find that increases in unemployment rates during recessions is primarily driven by reductions in the job finding rates, which can explain about half of the cyclical fluctuations in the unemployment rate across all demographic groups. In contrast, we find that the gap in unemployment rates between each disadvantaged group and the respective counterpart demographic group can be primarily be attributed to the disadvantaged groups' higher rates of inflow to unemployment. We conclude that policies to reduce separation rates for these disadvantaged groups could address both the persistent and cyclical disparities in the unemployment rate across demographic groups.

JEL Classification: E24, J64, J63 **Keywords**: Unemployment rate, Unemployment Gap, Gross worker flows, Job finding rate, Separation rate, Employment exit rate

1 Introduction

Workers' labor market outcomes vary substantially across demographic groups. During the Great Recession, the unemployment rate increased dramatically, from a pre-recession low of 4.4% in May of 2007 to a high of 10% in October of 2009.[1] However, during the same period, young workers, non-white workers, and those without any college education experienced increases in unemployment rates of 7 to 8 percentage points, while prime age, white, and those with some college education saw increases of

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[1] Source: Bureau of Labor Statistics.

4 to 5 percentage points. In addition to the difference in the cyclical fluctuations, there are persistent differences in the stock of unemployment across demographic groups. The unemployment rates of young workers, non-white workers, and those without any college education are twice as large as that of counterpart workers (experienced, white, and some college, respectively) during both expansions and recessions. In this paper, we investigate worker flows to determine the sources underlying the heterogeneity in cyclical fluctuations and level differences in the unemployment rates across demographic groups.

We quantify the impact of the transition rates between employment (E), unemployment (U), and out-of-the-labor-force (I) on the difference in the level and the fluctuations in the unemployment rate for these disadvantaged groups. The level or fluctuations in the unemployment rate can be attributed to the flows from employment to unemployment (i.e., separation rates), the flows to employment from unemployment (i.e., job finding rate), or changes in the transition between unemployment and out-of-the-labor-force (IU and UI, respectively). Examining the influence of differences in these transition flows has direct implications for well-designed labor market policy.

Specifically, our methodology is as follows. We first construct the unemployment rate and transition rates for each demographic group, using data from Current Population Survey (CPS). We document the following facts. Throughout the business cycle, we find that young workers, those without any college education, and non-white workers have substantially higher unemployment rates than each group's counterpart demographic group. By examining recessions dating back to the 1980s, we see that these three groups have substantially larger increases in unemployment rates during recessions compared with their counterpart demographic groups. In addition we find that all groups experience sharp decline in the job finding rate as well as significant increases in the separation rates during recessions. All disadvantaged groups have higher separation rates compared to those of their counterpart workers, while only non-white workers and these without any college education have lower job finding rates compared to their counterpart demographic groups.

In order to quantify the relative contributions of these transition events, we then turn to a more formal decomposition. We first derive approximated unemployment rates based on the steady state identity proposed by Shimer (2012), which connects unemployment rates with workers' transition flows between labor market states. We then decompose unemployment rates and fluctuations into their component flows by extending the two state methodology of Fujita and Ramey (2009) to include flows in and out of the labor force.

We find that 40 to 50% of the total cyclical fluctuations in unemployment rates across demographic groups can be accounted for by fluctuations in the job finding rates. In contrast, only around 20% of the total fluctuations in unemployment rates can be explained by the fluctuations in the separation rates, while the transition flows between U and I explains another 20%. Overall, outflows from unemployment explain about 2/3 of the cyclical variation in unemployment rates while inflows to unemployment explain about 1/3. Moreover, these estimates are very similar across disadvantaged and non-disadvantaged demographic groups.

We then focus on the unemployment rate gap, which we define for each disadvantaged group as the difference in the unemployment rate compared to the counterpart group (e.g. young workers versus experienced workers and so forth). Here we find that inflows to unemployment can explain the vast majority of the unemployment rate gap for each of the three groups, with flows from employment to unemployment explaining a substantial portion of the gap for all three groups. However, there are important differences across groups. For non-white workers, hiring from unemployment can explain a larger share of the unemployment rate gap than separations from employment, suggesting employer discrimination may play a role. In contrast, for individuals without a college degree and young workers, this hiring margin can explain little to none of the gap. In addition, for young workers, flows into unemployment from out-of-the-labor-force are the largest factor, consistent with entering the labor market from schooling.

We conclude that cyclical increases in the unemployment rate and secular gaps in the unemployment rate between demographic groups can be attributed to different sources. While outflows from unemployment are the primary driver of cyclical increases in unemployment rates, inflows to unemployment are the primary driver of persistent gaps in unemployment rates between demographic groups.

This paper contributes to a growing literature on the flow decomposition approach to understanding cyclical properties of the unemployment rate. Early contributors argued that increases in the unemployment rate during recessions was primarily driven by the increases in the separation rates,[2] but more recent papers such as Shimer (2012) have found that reductions in job finding rates play a larger role. By analyzing the unemployment duration and the reasons of unemployment, Elsby et al. (2009) emphasized the importance of separation rates is equal to that of job finding rates for us to understand unemployment rates fluctuations. Fujita and Ramey (2009) argued that the relative importance of separation rates and job finding rates in explaining unemployment fluctuations depends on the way we detrend data. In addition, Elsby et al. (2015b) emphasized the importance of the transition flows between unemployment and out-of-the-labor-force in explaining unemployment rates fluctuations.

Consistent with these papers, we find that job finding rates are the largest contributor to unemployment fluctuations across demographic groups while the role of separation rates in accounting for unemployment fluctuations is also important. Moreover,

[2] See Elsby et al. (2009) for a survey of the literature.

as in Elsby et al. (2015b), we find that the importance of the transition flows between unemployment and out-of-the-labor-force in explaining unemployment rates fluctuations is similar to that of separation rates. We find that the relative magnitudes exhibit little variation across demographic subgroups.

Our paper also relates to a literature seeking to explain the sources of poor labor market outcomes for various demographic groups. Choi et al. (2015) decomposes unemployment flows for young workers and finds that high unemployment rates are primarily due to separation rates. This is consistent with our results, which we show is not unique to young workers but also applies to non-white workers and those without any college education.

Our results also complement a literature on whether certain demographic groups are the first to be fired during recessions or the last to be hired during recoveries. Couch and Fairlie (2010) and Couch et al. (2016) test this hypothesis for non-white workers, while Xu and Couch (2017) focuses on young workers, finding evidence that supports the 'first-fired' hypothesis but not the 'last-hired' hypothesis. Our approach offers a methodological improvement by analyzing the cyclical transition dynamics, which allows us to show that while separations are an important part of the story, hiring dynamics play a larger role in explaining the high unemployment rates for these groups during recessions.

Finally, our paper also contributes to a literature on the racial employment gap. We find that the hiring margin can explain a larger fraction of the unemployment gap for non-white groups than for other disadvantaged groups. This is consistent with a large literature on racial discrimination, including Lang and Lehmann (2012) and Borowczyk-Martins et al. (2017). In addition, work by Gobillon et al. (2014) argues that spatial mismatch between non-white job applicants and job openings could explain around 1.5% of the unemployment rate gap via the hiring margin.

The remaining parts of this paper is organized as follows. The details of data source and these estimation exercises are explained in Section 2. Section 3 explains the decomposition approach for unemployment fluctuations and offer the estimated contributions for various transition flows. In Section 4, we use a similar analysis approach for unemployment gap and discuss the results. Section 5 concludes the paper and discusses policy implications.

2 Data and Methodology

We use monthly U.S. data from the Current Population Survey (CPS) spanning January 1978 through November 2017, retrieved from the IPUMS repository.[3] This yields a total

[3]Sarah Flood, Miriam King, Steven Ruggles, and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 5.0. [dataset]. Minneapolis: University of Minnesota, 2017.

of over 36 million individual monthly observations. In order to measure flows between labor force status (employed (E), unemployed (U), and out-of-the-labor-force (I)), we match individuals between consecutive months.[4] After we match the data, we correct misclassification errors based on the method proposed by Elsby et al. (2015b). Then, we construct transition rates and correct the time aggregation errors based on the methodology proposed by Shimer (2012).

Since we are interested in comparing labor market flows and outcomes between demographic groups, we divide our sample into three overlapping groups of comparison pairs according each individual's potential labor market experience, race, and educational attainment. First, we define young workers as those with less than ten years of potential experience (age less education less six), who we compare with experienced workers, that is, those with more than 10 years of potential experience. Second, for race, we compare non-white workers with white workers. Third, for educational attainment, we compare those without any college education with those with at least some college.[5]

To discover the connection between the unemployment rates and the transition flows, we first identify the dates when the unemployment rates are larger than the HP filtered trend. We compare the difference between the unemployment rates and transition rates in these dates and those during periods where the unemployment rates are lower than HP filter trend for different demographic groups. This exercise can help determine the changes in the transition rates when the unemployment rates are significantly larger than the trend.

2.1 Constructing Transition and Unemployment Rates

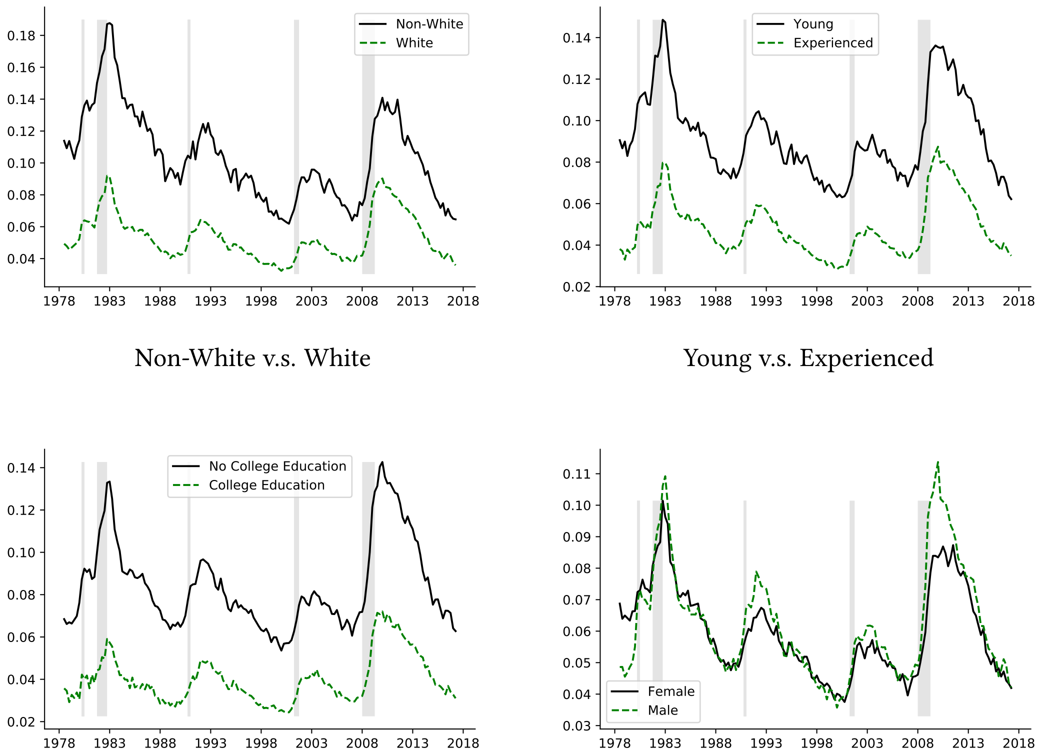
The first step in our analysis is to construct the raw transition rates between the three labor force states and the unemployment rate for each of our six demographic groups. Let $1^{ij}_{h,t,g}$ be an indicator that captures whether individual h who belongs to demographic group g transitioned from labor force state $i \in \{E, U, I\}$ at time $t-1$ to state $j \in \{E, U, I\}$ at time t. Here, we use t to denote a specific month in a year. Therefore, the flow of individuals from state i to state j at time t can be written

$$z^{ij}_{t,g} = \sum_{h=1}^{H} 1^{ij}_{h,t,g} \times w_{h,t,g} \tag{2.1}$$

https://doi.org/10.18128/D030.V5.0.

[4]Specifically, we match individuals using gender and the IPUMS-CPS defined variable (CPSIDP) that is constructed to uniquely identify individuals. By using CPSIDP, we can avoid the issues that CPS identification number may not represent the same individual and simplify the matching process although CPSIDP is consistent only after 1978.

[5]Table A.1 in the Appendix A shows the relative frequencies of each of these six demographic categories.



Non-White v.s. White

Young v.s. Experienced

Without v.s. With Some College Education

Female v.s. Male

Figure 1: Unemployment Rate

Note: The gray-rectangle area indicates NBER Recession periods. Data source: FRED & IPUMS-CPS.

where $w_{h,t,g}$ is the CPS sampling weight for the individual h who belongs to demographic group g at time t.[6]. Using this expression, we can construct the unemployment rate for workers who belong to demographic group g as follows

$$u_t^g = \frac{\sum_{h=1}^{H} \sum_{i\in\{E,U,I\}} z_{t,g}^{iU}}{\sum_{i\in\{E,U,I\}} z_{t,g}^{iU} + \sum_{i\in\{E,U,I\}} z_{t,g}^{iE}}. \tag{2.2}$$

Figure 1 plots the group unemployment rates constructed using Equation (2.2) for eight demographic groups: non-white, white, young, experienced, female, male, individuals with no college education, and those with some college education. There are two important features to note. First, non-white workers, young workers, and individuals with no college education have substantially higher unemployment rates than white workers, experienced workers, and workers with some college education. Second, these groups with elevated unemployment rates also experience more dramatic

[6]Due to the rotation feature of CPS data, we have two CPS sample weight: one is the weight in the beginning of a month and another is that in the end of a month. Following Shimer (2012), we use the average of these two weight as the CPS sample weight $w_{h,t,g}$

Table 1: Unemployment Rate: Minimum to the Maximum

Date	Non-White	White	Young	Experienced
1980s Recession	8.87%	4.91%	6.69%	4.75%
1990s Recession	3.24%	2.41%	3.57%	2.25%
2000s Recession	3.39%	2.01%	3.28%	1.98%
Great Recession	7.52%	5.21%	6.84%	5.27%
Date	No College	With College	Female	Male
1980s Recession	6.97%	3.24%	4.43%	6.20%
1990s Recession	3.51%	2.15%	1.60%	3.42%
2000s Recession	2.99%	1.84%	1.73%	2.76%
Great Recession	7.94%	4.28%	4.28%	6.87%
	1980s Recession	1990s Recession	2000s Recession	Great Recession
Date	1979/07–1982/11	1989/03–1992/01	2000/01–2003/06	2007/03–2010/02

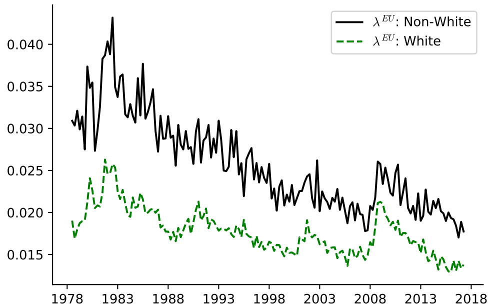
Note: The top and the middle parts of this table report the changes in the unemployment rate for each type of workers during reach recession periods. The dates for recession periods are reported in the last part of the table.

increases in unemployment rates during recessions. This is consistent with previous research, such as Hoynes et al. (2012).

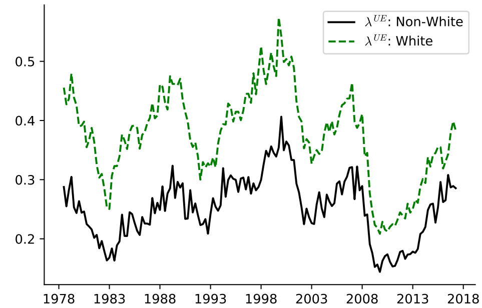
Table 1 measures the increase in the unemployment rates for each demographic group for each of the last four recessionary periods.[7] Since we are interested in labor market outcomes, we use a broader definition of recessionary periods rather than reported by the National Bureau of Economic Research (NBER) Business Cycle Dating Committee. In particular, we measure recessions as trough to peak unemployment rate from the pre-recession series minimum unemployment rate to the maximum unemployment following the recession. For the beginning of a recession, we choose the month with the minimum unemployment rate around the beginning of the NBER recession periods. Similarly, we choose the month with the maximum unemployment rate around the end of the NBER recession periods as the end of a recession. Here we see increases in the unemployment rates for non-white, young, and less educated workers are almost twice the increase in the unemployment for their respective comparison groups.

Based on the persistent levels of the unemployment rate as well as cyclical changes in the unemployment rate, we focus on three demographic categories as particularly hard-hit during recessions: young workers, non-white workers, and those without any college education. In contrast, Figure 1 shows that there are no persistent level differences between female workers' unemployment rates and that of male workers. Moreover, Table 1 shows that the increase in the unemployment rates during recessions

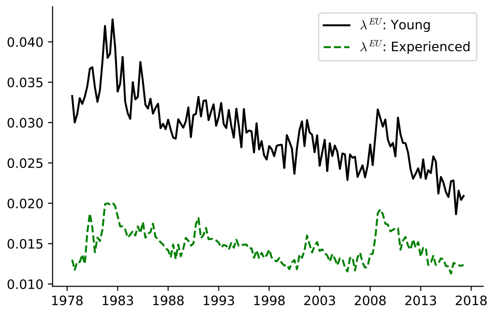
[7]Since the unemployment rate did not appreciably recover between the 1980 recession and the 1981 recession, we combine the two recessions together.



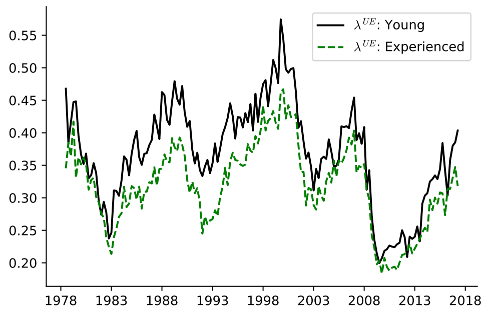
Non-White v.s. White



Non-White v.s. White



Young v.s. Experienced



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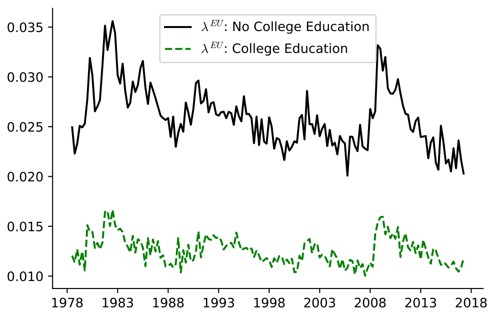
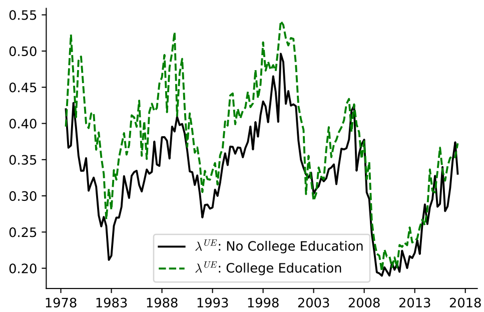


Without v.s. With Some College Education



Without v.s. With Some College Education

Figure 2: Between Employment and Unemployment: λ^{EU} and λ^{UE}

Note: The left reports the transition rate from employment to unemployment (λ^{EU}) while the right shows the the transition rate from unemployment to employment (λ^{UE}). The gray-rectangle area indicates NBER Recession periods. Data source: FRED & IPUMS-CPS.

of male workers is higher than that of female workers. We therefore leave the analysis of female workers for the appendix.[8]

In order to understand the source of the differences in the unemployment rate between demographic groups, we next turn to decomposing each group's unemployment rate into the component flows. From the definition of the unemployment rate in Equation (2.2), the share of workers unemployed at any moment in time is a function of the flows in and out of unemployment. Returning to the notation from Equation (2.1), we can write the transition rate between labor market state i and j for workers who belong to demographic group g as

$$\lambda_{t,g}^{ij} = \frac{z_{t,g}^{ij}}{\sum_{i \in \{E,U,I\}} z_{t,g}^{ij}}. \tag{2.3}$$

In Figure 2, we show the transition rates between unemployment and employment (i.e., job finding rate λ^{UE} and separation rate λ^{EU}). First, we see that during recessionary periods, separation rates increase and job finding rates decrease for all six demographic groups. Second, we see that our three disadvantaged demographic groups (young workers, non-white workers, and those without a college education) have higher separation rates compared to their counterpart groups (experienced workers, white workers, and those with at least some college, respectively). These results suggest that, while both job finding and separation rates likely play a role in elevated unemployment rates for all demographic groups during recessions, separation rates are likely to play an important role in explaining the relative differences in the level of the unemployment rate between disadvantaged and counterpart demographic groups.[9]

As a first step in quantifying the differences in transition rates between demographic groups, we estimate a series of linear regression models, in which we compare unemployment rates or transition rates between pairs of demographic groups (non-white/white, young/experienced, and no college/some college). We define recessionary periods as times in which the aggregate unemployment rate is larger than the time trend based on the HP-filter method.[10] Then we analyze the behavior for the transition

[8]The the differences between female workers' unemployment rates and male workers' (i.e., gender unemployment gap) was was positive before early 1980s and disappeared after 1980s. In the Appendix B, we conduct the analysis to understand the source that caused the gender unemployment gap to disappear. We find the transition rate from employment to unemployment accounts for the disappearance of gender unemployment gap. Our finding is similar to that of Albanesi and Şahin (2018). We also analyze which transition event caused male workers' unemployment rate to rise during recessions. We find the decline in the job finding rates explains the increase in male workers' unemployment rate.

[9]In the Appendix A, Figure A.1 and A.2 show the remaining four transitions in and out of the labor force. We find that the disadvantaged groups tend to have higher transition rates in and out of the labor market compared with their counterpart groups.

[10]In the Appendix C, we repeat the similar exercise but set the dates dummy according to periods of recessions in Table 1. We report the results in Table C.1.

rates during this period to discover the connection between unemployment rates and transition rates.

The regression model is

$$y_t = \beta_0 + \beta_d 1_d + \beta_r 1_r + \beta_r^d (1_r \times 1_d) + \sum_m a_m 1_m + \epsilon_t. \tag{2.4}$$

where 1_d is an indicator for the disadvantaged demographic group, 1_r is an indicator for periods during which the aggregated unemployment rates are larger than that of the HP filter trend, and 1_m are month-by-year fixed effect. Here, we use y_t to represent either the unemployment rate or transition rates, which are constructed based on Equations (2.2) and (2.3), respectively.

Table 2 reports the regression results for each of the three specifications. In each of the three panels we compare pairs of demographic groups: white versus non-white (top), young versus experienced (middle), and those without college versus those with some college education (bottom). In the first column, we compare the unemployment rates. Here we see that across our time period, the three disadvantaged demographic groups have average unemployment rates that are over (or around) four percentage points higher than the counterpart demographic groups. In addition, although all demographic groups experience elevated unemployment rates during the periods where aggregate unemployment rates are larger than the time trend of HP filter, the unemployment rate for these disadvantaged groups are substantially larger (0.6–1 percentage point). Thus, the regression results are consistent with the time series trends we observed in Figure 1.

Next we want to compare the transition rates across demographic groups. In the second and third columns, we consider exit rates from employment, either to unemployment (Column 2, λ^{EU}) or out-of-the-labor-force (Column 3, λ^{EI}). Here we observe that each of our three disadvantaged demographic groups has substantially larger exit rates from employment compared to their counterpart demographic groups. Thus, higher employment exit rates are likely to be an important source to explain these disadvantaged workers' relative higher unemployment rates.

Although all groups have higher exit rates to unemployment during periods of high unemployment, only young workers have an additional relative increase in exits compared with their counterpart group (experienced workers). Exits to out-of-the-labor force are not statistically different during periods of high unemployment, except for young workers who are somewhat less likely to exit the labor force. We conclude that exits from employment to unemployment are likely to be an important source of increased unemployment rates during recessions for all demographic groups.

In Columns 4 and 5, we consider flows out of unemployment, either to employment (Column 4, λ^{UE}) or out-of-the-labor-force (Column 5, λ^{UI}). Here we see key differences across demographic groups. Although all three disadvantaged groups have

Table 2: Estimated Transitions: Disadvantaged Workers

Non-White	u	λ^{EU}	λ^{EI}	λ^{UE}	λ^{UI}	λ^{IE}	λ^{IU}
β_0: Intercept	5.049***	1.229***	2.467***	29.779***	21.356***	4.152***	2.005***
	(0.238)	(0.049)	(0.221)	(0.652)	(0.401)	(0.365)	(0.089)
β_r: Higher Unemp	1.780***	0.244***	0.058	-5.222***	-2.315***	0.135	0.450***
	(0.177)	(0.036)	(0.164)	(0.484)	(0.298)	(0.271)	(0.066)
β_d: Non-White	4.487***	0.697***	0.758***	-9.020***	6.275***	0.620**	2.212***
	(0.170)	(0.035)	(0.159)	(0.467)	(0.287)	(0.261)	(0.064)
β_r^d: Higher Unemp × Non-White	0.932***	-0.005	-0.050	1.819***	-0.409	-0.372	0.212**
	(0.250)	(0.052)	(0.232)	(0.684)	(0.421)	(0.383)	(0.094)
R^2	0.67	0.51	0.13	0.52	0.56	0.08	0.75
N	980	980	980	980	980	980	980
Young	u	λ^{EU}	λ^{EI}	λ^{UE}	λ^{UI}	λ^{IE}	λ^{IU}
β_0: Intercept	4.577***	1.046***	1.945***	26.215***	20.186***	2.085***	1.139***
	(0.168)	(0.041)	(0.207)	(0.629)	(0.449)	(0.747)	(0.147)
β_r: Higher Unemp	1.769***	0.239***	0.183	-4.248***	-2.728***	0.195	0.368***
	(0.125)	(0.030)	(0.153)	(0.467)	(0.333)	(0.555)	(0.109)
β_d: Young	4.009***	1.021***	2.024***	2.877***	5.939***	7.159***	4.910***
	(0.121)	(0.029)	(0.148)	(0.450)	(0.321)	(0.535)	(0.105)
β_r^d: Higher Unemp × Young	0.692***	0.050	-0.425*	-0.885	1.010**	-0.251	0.626***
	(0.177)	(0.043)	(0.217)	(0.660)	(0.471)	(0.784)	(0.154)
R^2	0.76	0.75	0.33	0.41	0.52	0.31	0.84
N	980	980	980	980	980	980	980
No College	u	λ^{EU}	λ^{EI}	λ^{UE}	λ^{UI}	λ^{IE}	λ^{IU}
β_0: Intercept	3.891***	0.911***	1.957***	31.015***	19.398***	5.668***	2.246***
	(0.158)	(0.031)	(0.262)	(0.673)	(0.411)	(0.510)	(0.047)
β_r: Higher Unemp	1.410***	0.189***	0.025	-5.187***	-2.235***	0.411	0.505***
	(0.117)	(0.023)	(0.195)	(0.500)	(0.305)	(0.379)	(0.035)
β_d: No College	3.791***	0.935***	1.336***	-4.165***	5.639***	-2.117***	0.182***
	(0.113)	(0.023)	(0.188)	(0.482)	(0.294)	(0.365)	(0.034)
β_r^d: Higher Unemp × No College	1.244***	0.151***	0.123	0.628	-0.110	-0.572	-0.027
	(0.165)	(0.033)	(0.275)	(0.707)	(0.431)	(0.536)	(0.050)
R^2	0.79	0.82	0.16	0.41	0.51	0.12	0.53
N	980	980	980	980	980	980	980

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

higher transition rates from unemployment to out-of-the-labor-force (λ^{UI}) compared to their counterpart groups, the job finding rates (λ^{UE}) for non-white workers and those without any college education are substantially lower than their counterparts. In contrast, young workers have substantially larger job finding rates than experienced workers. Thus, we should expect that the job finding rate can explain the higher levels of unemployment for non-white workers and those without any college education. However, job finding rates will not be able to explain the higher level in the unemployment rates for young workers, since they are in fact hired at faster rates than experienced workers.

We see that all groups experienced sharp decline in both job finding rates and the transition rates from unemployment to out-of-the-labor-force during the periods with relatively high unemployment rates. We therefore expect that the decline in the job finding rates and the transition rates from unemployment to out-of-the-labor-force to be key drivers of the increases in the unemployment rates during recessions for all demographic groups. Interestingly, the gap in job-finding rates between non-white and white job seekers narrows somewhat during periods of high-unemployment rates.

In Columns 6 and 7, we consider movements back into the labor force, either from out-of-the-labor-force directly to employment (λ^{IE}) or to unemployment (λ^{IU}). All three disadvantaged groups have higher rates of movements from out-of-the-labor-force to unemployment, compared to their counterpart groups. Young and non-white workers have higher rates of movement into employment, while those without any college education have smaller rates than more educated workers. Thus, we expect that the lower transition probability from out-of-the-labor-force to unemployment contribute to the higher level in the unemployment rates for all disadvantaged workers. In contrast, the inflows to employment from out-of-the-labor-force can only explain the higher level in the unemployment rates for these workers without any college education.

Finally, we do not see any statistically significant patterns in cyclical movements from out-of-the-labor-force to employment. However, the transition probability from out-of-the-labor-force to unemployment increases during the periods with relatively high unemployment rates. In particular, for non-white and young workers this transition probability is even higher during the same period in the comparison with the counterpart demographic group. Thus, movements from out-of-the-labor-force to unemployment are likely to be an important source of the cyclical increase in the unemployment rate for all demographic groups, but may also contribute to the stronger cyclical responses for both non-white and young workers compared with white and experienced workers, respectively.

In sum, the estimation exercises show that these disadvantaged workers have significantly higher unemployment rates than that of workers from counterpart demographic groups and the increase in the unemployment during the periods of recessions for these workers are also larger. In addition, all disadvantaged groups have higher separation rates and lower job finding rates (except young workers) than that of their counterpart demographic groups. Moreover, these disadvantaged workers move in and out of the labor force more frequently than workers from counterpart demographic groups. In addition, during periods of high unemployment, movements into unemployment increased (from either employment or out-of-the-labor force) while movements out of unemployment decreased (either to employment or out-of-the-labor-force). Although there were some differences in cyclical responses between demographic groups, these regression results suggest the cyclical increases in the unemployment rates for disadvantaged groups may be driven by secular differences in transition rates rather than cyclical variation in the transitions themselves.

Although these estimation exercises help us understand the fluctuations in unemployment and transition flows across demographic groups, they cannot help us measure the importance of these transition rates in explaining the unemployment gap and the sharp increase in the unemployment rate during recessions. We quantify the importance of these transition flows in the next section.

2.2 Linking Transition Rates and Unemployment Rates

In order to measure how much each transition rate contributes to the unemployment rate, we follow methodology developed in Shimer (2012). Specifically, we construct a steady-state approximation of the unemployment rate as a function of the transition rates. We begin by expressing a steady state accounting identity, in which outflows from each labor market state must equal inflows. Therefore, we have the following conditions:

$$
\begin{aligned}
(\lambda^{EU} + \lambda^{EI})E &= \lambda^{UE}U + \lambda^{IE}I, \\
(\lambda^{UE} + \lambda^{UI})U &= \lambda^{EU}E + \lambda^{IU}I, \\
(\lambda^{IE} + \lambda^{IU})I &= \lambda^{UI}U + \lambda^{EI}E.
\end{aligned} \tag{2.5}
$$

By this steady-state identity, then we can express the stock of employed and unemployed as follows:

$$U = \overline{C} \cdot (\lambda^{EI}\lambda^{IU} + \lambda^{IE}\lambda^{EU} + \lambda^{IU}\lambda^{EU}), \tag{2.6}$$

$$E = \overline{C} \cdot (\lambda^{IU}\lambda^{UE} + \lambda^{UI}\lambda^{IE} + \lambda^{IE}\lambda^{UE}). \tag{2.7}$$

Here, $\overline{C}$ is a constant such that total population $U + E + I$ can be normalized as a fixed number.[11] Given the unemployment and employment inflow in Equations (2.6) and

[11]Here, we can derive $\overline{C} = C/[\lambda^{EU}(\lambda^{IE} - \lambda^{UE}) + \lambda^{IE}(\lambda^{UE} + \lambda^{UI}) + \lambda^{IU}(\lambda^{UE} + \lambda^{EI} + \lambda^{EU}) + \lambda^{UE}(\lambda^{EI} + \lambda^{EU}) + \lambda^{UI}(\lambda^{EI} + \lambda^{EU})]$, where C is the sum of the number of unemployment, employment and not-in-the-labor-force.

Table 3: Constructed and Observed Unemployment

Workers' Type	Non-White	White	Young	Experienced
Correlation	0.964	0.977	0.969	0.972
R^2	0.929	0.955	0.939	0.945
Workers' Type	No College	With College	All	
Correlation	0.973	0.958	0.978	
R^2	0.946	0.917	0.956	

Note: This table reports the correlation and R^2 between the observed unemployment rates (u_t) and constructed ones ($u_t^{g,c}$) based on Shimer (2012).

(2.7), we are able to derive steady state unemployment rate as

$$u = \frac{U}{U+E} = \frac{\lambda^{EI}\lambda^{IU} + \lambda^{IE}\lambda^{EU} + \lambda^{IU}\lambda^{EU}}{(\lambda^{EI}\lambda^{IU} + \lambda^{IE}\lambda^{EU} + \lambda^{IU}\lambda^{EU}) + (\lambda^{UI}\lambda^{IE} + \lambda^{IE}\lambda^{UE} + \lambda^{IU}\lambda^{UE})},$$

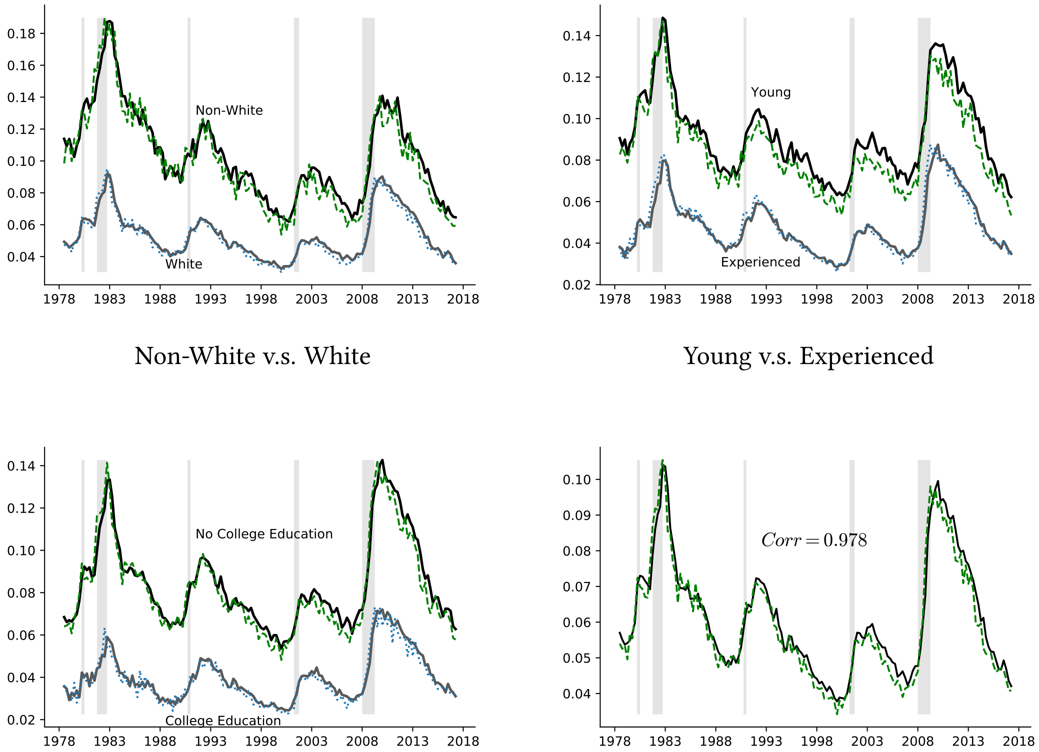
which describes how the unemployment rate can be rewritten as a function of six transition rates. Following Shimer (2012), we can use the expression of steady state unemployment rate as a function of the six different transition rates to approximate the time-varying observed unemployment rate. The approximation formula can be written as

$$\begin{aligned} u_t^{g,c} &= \frac{U_t}{E_t + U_t} \\ &= \frac{\lambda_t^{EI}\lambda_t^{IU} + \lambda_t^{IE}\lambda_t^{EU} + \lambda_t^{IU}\lambda_t^{EU}}{(\lambda_t^{EI}\lambda_t^{IU} + \lambda_t^{IE}\lambda_t^{EU} + \lambda_t^{IU}\lambda_t^{EU}) + (\lambda_t^{UI}\lambda_t^{IE} + \lambda_t^{IE}\lambda_t^{UE} + \lambda_t^{IU}\lambda_t^{UE})}. \end{aligned} \tag{2.8}$$

Here, $u_t^{g,c}$ represents the constructed unemployment rate based on the steady-state identity approximation for observed unemployment rate u_t^g for workers who belong to demographic group g. Here, we use c to denote the constructed unemployment rate based on Equation (2.8). This expression for the unemployment rate allows us to disentangle how transitions between employment, unemployment, and out of the labor force contribute to the overall unemployment rate.

The expression (2.8) is based on a continuous time model of employment dynamics. Since the CPS data is at a monthly frequency, we will miss rapid transitions that occur within a month. To correct for this time-aggregation bias, we follow Shimer (2012) and Gomes (2015), and explicitly map the continuous frequency of flows into the monthly data. In addition, we follow Elsby et al. (2015a) in adjusting our measured transitions to account for misclassification error. In the Appendix D, we discuss these error corrections in detail.

Figure 3 shows our constructed unemployment rate $u_t^{g,c}$ tracks closely with the observed unemployment rate for each demographic subgroup (u_t^g), while Table 3 shows



Non-White v.s. White

Young v.s. Experienced

Without v.s. With Some College Education

All Workers

Figure 3: Observed v.s. Constructed Unemployment Rate

Note: The gray-shaded area indicates NBER Recession periods. The solid lines represent the observed unemployment rate while dashed line and dotted line represent constructed unemployment rate based on Shimer's steady state identity for disadvantaged and counterpart workers respectively. Data source: FRED & IPUMS-CPS.

the correlation coefficients and R^2 between constructed and observed unemployment rates are all close to 1. This indicates that this method for expressing the unemployment rate in terms of transition rates works well for all demographic subgroups. Next, in Sections 3 and 4, we estimate how much each transition rate contributes to unemployment rate fluctuations and levels, respectively.

3 Decomposing Unemployment Fluctuations

For our first set of results, we focus on decomposing the cyclical fluctuations in the unemployment rate into the transition rates. In order to isolate the cyclical component of the unemployment rate, we log linearize the constructed unemployment rate, which is based on the steady state approximation in Equation (2.8), around the time trend over the time period for each demographic group g. In particular, we use an HP-filter to derive the time trend for the constructed unemployment rate.[12]

We use $\Lambda_{g,t}$ to represent the vector of the six transition rates between employment, unemployment, and not-in-the-labor-force for demographic group g. In other words, $\Lambda_{g,t}$ includes $\lambda^{EU}_{g,t}$, $\lambda^{EI}_{g,t}$, $\lambda^{UE}_{g,t}$, $\lambda^{UI}_{g,t}$, $\lambda^{IE}_{g,t}$, and $\lambda^{IU}_{g,t}$. The log-linearization expression for the constructed unemployment rate can be written as

$$\begin{aligned} \ln u^{g,c}_t &\approx \ln \bar{u}^{g,c}_t + \sum_{x\in\mathcal{X}} \left.\frac{\partial \ln u^{g,c}_t}{\partial \lambda^x_{g,t}}\right|_{\Lambda_{g,t}=\bar{\Lambda}_{g,t}} \times (\lambda^x_{g,t} - \bar{\lambda}^x_{g,t}) \\ &= \ln \bar{u}^{g,c}_t + \sum_{x\in\mathcal{X}} \left.\frac{\partial \ln u^{g,c}_t}{\partial \lambda^x_{g,t}}\right|_{\Lambda_{g,t}=\bar{\Lambda}_{g,t}} \times \bar{\lambda}^x_{g,t} \cdot (\ln \lambda^x_{g,t} - \ln \bar{\lambda}^x_{g,t}). \end{aligned} \tag{3.1}$$

Here, we use $\bar{u}^{g,c}_t$ and $\bar{\lambda}^x_t$ to denote the time trends for constructed unemployment rate $u^{g,c}_t$ and transition rates λ^x_t, respectively, where $x \in \mathcal{X} = \{EU, EI, UE, UI, IE, IU\}$. We compute the time trend based on an HP-filter. Equation (3.1) shows that we can decompose the unemployment fluctuation (log-deviation from time trend), $\ln u^{g,c}_t - \ln \bar{u}^{g,c}_t$, into the components that depend on transition events. Figure 4 compares the log-linearized approximation of the unemployment fluctuations based on the right-hand-side in Equation (3.1) and observed fluctuations in the unemployment rate. We construct observed fluctuations in the unemployment rate by removing the time trend based on the HP-filter from observed unemployment rates, which are obtained according to Equation (2.2). Figure 4 shows that the log-linearized approximation based on the transition events can capture more than 99% of the fluctuations in the observed unemployment rate, despite the fact that we only include the first order terms in the Taylor expansion in Equation (3.1). Thus, nearly all of the cyclical variation in the unemployment rate can be attributed to fluctuations in the individual transition rates.

In the Appendix E, we analytically express workers' total unemployment fluctuations $F^{tot}_t = \ln u^g_t - \ln \bar{u}^g_t$ in terms of six factors, each of which depend on a different transition event

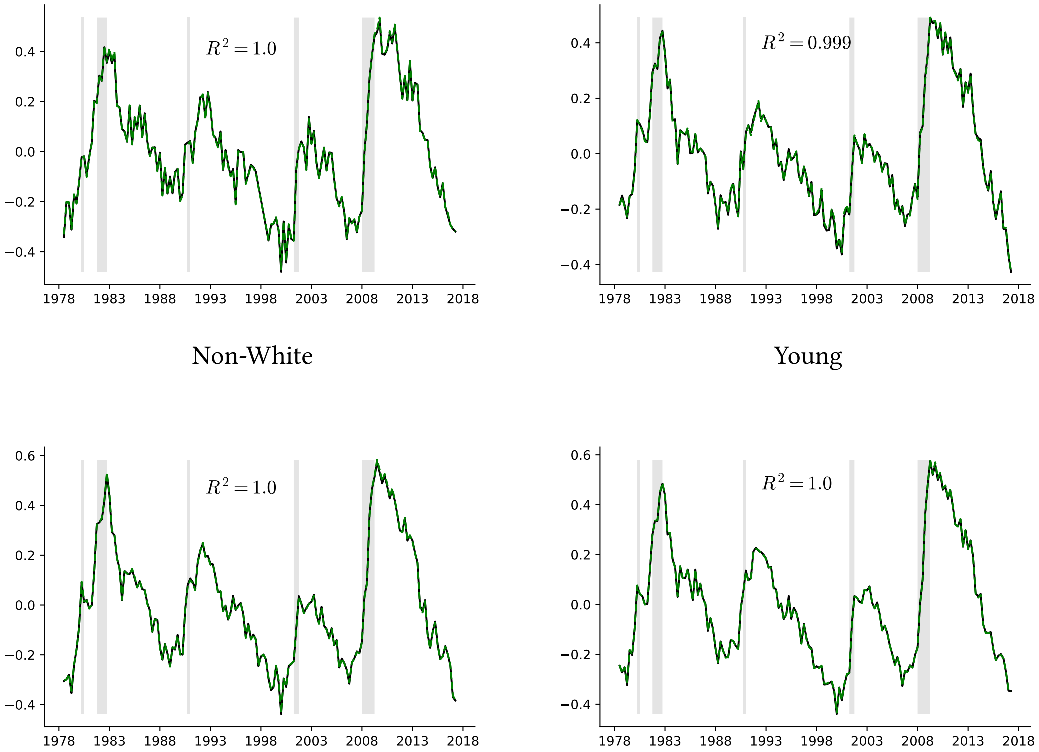
$$F^{tot}_t = F^{EU}_t + F^{EI}_t + F^{UE}_t + F^{UI}_t + F^{IE}_t + F^{IU}_t + \epsilon_t. \tag{3.2}$$

The first two factors are related to employment exit rates while the third and the fourth elements are related to unemployment outflows. The last two factors depend on workers' labor force participation.[13]

Based on Fujita and Ramey (2009), we use this decomposition approach to analyze the source of unemployment fluctuations for each demographic group. Based on Equa-

[12] After transforming frequency of data to quarterly, we follow Fujita and Ramey (2009) and Shimer (2012) and use an HP-filter with parameter 10^5 to decompose trend and cyclical components. In the Appendix F, we show our results are similar if we instead use the sample average as the mean.

[13] Alternatively, the unemployment rate can be decomposed into compound transitions, such as employment to out-of-the-labor-force to unemployment. We show in the Appendix E that our results are similar using either methodology.



Non-White | Young

without any college education | All

Figure 4: Observed Unemployment Fluctuation v.s. Approximation

Note: The gray-rectangle area indicates NBER Recession periods. Black solid line represents observed unemployment fluctuations and green dashed line represents approximated first-order log-linearized unemployment fluctuations. Data source: FRED & IPUMS-CPS.

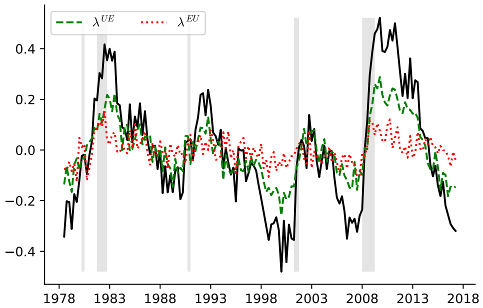
tion (3.2), the variance of total unemployment fluctuation $cov(F_t^{tot}, F_t^{tot})$ can be written as

$$cov(F_t^{tot}, F_t^{tot}) = var(F_t^{tot}) = \sum_{x \in \mathcal{X}} cov(F_t^{tot}, F_t^x) + cov(F_t^{tot}, \epsilon_t), \tag{3.3}$$

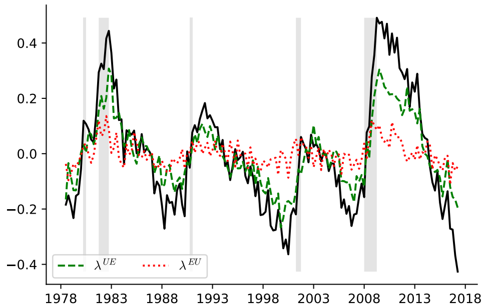
which can be further be rewritten as

$$1 = \sum_{x \in \mathcal{X}} \frac{cov(F_t^{tot}, F_t^x)}{var(F_t^{tot})} + \frac{cov(F_t^{tot}, \epsilon_t)}{var(F_t^{tot})} = \sum_{x \in \mathcal{X}} \beta^x + \beta^\epsilon. \tag{3.4}$$

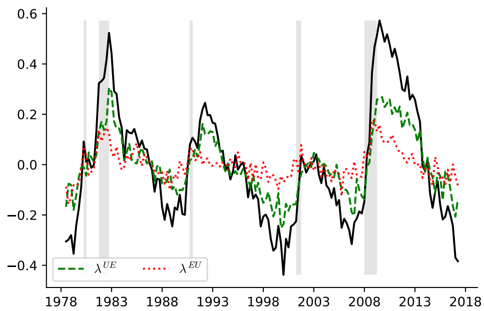
Here, $\mathcal{X}$ is the set for flows EU, UE, EI, UI, IU and IE as we specified in Equation (3.2). Based on Equation (3.4), we normalize the total contributions to unity, so each β coefficient represents the percentage of unemployment fluctuation that can be attributed to flows x or the error term. In particular, we estimate the model $F_t^x = a + \beta^x F_t^{tot} + e_t$ to isolate β^x and its confidence interval. This allows us to compare the β coefficients between different groups and across different time periods.



Non-White Workers



Young Workers



No College Education

Figure 5: Sources of Unemployment Fluctuation

Note: The gray-rectangle area indicates NBER Recession periods. Black solid line represents observed unemployment fluctuations. The green dashed line represents the factor which depends on job finding rate and the red dotted line represents the factor that depends on separation rate. Data source: FRED & IPUMS-CPS.

Now that we have decomposed the unemployment rate into cyclical components, we begin by examining the cyclical fluctuations in separations (F^{EU}) and hiring (F^{UE}) for each of our focal demographic groups. In Figure 5, we see that hiring closely tracks the unemployment rate over the business cycle for each group, while separations exhibit substantially less cyclicality. Thus, it appears that fluctuations in the unemployment rate for disadvantaged groups, including the large increase during the Great Recession, is primarily driven by firm hiring behavior.

Next, we want to analytically compare the magnitude of these fluctuations between different groups. To do so, we estimate the β coefficients derived in Equation (3.4). The results are reported in Table 4. These β's represent the share of the fluctuations in the unemployment rate for the demographic group that is captured by the transition of interest. Here we see several common trends across the six demographic groups. First, the contribution of hiring margins F^{UE} is significantly larger than that of separation

Table 4: β Coefficient: Unemployment Fluctuations, Overall

	Non-White	**Young**	**No College**	**All**
λ^{EU}	0.167	0.158	0.213	0.206
	(0.014)	(0.013)	(0.012)	(0.01)
λ^{EI}	-0.054	-0.056	-0.05	-0.037
	(0.009)	(0.009)	(0.006)	(0.006)
λ^{UE}	0.49	0.57	0.503	0.512
	(0.013)	(0.014)	(0.012)	(0.01)
λ^{UI}	0.155	0.117	0.139	0.138
	(0.01)	(0.009)	(0.008)	(0.007)
λ^{IE}	0.139	0.145	0.1	0.075
	(0.009)	(0.007)	(0.006)	(0.005)
λ^{IU}	0.11	0.073	0.102	0.111
	(0.011)	(0.011)	(0.008)	(0.008)
ϵ	-0.006	-0.006	-0.007	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)
	White	**Experienced**	**With College**	**All**
λ^{EU}	0.218	0.246	0.216	0.206
	(0.011)	(0.012)	(0.012)	(0.01)
λ^{EI}	-0.03	-0.024	-0.017	-0.037
	(0.005)	(0.005)	(0.007)	(0.006)
λ^{UE}	0.522	0.464	0.523	0.512
	(0.011)	(0.01)	(0.013)	(0.01)
λ^{UI}	0.128	0.149	0.12	0.138
	(0.007)	(0.007)	(0.008)	(0.007)
λ^{IE}	0.058	0.052	0.042	0.075
	(0.005)	(0.005)	(0.006)	(0.005)
λ^{IU}	0.108	0.118	0.12	0.111
	(0.008)	(0.008)	(0.009)	(0.008)
ϵ	-0.005	-0.005	-0.004	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)

Note: Standard errors in parentheses.

F^{EU} for all groups. Second, the total contributions of the flows between unemployment and out-of-the-labor-force, $F^{IU} + F^{UI}$, is larger than that of the separation margin for all groups. The findings about the flows between unemployment and out-of-the-labor-force are similar to those in Elsby et al. (2015b).

Finally, we see that the magnitudes of the components are similar across demographic groups. However one exception is that the contribution of the hiring margin is larger for young workers compared with that of experienced workers, indicating that the decline in job finding rates contributes relatively more to the increase in young workers' unemployment rate during recessions than for experienced workers'.

Finally, in the Appendix C, we estimate the β coefficients separately for recessionary periods and Table C.6 reports the results. Here we see similar results to Table 4, in that the hiring margin explains a substantially larger component of the cyclical fluctuations than the separation margin. Thus, despite the fact that the magnitude of unemployment fluctuations are larger for disadvantaged groups, we see that the variation in firm hiring explains the largest share of the cyclical variation in the unemployment rate across all demographic workers.

4 Decomposing Level Differences between Groups

Now that we have determined cyclical fluctuations in the unemployment rate are primarily driven by movements from unemployment to employment, we turn to explaining differences in the level of the unemployment rate between groups. Recall from Figure 1 that non-white, young, and workers without any college education have substantially higher unemployment rates at all phases of the business cycle than their counterpart demographic groups (white, experienced, and workers with some college, respectively). In order to determine which transition rates can explain these gaps, we return to the unemployment rate decomposition that we derived in Section 3. As in Equation (3.1), the (log) unemployment gap between disadvantaged demographic group g and the counterpart demographic group $\tilde{g}$ can be written as follows

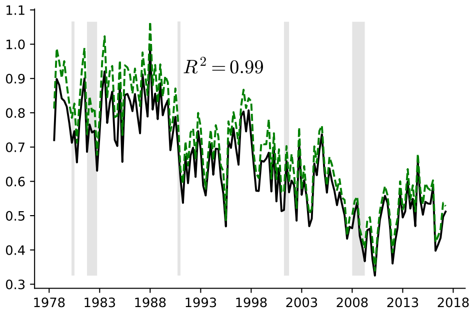
$$\begin{aligned}\ln u_t^{c,g} - \ln u_t^{c,\tilde{g}} &\approx \sum_{x\in\mathcal{X}} \left.\frac{\partial \ln u_t^c}{\partial \lambda_t^x}\right|_{\Lambda_t^c=\Lambda_t^{\tilde{g}}} \times (\lambda_t^{x,g} - \lambda_t^{x,\tilde{g}}) \\ &\approx \sum_{x\in\mathcal{X}} \left.\frac{\partial \ln u_t^c}{\partial \lambda_t^x}\right|_{\Lambda_t^g=\Lambda_t^{\tilde{g}}} \times \lambda_t^{x,\tilde{g}} \cdot (\ln \lambda_t^{x,g} - \ln \lambda_t^{x,\tilde{g}}).\end{aligned} \tag{4.1}$$

Here, as before, we use c to denote that the unemployment rates are constructed according to Equation (2.8) and $\mathcal{X}$ to represent the set of flows: EU, UE, EI, UI, IE, IU. The decomposition approach in Equation (4.1), which is similar to Equation (3.1), shows that the difference between the unemployment rate of demographic group g and that of demographic group $\tilde{g}$ can be decomposed into the difference in the transition rates of demographic group of g and those of demographic group $\tilde{g}$. Thus, we can express the level difference in the unemployment rate between two demographic groups depends on six transition events as follows:

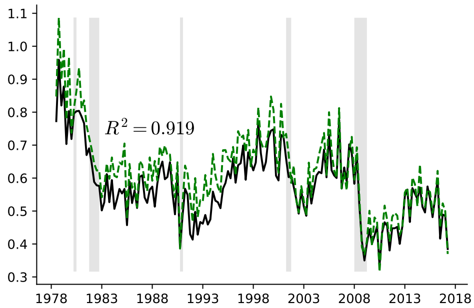
$$F_t^{gap} = F_t^{EU} + F_t^{EI} + F_t^{UE} + F_t^{UI} + F_t^{IE} + F_t^{IU} + \epsilon_t,$$

where F_t^{gap} is equal to the observed log unemployment gap, $\ln u_t^{c,g} - \ln u_t^{c,\tilde{g}}$. In the right-hand-side, for example, F^{EU} represents the proportion in the unemployment gap that is caused by the difference in the separation rates λ^{EU} between the two demographic groups.

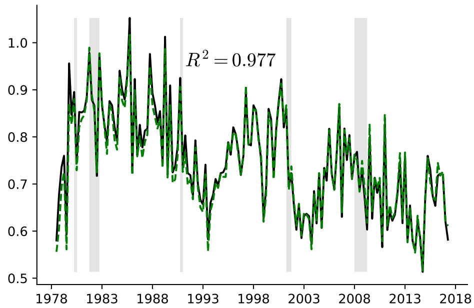
In order to evaluate how well the first-order log-linearizion approximation based on Equation (4.1) performs in capturing the observed gap in the unemployment rate for pairs of demographic groups, we obtain the approximated unemployment gap based



Non-White Workers



Young Workers



No College Education

Figure 6: Observed Unemployment Gap v.s. Approximation

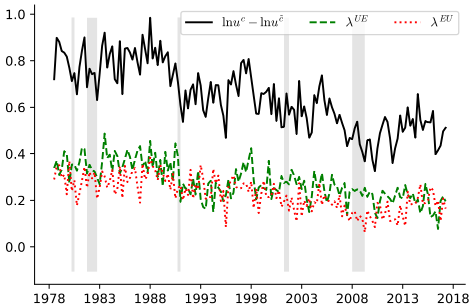
Note: The gray-rectangle area indicates NBER Recession periods. Black solid line represents observed unemployment gap and green dashed line represents approximated first-order log-linearized unemployment gap. Data source: FRED & IPUMS-CPS.

on the right-hand-side of Equation (4.1). Figure 6 compares the approximated unemployment gap with the observed ones. We can see that our approximation method can capture 99% of the difference in unemployment rates for each pair of demographic groups. This indicates the decomposition approach we propose in Equation (4.1) is reliable.

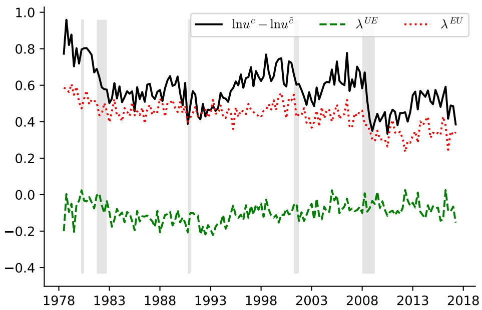
To assess how much of the difference in the unemployment rate can be accounted for by differences in transition rates, we use the following identity:

$$1 = \frac{F_t^{EU}}{F_t^{gap}} + \frac{F_t^{EI}}{F_t^{gap}} + \frac{F_t^{UE}}{F_t^{gap}} + \frac{F_t^{UI}}{F_t^{gap}} + \frac{F_t^{IE}}{F_t^{gap}} + \frac{F_t^{IU}}{F_t^{gap}} + \frac{\epsilon_t}{F_t^{gap}} = \sum_{x \in \mathcal{X}} r_t^k + r_t^{\epsilon} \tag{4.2}$$

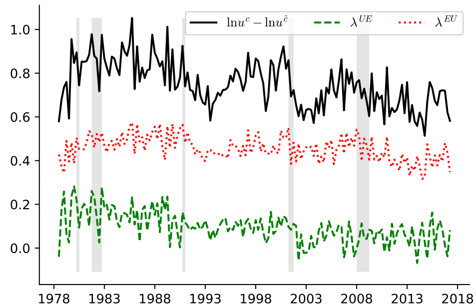
where $\mathcal{X}$ is again the set of flows: EU, UE, EI, UI, IE, IU. By estimating each ratio r_t^k and constructing confidence intervals for r_t^k, we can compare the relative contribution of each transition rate in explaining the total difference in unemployment rates



Non-White Workers



Young Workers



No College Education

Figure 7: Sources of Unemployment Gap

Note: This figure reports percentage in total unemployment gap that can be accounted for by job finding and separation rates for each type of disadvantaged workers. Data source: FRED & IPUMS-CPS.

between groups.[14]

We begin by examining the contribution of separation rates λ^{EU} (component F^{EU}) and job finding rates λ^{UE} (component F^{UE}) in explaining the difference in unemployment rates between each pair of demographic groups. Figure 7 shows that for young workers and those without a college education, the separation rate explains the largest share of the difference in unemployment rates between these workers and their counterpart demographic group, while the job finding rate explains none of the difference for young workers and little of the unemployment gap for workers without any college education. However, for non-white workers, we see that separation and job finding rates have similar magnitudes.

To compare these demographic differences analytically, Table 5 reports r^k, the estimated fraction of the difference in the unemployment rate that can be attributed to

[14]The β coefficients can only reveal the importance of each transition event in explaining variation of unemployment gap so we compute the ratio r here. In the Appendix G, we apply Equation (3.4) to unemployment gap and report these estimated β coefficients.

transition flow event λ^k. Positive values indicate that the flow contributes to a larger gap in the unemployment rate between the two groups, while a negative value indicates the flow serves to attenuate differences in the unemployment rate between the two groups. We first note that the signs on the direct flows in and out of unemployment are consistent with the regression results in Table 2. In particular, faster inflow rates from employment and not-in-the-labor-force for disadvantaged groups serve to increase the unemployment gap, while slower outflows from unemployment to not-in-the-labor-force serve to decrease the gap. Flows from unemployment to employment differ across demographic groups: for non-white workers and those without any college education, this flow increases the unemployment rate gap since these groups have relatively lower hiring rates from unemployment. On the other hand, for young workers, the flow from unemployment to employment decreases the unemployment rate gap, since young workers have higher hiring rates from unemployment than more experienced individuals.

In the regression results in Table 2, it is hard to evaluate the impact of flows between employment and not-in-the-labor-force on the unemployment rate. From Table 2, we see that the disadvantaged groups have relatively higher flow rates between employment and not-in-the-labor-force, except for individuals without a college education, who are relatively less likely to be hired directly from out-of-the-labor-force. In Table 5, we see that flows from employment to not-in-the-labor-force increase the unemployment rate gap for all three groups, while flows from not-in-the-labor-force to employment attenuates the unemployment rate gap for non-white and young workers, but increases the gap for workers without a college education.

In addition to evaluating each flow for whether it increases or decreases the unemployment rate gap, we can also use the magnitudes of the r^k estimates to rank the relative importance of each flow. Here we see somewhat different stories for each of the three disadvantaged demographic groups. We evaluate each in turn.

For non-white workers, flows from unemployment to employment are the largest factor (0.44), followed by flows from employment to unemployment (0.35) and flows from not-in-the-labor-force to unemployment (0.29). All other flows are relatively small in magnitude. These results indicate that lower hiring rates from unemployment for non-white workers compared with white workers is the most important factor for explaining elevated unemployment rates for non-white workers. This is in contrast to young workers and those without a college degree, for whom the hiring margin plays a small role (for those without a college education) or attenuates the unemployment rate gap (young workers). The importance of hiring for non-white workers is consistent with audit study evidence (see e.g., Freeman 1973 and Bertrand and Mullainathan 2004) that non-white job applicants face dramatically lower callback rates compared with otherwise identical white job applicants.

Table 5: r Ratio: Compositions of Unemployment Gap, Overall

	Non-White	**Young**	**No College**
λ^{EU}	0.35	0.776	0.616
	(0.005)	(0.008)	(0.004)
λ^{EI}	0.12	0.351	0.185
	(0.003)	(0.005)	(0.003)
λ^{UE}	0.436	-0.188	0.116
	(0.006)	(0.007)	(0.006)
λ^{UI}	-0.094	-0.193	-0.079
	(0.003)	(0.006)	(0.003)
λ^{IE}	-0.056	-0.6	0.178
	(0.004)	(0.009)	(0.002)
λ^{IU}	0.293	0.857	0.011
	(0.004)	(0.01)	(0.003)
ϵ	-0.048	-0.002	-0.027
	(0.002)	(0.001)	(0.001)

Note: Standard errors in parentheses.

In contrast, for young workers, the largest component of the unemployment rate gap compared with experienced workers is flows from not-in-the-labor-force to unemployment (0.86), followed by flows from employment to unemployment (0.78) and flows from employment to not-in-the-labor-force (0.35). This is consistent with young individuals entering the labor market from schooling or child-rearing.[15] However, the higher rates of exit from employment to unemployment also explain a large fraction of the unemployment rate gap for young workers. Finally, several transitions serve to attenuate the unemployment rate gap: direct hires from not-in-the-labor-force (-0.6), movements from unemployment to not-in-the-labor-force (-0.19), and hires from unemployment (-0.19).

Finally, for workers without a college education, movements from employment to unemployment are by far the largest contributor to the unemployment rate gap (0.61). The next two largest flows are substantially smaller in magnitude: employment to not-in-the-labor-force (0.19) and not-in-the-labor-force to employment (0.18), both of which only indirectly impact the unemployment rate.

In addition, we can evaluate whether inflows to unemployment or outflows from unemployment can explain a larger share of the unemployment rate gap between disadvantaged groups and their counterpart demographic groups. For all groups, flows into unemployment explain a substantially larger fraction of the unemployment rate gap than flows out. However, for non-white workers, outflows can explain about 1/3 of the gap, while for young workers and workers without any college education, outflows explain almost none of the gap.

[15]See Guo (2018) for an analysis of young workers' educational decisions over the business cycle.

Because the source of unemployment gap may differ during recessions, as in Section 3, we estimate fraction r^k and their confidence interval for the four periods of recession. We report the estimation results during the recession periods in Table C.7 in the Appendix C. We find that the results in Table 5 hold for all four recessions in our sample periods. Thus, we conclude that the unemployment gap is acyclical for all three demographic groups.

5 Conclusion

In this paper, we examine the source of elevated unemployment rates for three demographic subgroups: young workers, nonwhite workers, and workers without any college education. We decompose the unemployment rate into flows between employment, unemployment, and out-of-the-labor-force. We find that the largest component of the fluctuations in the unemployment rate can be attributed to reductions in outflows from unemployment, with reductions in flows from unemployment to employment explaining about half of the cyclical fluctuations in unemployment rates for all demographic groups. In contrast, we find that the persistent gap in the unemployment rate between these disadvantaged demographic groups and other demographic groups can primarily be attributed to flows into unemployment, although the job finding rate can explain about 40% of the gap for nonwhite workers.

These results have important policy implications for addressing heterogeneity in the incidence of unemployment across demographic groups. Our analysis shows that the cyclical properties of unemployment can be attributed to a reduction in hiring during recessions that affects all job seekers. Although the reduction in hiring leads to a larger fraction unemployed for these disadvantaged groups, this is because these disadvantaged groups begin from an elevated unemployment stock during expansionary periods. Therefore, a common shock due to recession results in a larger increase in the stock. Moreover, since these groups also have a faster inflow to unemployment, a reduction in the outflow from unemployment leads to a bigger increase in the unemployment rate. Thus, policies that lead to reductions in the exit rate from employment at all points in the business cycle should improve disparities in the unemployment rates across demographic groups during expansions as well as recessions.

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Appendix A Supplement Tables and Figure: Basic

This appendix reports the tables related to data. Table A.1 shows the percentage of the eight types of workers in total number of sample. Table A.2 reports the dates that unemployment rate increase from the minimum to the maximum around the NBER recessions periods. In the main context, we use the dates derived based on all workers to compute the changes in the unemployment rate during recessions for these eight types of workers and report the results in Table 1. Because the periods that unemployment rate increases from minimum to maximum around recessions may differ for different demographic groups, we use the dates based on non-white, young, female workers and those without any college education to compute the changes in the unemployment rate for these eight types of workers. For example, we determine the periods when unemployment rate of non-white workers increases from the minimum to the maximum and use this period to compute the changes in the unemployment rate for both non-white and white workers. In the top of Table A.2, we report these results. The results in Table 1 stills hold when we relax the dates.

In the main context, we report the transition rates from employment to unemployment and that from unemployment to employment. In this appendix, we report the transition rates between employment and out-of-the-labor-force (i.e., λ^{IE} and λ^{EI}) and that between unemployment and out-of-the-labor-force (i.e., λ^{IU} and λ^{UI}). Moreover, Figure 4 reports that our log-linear approximation is a good measure for disadvantaged workers' unemployment fluctuations. Figure A.3 shows that our approach is also a accurate approximation for counterpart workers' unemployment fluctuations.

Table A.1: Data Summary

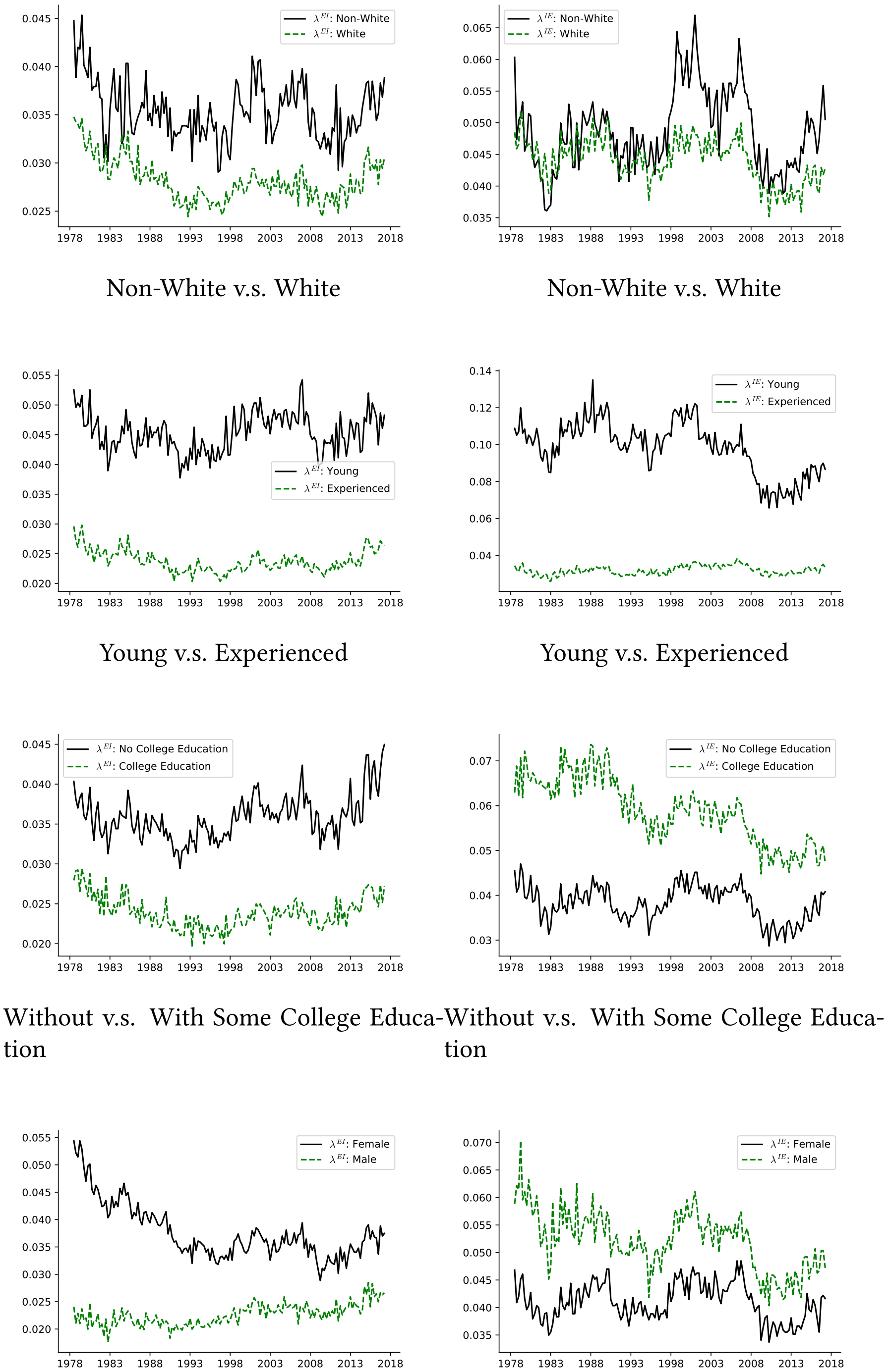
	Non-White	White	Young	Experienced
No Weighted	14.65%	85.34%	25.19%	74.80%
Weighted	16.66%	83.33%	26.02%	73.97%
	No College	With College	Female	Male
No Weighted	54.69%	45.30%	52.74%	47.25%
Weighted	53.23%	46.76%	52.11%	47.88%

Note: This table reports the percentage of each type of workers in our data. Weighted numbers are computed according to CPS weight.

Table A.2: Dates: Minimum to the Maximum

	Non-White	White	Young	Experienced
1980s Recessions	9.03%	4.59%	7.09%	4.39%
1990s Recessions	4.24%	2.00%	3.72%	2.02%
2000s Recessions	4.03%	1.73%	3.41%	1.77%
Great Recessions	7.79%	4.50%	7.31%	4.56%
	No College	**With College**	**Female**	**Male**
1980s Recessions	6.97%	3.24%	4.47%	5.48%
1990s Recessions	3.54%	2.14%	2.30%	2.56%
2000s Recessions	3.30%	1.54%	2.20%	1.92%
Great Recessions	8.29%	4.09%	4.68%	5.76%
	1980s Recessions	**1990s Recessions**	**2000s Recessions**	**Great Recessions**
Non-White	1979/07–1983/01	1989/07–1992/12	2000/12–2003/03	2007/02–2010/01
Young	1979/05–1982/11	1990/02–1992/06	2000/06–2003/09	2007/02–2009/08
No College	1979/07–1982/11	1989/03–1992/01	2000/02–2003/06	2007/03–2009/12
Female	1979/07–1982/10	1989/08–1992/09	2000/10–2003/08	2007/02–2009/08
All	1979/07–1982/11	1989/03–1992/01	2000/06–2003/06	2007/03–2010/01

Note: This table reports the dates with minimum of unemployment rate and the dates with the maximum of unemployment rate around the periods of recession for these four types of workers and that for all workers.



Non-White v.s. White

Non-White v.s. White

Young v.s. Experienced

Young v.s. Experienced

Without v.s. With Some College Education

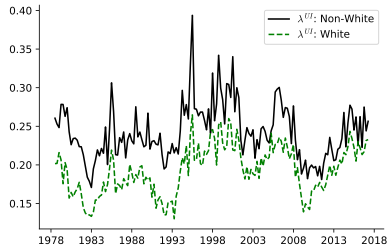
Without v.s. With Some College Education

Female v.s Male

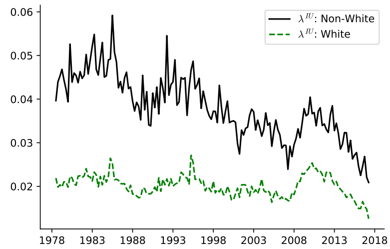
Female v.s Male

Figure A.1: λ^{EI} and λ^{IE}

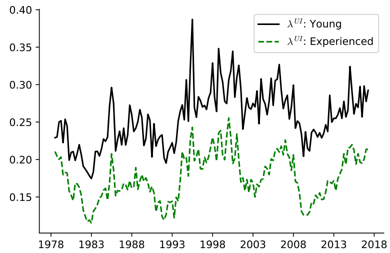
Note: The left panel shows λ^{EI} and the right reports λ^{IE}. The gray-rectangle area indicates NBER Recession periods. Data source: FRED & IPUMS-CPS.



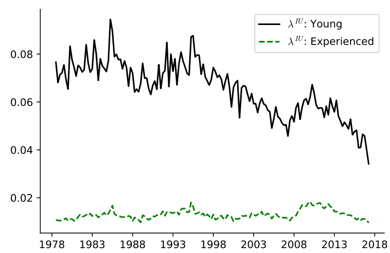
Non-White v.s. White



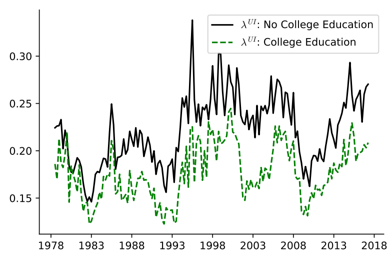
Non-White v.s. White



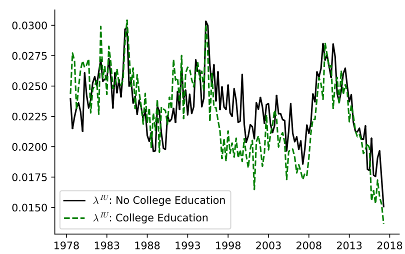
Young v.s. Experienced



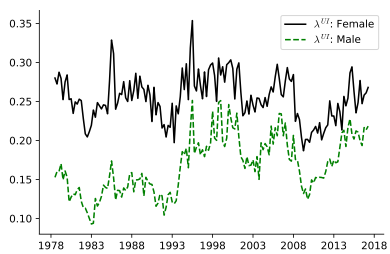
Young v.s. Experienced



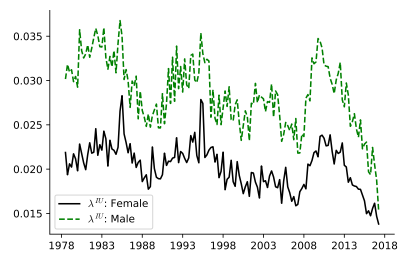
Without v.s. With Some College Education



Without v.s. With Some College Education



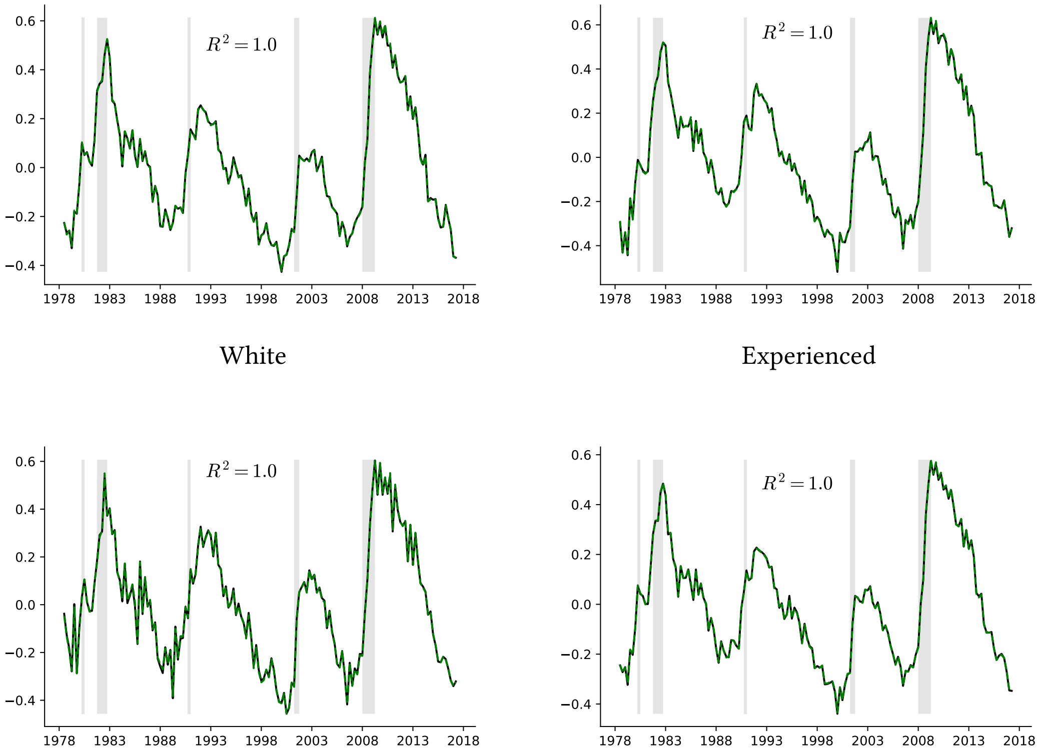
Female v.s Male



Female v.s Male

Figure A.2: λ^{UI} and λ^{IU}

Note: The left panel shows λ^{UI} and the right reports λ^{IU}. The gray-rectangle area indicates NBER Recession periods. Data source: FRED & IPUMS-CPS.



White

Experienced

With Some College Education

All

Figure A.3: Observed Unemployment Fluctuation v.s. Approximation

Note: The gray-rectangle area indicates NBER Recession periods. Black solid line represents observed unemployment fluctuations and green dashed line represents approximated first-order log-linearized unemployment fluctuations. Data source: FRED & IPUMS-CPS.

Appendix B Gender Difference in Unemployment

Although the difference between female workers' unemployment rate and that of male workers (i.e., gender unemployment gap) was not persistently positive, this gap existed before 1980s while vanished after 1980s. Moreover, the increase in male workers' unemployment during recessions is much larger than that of female workers. In this appendix, we therefore discover the sources that cause gender unemployment gap before 1980s and why this gap disappeared after 1980s. In addition, we examine which transition rates caused the cyclical fluctuations in the unemployment rates for both male and female workers.

Before we conduct our quantitative analysis, we review the dynamics of observed transition rates. Figure B.1 plots the transitions rates between employment, unemployment and out-of-the-labor-force of female and male workers. There are some important features for us to note. First, we would expect the sharp increases in the separation rates λ^{EU} (especially for male workers) and the significant decline in the job finding rates λ^{UE} are the main sources that caused the increase in the unemployment rates during the periods of recession. Second, after 1980s, we see the decline trend for female workers' transition rates from employment to out-of-the-labor-force (λ^{EI}) while after 1980s, the difference between male workers' λ^{EU} and that of female workers significantly enlarged, particularly during recessions. The decline in in female workers' λ^{EI} means that female workers are more likely to stay in the labor force. Because female workers have lower λ^{EU} and similar λ^{UE} compared to male workers, the decline in λ^{EI} can reduce the unemployment rate for female workers and therefore cause the gender unemployment gap to vanish. Moreover, male workers' higher separation rates λ^{EU} would further cause that the gender unemployment gap not just vanished and even became negative.

To better understand the impact of these transition events on female and male workers' unemployment fluctuations, we first repeat our exercise in Section 3. Figure B.2 plots the approximation of unemployment fluctuation based on Equation (3.1) and the observed ones for both female and male workers. The correlation between approximated fluctuation and observed one is 0.99. Therefore, our analysis approach for unemployment fluctuations in Section 3 is reliable for female and male workers.

We follow Equation (3.4) to measure the contribution of each transition flows in explaining unemployment fluctuations. The left part of Table B.1 reports the β coefficients, which measure the importance of transition rates in accounting for unemployment fluctuations. To understand the gender effect, as in Table 4, we report β coefficients for all workers as a whole (i.e., fluctuations in the aggregate unemployment) here. As we expect, the variation in the job finding rate λ^{UE} is the major sources that cause the unemployment rate to fluctuate. It accounts for sixty percentage of the total fluctuations in the female workers' unemployment rates while explains half of the total fluctuations in male workers'. In contrast, the change in the separation rates λ^{EU} explains thirty percentage in the total fluctuations in male workers' unemployment rates; however, for female workers' unemployment fluctuations, λ^{EU} only explains around 11 percentage. In comparison with the impact of job finding and separation rates on aggregate unemployment rates fluctuations, we can find that the separation margin play a relatively important role in explaining male workers' unemployment fluctuation while hiring margin accounts for more fluctuations in female workers' unemployment rates.

In the second exercise, we begin to analyze the sources that influence gender unemployment gap, the level difference between female workers' unemployment rates and that of male workers. Figure 1 shows that the gender unemployment gap did not persistently exist. We therefore analyze the source that caused the gap to vanish in following way. First, we compute number of the gender unemployment gap during the period from July 1978 to May 1979 when the gender unemployment gap existed. Second, we replace each transition rate (e.g., separation rate) during July 1978 to May 1979 by the average of this transition rate during periods when gender unemployment gap disappeared. Then, based on Equation (2.8), we compute the counterfactual female workers' unemployment rate during July 1978 to May 1979 given the transition rates during the periods when gender unemployment gap disappeared and construct counterfactual gender unemployment gap. We choose the period from January 1993 to December 1993 for the period when gender unemployment gap disappeared because the average unemployment rate (6%) is similar to the average (6.1%) during the period from July 1978 to May 1979.

We compute the percentage changes between observed gender unemployment gap and the counterfactual one to understand which caused the gender unemployment gap to exist and vanish. The right part of Table B.1 shows that when female workers have the average of separation rates during January 1993 to December 1993, forty percentage of the total gender unemployment gap during July 1978 to May 1979 may diminish. Moreover, the decline in female workers' transition rates from employment to out-of-the-labor-force λ^{EI} caused 65 percentage of the total gender unemployment gap to disappear.

Our findings for gender unemployment gap based on Equation (2.8) are similar to those in Albanesi and Şahin (2018), who argued that the decline in λ^{EI} shows that the labor force attachment of female workers converged to that of male workers. Moreover, Albanesi and Şahin (2018) indicated that because female and male workers intend to choose to work in different industry, the male workers' separation rates therefore differed from that of female workers

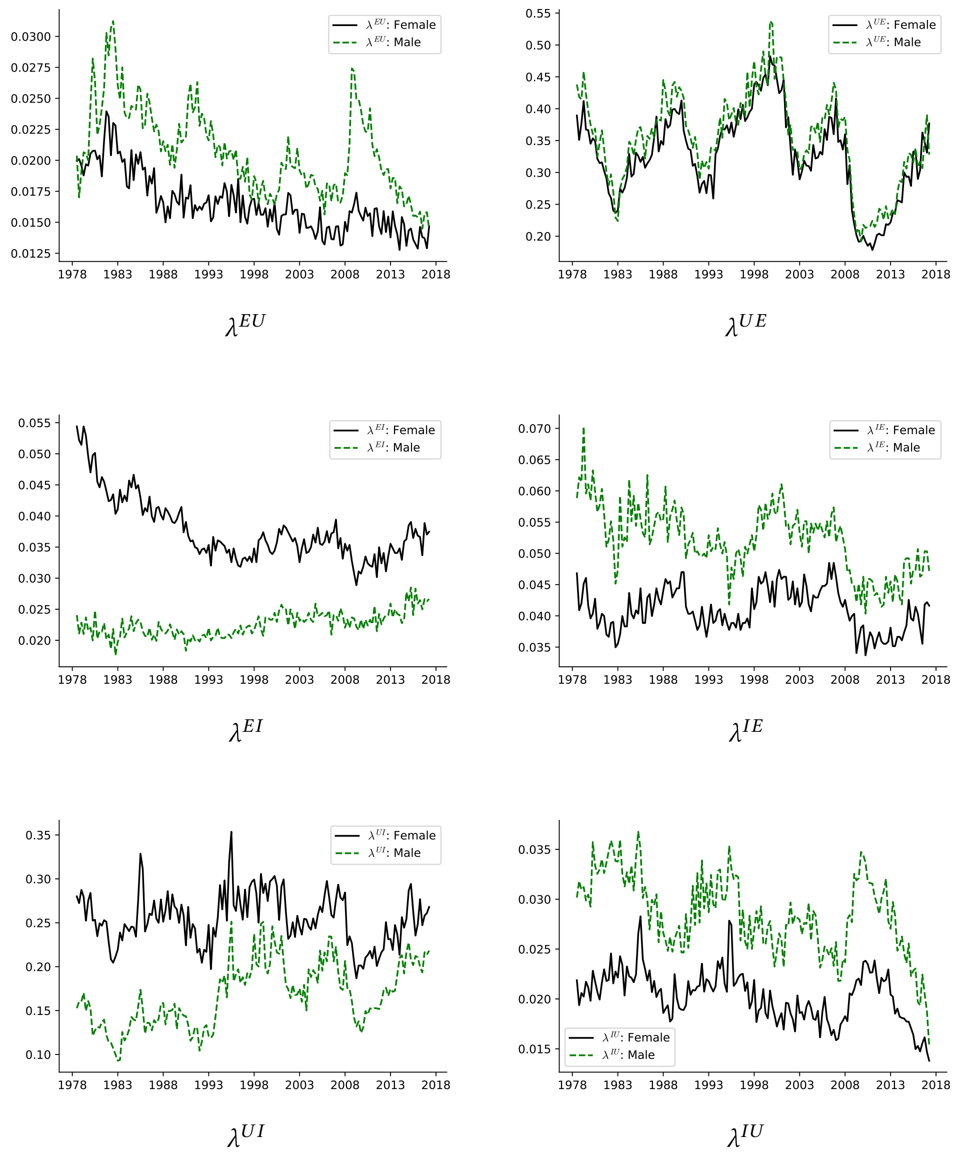
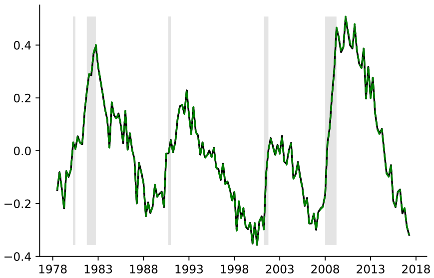
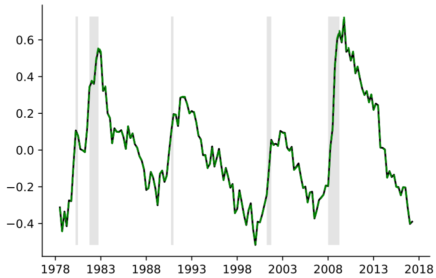


Figure B.1: Transition Rates: Female and Male Workers

Note: The gray-rectangle area indicates NBER Recession periods. Data source: FRED & IPUMS-CPS.



Female Workers



Male Workers

Figure B.2: Approximated Unemployment Fluctuations v.s. Observed Ones

Note: The gray-rectangle area indicates NBER Recession periods. Data source: FRED & IPUMS-CPS. The left figure compares the approximation of female workers' unemployment fluctuations and the observed one while the right repeat this comparison for male workers.

Table B.1: Quantitative Analysis: Fluctuations and Gap

β Coefficients	Female	Male	All		% Change in Gap
λ^{EU}	0.107	0.28	0.206	λ^{EU}	39.37
	(0.013)	(0.012)	(0.01)		
λ^{EI}	-0.056	-0.024	-0.037	λ^{EI}	64.99
	(0.01)	(0.005)	(0.006)		
λ^{UE}	0.561	0.483	0.512	λ^{UE}	-67.38
	(0.014)	(0.011)	(0.01)		
λ^{UI}	0.135	0.124	0.138	λ^{UI}	-24.23
	(0.01)	(0.006)	(0.007)		
λ^{IE}	0.109	0.054	0.075	λ^{IE}	-16.34
	(0.008)	(0.004)	(0.005)		
λ^{IU}	0.149	0.089	0.111	λ^{IU}	-5.64
	(0.011)	(0.007)	(0.008)		
ϵ	-0.004	-0.006	-0.005		
	(0.001)	(0.001)	(0.001)		

Note: 95% Confidence Interval in brackets.

Appendix C Supplement Tables: Recessions

This appendix contains the tables that report more detailed information during recessions. Table 2 considers only the dates dummy when the aggregate unemployment rates are higher than HP filter trend. Because one may want to understand the dynamics of the transition rates during recessions, we therefore repeat the estimation in the main context but replace the dates dummy with the recession periods with the largest increase in the unemployment rates.

Although there exists four periods of recessions: 1980s, 1990s, 2000s and the Great Recession in our sample, in the first exercise, we do not distinguish the recession periods. Table C.1 reports the basis results. We can see because the unemployment rates increased from the minimum to the maximum, the average unemployment rates during recessions are not significantly different from that of sample average. This is why we use the deviation from HP filter trend rather than recession periods in the main context because we can clearly determine the relationship between the unemployment rates and the transition rates. Then, we separate the recessions to four sub recession periods: 1980s, 1990s, 2000s and the Great Recession. We therefore redo the estimation and consider recession dummies for each four recessions. Table C.2, C.3, C.4 and C.5 report the estimation results respectively for non-white, young workers, those without any college education and female workers. The main difference is that non-white workers and young workers suffer more during the 1980s recessions in the comparison with their situation in the Great Recession. In contrast, the situations of those without any college education are similar in both 1980s and the Great Recession. Moreover, during the recession period where the average unemployment is larger than the sample average, we see similar changes in the transition rates. For example, separation rates increased while job finding rates decline for non-white workers during the Great Recessions. This is consistent with the findings in Table 2.

Table 4 and Table 5 report the contributions of each transition event to unemployment fluctuations and gap respectively. One may want to understand whether or not the importance of these transition events change during recessions. We therefore repeat the exercises but specifically for recessions only. The recessions periods are based on that reported in Table A.2 based on all workers. We report the results in Table C.6 for unemployment fluctuations and in Table C.7 for unemployment gap. Basically, recessions do not alter the conclusions based on Table 4 and Table 5.

Table C.1: Estimated Transitions: Disadvantaged Workers

Non-White	u	λ^{EU}	λ^{EI}	λ^{UE}	λ^{UI}	λ^{IE}	λ^{IU}
Intercept	5.740***	1.292***	2.552***	27.542***	20.964***	4.281***	2.196***
	(0.269)	(0.049)	(0.216)	(0.688)	(0.410)	(0.356)	(0.093)
Recession	0.245	0.141***	-0.184	-0.249	-1.959***	-0.206	0.013
	(0.220)	(0.040)	(0.176)	(0.562)	(0.336)	(0.291)	(0.076)
Non-White	4.928***	0.695***	0.723***	-8.048***	5.781***	0.449*	2.325***
	(0.175)	(0.032)	(0.140)	(0.446)	(0.266)	(0.231)	(0.061)
Recession × Non-White	-0.023	-0.002	0.036	-0.402	0.966**	-0.010	-0.044
	(0.311)	(0.057)	(0.249)	(0.795)	(0.475)	(0.411)	(0.108)
R^2	0.55	0.48	0.13	0.44	0.52	0.08	0.71
N	980	980	980	980	980	980	980

Young	u	λ^{EU}	λ^{EI}	λ^{UE}	λ^{UI}	λ^{IE}	λ^{IU}
Intercept	5.320***	1.117***	2.109***	24.400***	19.629***	2.253***	1.310***
	(0.208)	(0.042)	(0.202)	(0.675)	(0.447)	(0.728)	(0.150)
Recession	0.076	0.104***	-0.248	-0.122	-2.066***	-0.247	-0.058
	(0.170)	(0.034)	(0.165)	(0.552)	(0.366)	(0.596)	(0.123)
Young	4.234***	1.017***	1.759***	2.541***	6.243***	7.107***	5.155***
	(0.135)	(0.027)	(0.131)	(0.437)	(0.290)	(0.472)	(0.097)
Recession × Young	0.310	0.087*	0.216	-0.242	0.528	-0.208	0.146
	(0.240)	(0.049)	(0.233)	(0.780)	(0.517)	(0.842)	(0.174)
R^2	0.62	0.72	0.33	0.29	0.50	0.31	0.83
N	980	980	980	980	980	980	980

No College	u	λ^{EU}	λ^{EI}	λ^{UE}	λ^{UI}	λ^{IE}	λ^{IU}
Intercept	4.504***	0.978***	2.006***	28.765***	18.860***	5.929***	2.473***
	(0.199)	(0.034)	(0.255)	(0.718)	(0.411)	(0.498)	(0.055)
Recession	-0.033	0.042	-0.125	-0.114	-1.390***	-0.230	-0.017
	(0.163)	(0.028)	(0.209)	(0.588)	(0.336)	(0.407)	(0.045)
No College	4.303***	0.963***	1.463***	-3.890***	5.844***	-2.423***	0.164***
	(0.129)	(0.022)	(0.165)	(0.466)	(0.266)	(0.323)	(0.035)
Recession × No College	0.213	0.136***	-0.224	0.056	-0.816*	0.126	0.017
	(0.230)	(0.039)	(0.295)	(0.831)	(0.475)	(0.576)	(0.063)
R^2	0.64	0.78	0.16	0.29	0.48	0.12	0.34
N	980	980	980	980	980	980	980

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.2: Estimated Transitions: Non-White Workers

	u	λ^{EU}	λ^{EI}	λ^{UE}	λ^{UI}	λ^{IE}	λ^{IU}
Const.	5.789***	1.301***	2.555***	27.483***	20.927***	4.274***	2.207***
	(0.242)	(0.044)	(0.216)	(0.668)	(0.398)	(0.356)	(0.088)
80*s*	1.379***	0.436***	0.099	-1.361	-3.730***	-0.179	0.208*
	(0.336)	(0.061)	(0.301)	(0.928)	(0.553)	(0.495)	(0.122)
90*s*	-0.244	0.122*	-0.309	1.524	-3.663***	-0.102	-0.129
	(0.361)	(0.065)	(0.323)	(0.996)	(0.594)	(0.532)	(0.131)
00*s*	-1.018***	-0.097	-0.207	3.038***	0.614	-0.011	-0.227*
	(0.332)	(0.060)	(0.297)	(0.918)	(0.547)	(0.490)	(0.121)
GR	0.908**	0.104	-0.357	-4.542***	-1.294**	-0.567	0.210
	(0.356)	(0.065)	(0.318)	(0.984)	(0.586)	(0.525)	(0.129)
Non-White	4.928***	0.695***	0.723***	-8.048***	5.781***	0.449*	2.325***
	(0.157)	(0.028)	(0.140)	(0.433)	(0.258)	(0.231)	(0.057)
80*s*× Non-White	2.453***	0.376***	0.010	-1.714	2.153***	-0.457	0.768***
	(0.475)	(0.086)	(0.425)	(1.312)	(0.782)	(0.700)	(0.172)
90*s*× Non-White	0.165	0.090	0.021	-1.271	1.618*	-0.160	0.232
	(0.510)	(0.092)	(0.456)	(1.409)	(0.839)	(0.752)	(0.185)
00*s*× Non-White	-1.402***	-0.175**	0.092	-0.596	0.422	0.486	-0.407**
	(0.470)	(0.085)	(0.420)	(1.298)	(0.773)	(0.693)	(0.170)
GR× Non-White	-1.418***	-0.320***	0.014	2.161	-0.388	0.069	-0.815***
	(0.503)	(0.091)	(0.450)	(1.391)	(0.829)	(0.742)	(0.183)
N	980	980	980	980	980	980	980
R^2	0.64	0.59	0.14	0.48	0.55	0.09	0.75

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3: Estimated Transitions: Young Workers

	u	λ^{EU}	λ^{EI}	λ^{UE}	λ^{UI}	λ^{IE}	λ^{IU}
Const.	5.351***	1.124***	2.109***	24.345***	19.575***	2.245***	1.319***
	(0.193)	(0.039)	(0.202)	(0.652)	(0.423)	(0.729)	(0.147)
80*s*	0.620**	0.236***	-0.108	-1.140	-3.240***	-0.368	-0.083
	(0.268)	(0.054)	(0.281)	(0.907)	(0.588)	(1.013)	(0.205)
90*s*	-0.189	0.104*	-0.370	0.794	-3.299***	-0.288	-0.122
	(0.287)	(0.058)	(0.302)	(0.974)	(0.631)	(1.088)	(0.220)
00*s*	-0.930***	-0.062	-0.206	2.868***	0.013	-0.085	-0.214
	(0.265)	(0.053)	(0.278)	(0.897)	(0.582)	(1.002)	(0.203)
GR	0.889***	0.147**	-0.341	-3.342***	-1.961***	-0.259	0.214
	(0.284)	(0.057)	(0.298)	(0.961)	(0.623)	(1.074)	(0.217)
Young	4.234***	1.017***	1.759***	2.541***	6.243***	7.107***	5.155***
	(0.125)	(0.025)	(0.131)	(0.423)	(0.274)	(0.472)	(0.095)
80*s*× Young	1.770***	0.477***	0.160	-0.970	-1.702**	-0.139	1.142***
	(0.379)	(0.076)	(0.397)	(1.282)	(0.831)	(1.432)	(0.289)
90*s*× Young	-0.342	0.077	0.134	1.205	-0.209	0.863	0.323
	(0.406)	(0.082)	(0.427)	(1.376)	(0.892)	(1.538)	(0.311)
00*s*× Young	-0.482	-0.079	0.316	0.059	1.956**	0.412	-0.238
	(0.374)	(0.075)	(0.393)	(1.268)	(0.822)	(1.417)	(0.286)
GR× Young	0.204	-0.153*	0.242	-1.169	2.120**	-2.050	-0.713**
	(0.401)	(0.081)	(0.421)	(1.359)	(0.881)	(1.518)	(0.307)
N	980	980	980	980	980	980	980
R^2	0.67	0.77	0.33	0.34	0.55	0.31	0.84

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.4: Estimated Transitions: Workers without Any College Education

	u	λ^{EU}	λ^{EI}	λ^{UE}	λ^{UI}	λ^{IE}	λ^{IU}
Const.	4.525***	0.982***	2.007***	28.727***	18.816***	5.932***	2.479***
	(0.188)	(0.033)	(0.256)	(0.696)	(0.389)	(0.498)	(0.053)
80*s*	0.206	0.122***	0.084	0.802	-1.940***	0.446	0.281***
	(0.262)	(0.045)	(0.356)	(0.968)	(0.541)	(0.693)	(0.073)
90*s*	-0.490*	-0.011	-0.285	1.530	-3.489***	0.414	0.015
	(0.281)	(0.049)	(0.382)	(1.039)	(0.580)	(0.744)	(0.079)
00*s*	-0.634**	-0.040	-0.131	2.252**	0.293	-0.524	-0.374***
	(0.259)	(0.045)	(0.352)	(0.957)	(0.535)	(0.685)	(0.073)
GR	0.841***	0.098**	-0.199	-5.515***	-0.690	-1.280*	0.030
	(0.277)	(0.048)	(0.377)	(1.026)	(0.573)	(0.734)	(0.078)
No College	4.303***	0.963***	1.463***	-3.890***	5.844***	-2.423***	0.164***
	(0.122)	(0.021)	(0.166)	(0.451)	(0.252)	(0.323)	(0.034)
80*s*× No College	1.066***	0.322***	-0.424	-2.242	-3.047***	-0.550	-0.096
	(0.370)	(0.064)	(0.503)	(1.368)	(0.764)	(0.979)	(0.104)
90*s*× No College	-0.159	0.143**	-0.312	-0.003	-0.520	-0.531	-0.206*
	(0.397)	(0.069)	(0.540)	(1.469)	(0.821)	(1.051)	(0.111)
00*s*× No College	-0.800**	-0.067	-0.049	0.645	0.971	0.714	0.183*
	(0.366)	(0.063)	(0.497)	(1.354)	(0.756)	(0.969)	(0.103)
GR× No College	0.784**	0.155**	-0.117	2.041	-0.647	0.848	0.170
	(0.392)	(0.068)	(0.533)	(1.450)	(0.810)	(1.038)	(0.110)
N	980	980	980	980	980	980	980
R^2	0.68	0.80	0.16	0.34	0.54	0.13	0.39

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.5: Estimated Transitions: Female Workers

	u	λ^{EU}	λ^{EI}	λ^{UE}	λ^{UI}	λ^{IE}	λ^{IU}
Const.	6.401***	1.543***	1.930***	27.550***	18.472***	5.181***	3.210***
	(0.413)	(0.098)	(0.141)	(1.052)	(0.368)	(0.190)	(0.068)
80*s*	1.400***	0.523***	-0.232***	-2.038***	-4.818***	0.052	0.555***
	(0.033)	(0.004)	(0.003)	(0.120)	(0.064)	(0.035)	(0.021)
90*s*	0.518***	0.307***	-0.334***	-0.532***	-4.753***	-0.420***	-0.004
	(0.023)	(0.003)	(0.004)	(0.103)	(0.049)	(0.025)	(0.014)
00*s*	-0.534***	-0.045***	-0.031***	0.331***	0.868***	-0.182***	-0.125***
	(0.003)	(0.002)	(0.007)	(0.021)	(0.014)	(0.004)	(0.002)
GR	1.750***	0.201***	-0.117***	-5.129***	-0.391***	-1.057***	0.310***
	(0.022)	(0.012)	(0.021)	(0.183)	(0.047)	(0.041)	(0.007)
Female	0.011***	-0.297***	1.610***	-3.350***	9.404***	-1.379***	-0.950***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
80*s*× Female	1.032***	0.308***	-0.435***	-2.002***	-2.819***	-0.656***	-0.136***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
90*s*× Female	-0.054***	0.125***	-0.347***	0.177***	-0.736***	-0.517***	-0.217***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
00*s*× Female	-0.785***	-0.063***	-0.053***	0.765***	0.979***	0.687***	0.179***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GR× Female	0.798***	0.156***	-0.128***	2.074***	-0.671***	0.825***	0.162***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	980	980	980	980	980	980	980
R^2	0.17	0.49	0.22	0.34	0.72	0.11	0.60

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.6: β Coefficient: Unemployment Fluctuations, Recessions

Non-White	1980s	1990s	2000s	Great Recession
λ^{EU}	0.315	0.159	0.115	0.207
	(0.055)	(0.073)	(0.047)	(0.03)
λ^{EI}	-0.116	-0.044	-0.019	-0.066
	(0.024)	(0.038)	(0.039)	(0.016)
λ^{UE}	0.445	0.468	0.524	0.476
	(0.041)	(0.101)	(0.052)	(0.03)
λ^{UI}	0.164	0.123	0.198	0.136
	(0.018)	(0.041)	(0.026)	(0.019)
λ^{IE}	0.153	0.151	0.101	0.109
	(0.024)	(0.036)	(0.027)	(0.014)
λ^{IU}	0.047	0.139	0.068	0.149
	(0.022)	(0.068)	(0.036)	(0.024)
ϵ	-0.008	0.005	0.015	-0.011
	(0.003)	(0.008)	(0.003)	(0.004)
Young	1980s	1990s	2000s	Great Recession
λ^{EU}	0.267	0.157	0.101	0.168
	(0.03)	(0.046)	(0.062)	(0.037)
λ^{EI}	-0.077	-0.089	0.023	-0.095
	(0.022)	(0.039)	(0.027)	(0.02)
λ^{UE}	0.562	0.579	0.599	0.597
	(0.042)	(0.056)	(0.087)	(0.033)
λ^{UI}	0.126	0.131	0.145	0.113
	(0.014)	(0.034)	(0.025)	(0.017)
λ^{IE}	0.092	0.167	0.114	0.12
	(0.014)	(0.022)	(0.027)	(0.012)
λ^{IU}	0.039	0.047	0.014	0.112
	(0.02)	(0.036)	(0.042)	(0.02)
ϵ	-0.01	0.009	0.005	-0.015
	(0.003)	(0.004)	(0.004)	(0.004)
No College	1980s	1990s	2000s	Great Recession
λ^{EU}	0.324	0.206	0.153	0.215
	(0.029)	(0.049)	(0.053)	(0.035)
λ^{EI}	-0.046	-0.087	-0.015	-0.06
	(0.014)	(0.018)	(0.025)	(0.016)
λ^{UE}	0.454	0.521	0.569	0.507
	(0.035)	(0.049)	(0.048)	(0.033)
λ^{UI}	0.129	0.138	0.152	0.149
	(0.014)	(0.021)	(0.023)	(0.015)
λ^{IE}	0.095	0.131	0.053	0.076
	(0.016)	(0.016)	(0.021)	(0.013)
λ^{IU}	0.053	0.086	0.073	0.126
	(0.012)	(0.027)	(0.022)	(0.014)
ϵ	-0.009	0.005	0.015	-0.013
	(0.003)	(0.003)	(0.002)	(0.004)

Note: Standard Error in parentheses.

Table C.7: Compositions of Unemployment Gap, Recessions

Non-White	1980s	1990s	2000s	Great Recession
λ^{EU}	0.361	0.374	0.328	0.302
	(0.013)	(0.014)	(0.021)	(0.023)
λ^{EI}	0.069	0.091	0.143	0.18
	(0.007)	(0.007)	(0.01)	(0.015)
λ^{UE}	0.472	0.441	0.467	0.519
	(0.012)	(0.022)	(0.02)	(0.028)
λ^{UI}	-0.102	-0.104	-0.094	-0.147
	(0.007)	(0.011)	(0.012)	(0.022)
λ^{IE}	0.009	-0.017	-0.102	-0.101
	(0.008)	(0.009)	(0.01)	(0.018)
λ^{IU}	0.263	0.27	0.3	0.301
	(0.009)	(0.012)	(0.017)	(0.022)
ϵ	-0.072	-0.055	-0.042	-0.054
	(0.004)	(0.005)	(0.006)	(0.01)
Young	1980s	1990s	2000s	Great Recession
λ^{EU}	0.724	0.88	0.778	0.753
	(0.017)	(0.027)	(0.021)	(0.027)
λ^{EI}	0.234	0.341	0.35	0.406
	(0.007)	(0.012)	(0.011)	(0.023)
λ^{UE}	-0.08	-0.27	-0.179	-0.136
	(0.019)	(0.029)	(0.021)	(0.027)
λ^{UI}	-0.112	-0.192	-0.205	-0.27
	(0.007)	(0.015)	(0.016)	(0.026)
λ^{IE}	-0.474	-0.63	-0.563	-0.57
	(0.015)	(0.027)	(0.019)	(0.033)
λ^{IU}	0.726	0.872	0.813	0.817
	(0.018)	(0.029)	(0.022)	(0.034)
ϵ	-0.019	-0.001	0.007	0
	(0.003)	(0.005)	(0.005)	(0.006)
No College	1980s	1990s	2000s	Great Recession
λ^{EU}	0.568	0.65	0.648	0.651
	(0.014)	(0.013)	(0.017)	(0.013)
λ^{EI}	0.119	0.151	0.204	0.197
	(0.007)	(0.006)	(0.007)	(0.006)
λ^{UE}	0.194	0.122	0.079	0.069
	(0.02)	(0.019)	(0.02)	(0.015)
λ^{UI}	-0.022	-0.068	-0.103	-0.086
	(0.007)	(0.007)	(0.009)	(0.007)
λ^{IE}	0.19	0.201	0.146	0.158
	(0.007)	(0.009)	(0.006)	(0.007)
λ^{IU}	-0.018	-0.028	0.048	0.039
	(0.008)	(0.01)	(0.009)	(0.009)
ϵ	-0.03	-0.027	-0.024	-0.028
	(0.002)	(0.002)	(0.003)	(0.002)

Note: Standard Error in parentheses.

Appendix D Data Error

In this appendix, we discuss two data errors that exist in the CPS data. The first one is time aggregation error. The frequency of observed CPS is monthly but the transition flows in the labor market may occur within a month so time-aggregation bias exist. The second one is misclassification error, which means that a worker' labor force status may be incorrectly recorded. We discuss how to correct these errors and report relevant figures here.

D.1 Time Aggregation Error

We correct time aggregation error according to Shimer (2012). By CPS, we can have the monthly transition matrix P_t^m for month t. Due to the multiple transition in a month, we have

$$P_t^m = (P_t)^n,$$

where P_t is the transition matrix for each sub-period (e.g., week) in a month. Here, we use n to represent the number of the sub-period in a month. The goal is to derive P_t based on observed P_t^m. For simplicity, I skip subscript t in the following derivation.

By eigen decomposition, we can write P^m as QMQ^{-1}. Therefore, we can have

$$P = QM^{1/n}Q^{-1}.$$

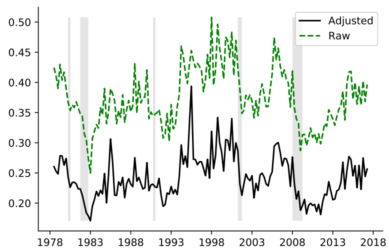
For example, if n is equal to 4, we can derive the weekly transition matrix P based on monthly transition matrix P^m. If time is continuous, then $n \to \infty$. As shown in Gomes (2015), we can have continuous time transition matrix

$$P = \lim_{x \to 0} \frac{QM^x Q^{-1} - I}{x}$$

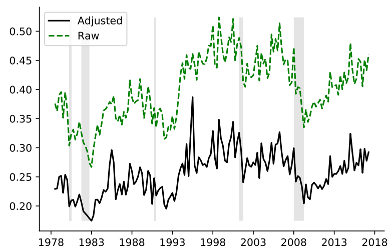
where x equals to $1/n$. In the main context, to avoid time aggregation, we use continuous time transition matrix, rather than observed monthly transition matrix, for all analysis.

D.2 Misclassification Error

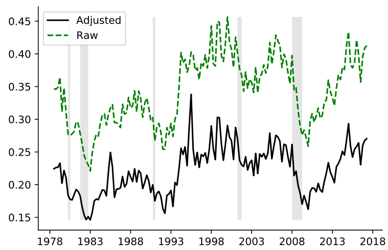
We correct this error based on the *deNUNified* approach proposed by Elsby et al. (2015b) to remove the high frequency movement between unemployment and out-of-the-labor-force. We compare the raw transition rates λ^{IU} and λ^{UI} and adjusted ones after we correct misclassification Error. As in Elsby et al. (2015b), the level of both transition rates decline. Because other transition rates are not affected based on this adjustment approach, we do not report them here.



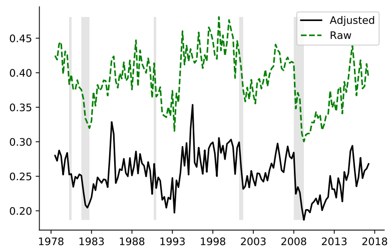
Non-White



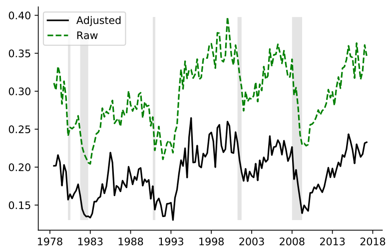
Young



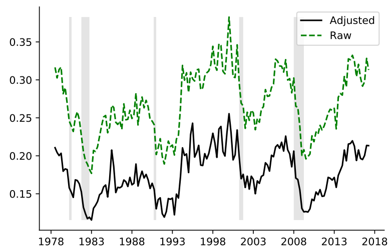
Without Any College Education



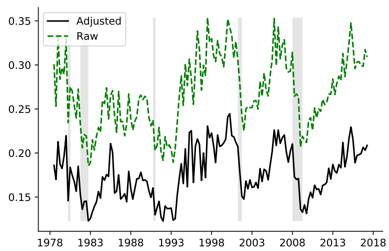
Female



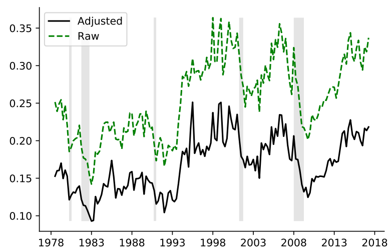
White



Experienced



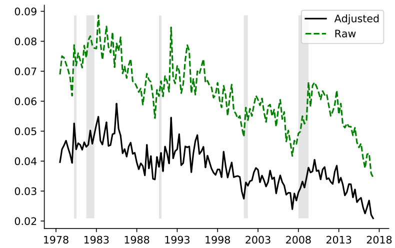
With Some College Education



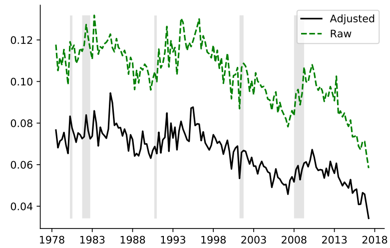
Male

Figure D.1: λ^{UI}: Adjusted v.s. Raw

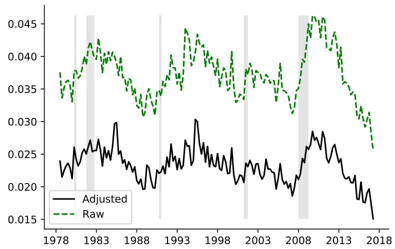
Note: The gray-rectangle area indicates NBER Recession periods. Data source: FRED & IPUMS-CPS.



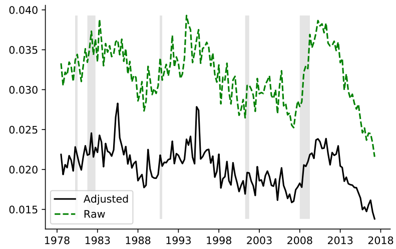
Non-White



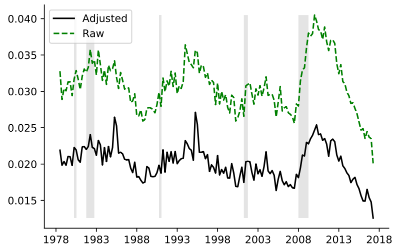
Young



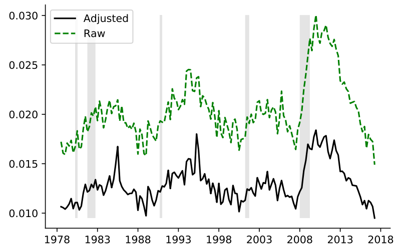
Without Any College Education



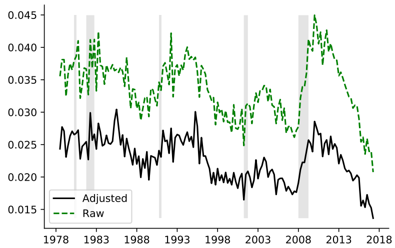
Female



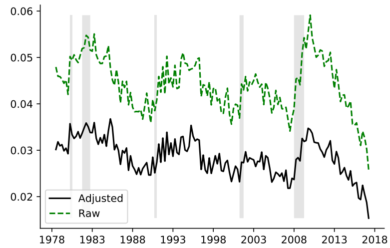
White



Experienced



With Some College Education



Male

Figure D.2: λ^{IU}: Adjusted v.s. Raw

Note: The gray-rectangle area indicates NBER Recession periods. Data source: FRED & IPUMS-CPS.

Appendix E Deriving Decomposition of the Unemployment Rate

By Taylor Theorem, we can rewrite the log difference in unemployment rate $\hat{u}_t = \ln u_t - \ln u_t^* = \ln u(\Lambda_t) - u(\Lambda_t^*)$ as log-difference in transition rates $\hat{\lambda}_t^x = \ln \lambda_t^x - \ln \lambda_t^{*x}$ where $x \in \mathcal{X} = \{EU, EI, UE, UI, IE, IU\}$. To understand workers' unemployment fluctuations, $\ln u_t - \ln \bar{u}_t$, we just to use trend component in workers' transition rate as λ_t^{*ij}. When we discuss disadvantaged workers' unemployment gap $\ln u_t^g - \ln u_t^{\tilde{g}}$, we just need to replace λ_t^{*ij} with counterpart workers' transition rate $\lambda_t^{\tilde{g},ij}$. The decomposition of the log difference in unemployment rate $\ln u_t - \ln u_t^* = \ln u(\Lambda_t) - u(\Lambda_t^*)$ can be explicitly written as below

$$\begin{aligned}
\ln u_t - \ln u_t^* &= \sum_{x \in \mathcal{X}} \left. \frac{\partial \ln u(\Lambda_t)}{\partial \lambda_t^x} \right|_{\Lambda_t = \Lambda_t^*} \times \lambda_t^{*x} \cdot (\ln \lambda_t^x - \ln \lambda_t^{*x}) + \epsilon_t \\
&= a_t^U (\lambda_t^{*IE} + \lambda_t^{*IU}) \lambda_t^{*EU} \cdot (\ln \lambda_t^{EU} - \ln \lambda_t^{*EU}) \\
&\quad + a_t^U \lambda_t^{*IU} \lambda_t^{*EI} \cdot (\ln \lambda_t^{EI} - \ln \lambda_t^{*EI}) \\
&\quad + a_t^E (\lambda_t^{*IE} + \lambda_t^{*IU}) \lambda^{*UE} \cdot (\ln \lambda_t^{UE} - \ln \lambda_t^{*UE}) \\
&\quad + a_t^E \lambda_t^{*IE} \lambda_t^{*UI} \cdot (\ln \lambda_t^{UI} - \ln \lambda_t^{*UI}) \\
&\quad + \left[a_t^U \lambda_t^{*EU} + a_t^E (\lambda_t^{*UE} + \lambda_t^{*UI}) \right] \lambda_t^{*IE} \cdot (\ln \lambda_t^{IE} - \ln \lambda_t^{*IE}) \\
&\quad + \left[a_t^U (\lambda_t^{*EU} + \lambda_t^{*EI}) + a_t^E \lambda_t^{*UE} \right] \lambda_t^{*IU} \cdot (\ln \lambda_t^{IU} - \ln \lambda_t^{*IU}) + \epsilon_t \\
&= F_t^{EU} + F_t^{EI} + F_t^{UE} + F_t^{UI} + F_t^{IE} + F_t^{IU} + \epsilon_t,
\end{aligned} \tag{E.1}$$

where the coefficient a_t^U is equal to $(1 - u_t^*)/U_t^*$ and a^E is equal to $-u_t^*/U_t^*$. Moreover, $U^* = \lambda^{*EU}\lambda^{*IU} + \lambda^{*IE}\lambda^{*EU} + \lambda^{*EI}\lambda^{*IU}$ represents the total inflows to unemployment given transition rates vector Λ_t^*. Equation (E.1) describes that the total log difference in unemployment $\ln u_t - \ln u_t^*$ consist of six factors (F) that depend on the log difference in transition rate $\ln \lambda_t - \ln \lambda_t^{*x}$. For example, F^{UE} account for the part of $\ln u_t - \ln u_t^*$ that is driven by job finding rate (i.e., $\ln \lambda_t^{UE} - \ln \lambda_t^{*UE}$). During the recessions, F_t^{UE} will increase because of the decline in job finding rate $\ln \lambda_t^{UE} - \ln \bar{\lambda}_t^{UE}$ and the negative component a_t^E. In the exercise about unemployment gap, F_t^{UE} would be positive because of the lower job finding rate of disadvantaged workers and $a_t^E < 0$. The error term ϵ_t account for the residual between $\ln u_t - \ln u_t^*$ and the sum of these six factors.

E.1 Different Transition Events

In a given month, an unemployed worker may directly become employed ($U \to E$) or may give up job searches and participate labor force again and find a job ($U \to I \to E$). In the same way, an employed worker may become unemployed but continue job search ($E \to U$) or may give up job searches but participate labor force again

($E \rightarrow I \rightarrow U$). We therefore do not naively decompose the unemployment rate according to each transition rates based on Equation (E.1). Recall Equation (2.6) and (2.7), transition rate λ^{UI} only influence $\lambda_t^{UI}\lambda_t^{IE}$. However, the transition rate λ_t^{IE} influence unemployment rate through the inflows to unemployment together with λ^{EU}, and the inflows to employment together with λ^{UI} and λ^{UE}. Therefore, we extract the component related to transition flows λ_t^{UI} from factor F_t^{IE} as f_t^{UIE}. We combine this extracted part f_t^{UIE} with F_t^{UI}, the component that depends on $\ln\lambda_t^{UI} - \ln\lambda_t^{*UI}$. We call $f_t^{UIE} + F_t^{UI}$ as F_t^{UIE} and define $F_t^{IE} - f_t^{UIE}$ as $\tilde{F}_t^{IE}$, which does not contain any component related to flows $U \rightarrow I \rightarrow E$. Similarly, because λ_t^{IU} influence unemployment rate through the inflows to unemployment together with λ^{EI} and λ^{EU}, and the inflows to employment together with λ^{UE}. Therefore, we combine f_t^{EIU}, the component related to transition flows λ_t^{EI} in factor F_t^{IU} together with F_t^{EI} as F_t^{EIU}. Again, we define $\tilde{F}_t^{IU} = F_t^{IU} - f_t^{EIU}$, which does not depend on the flows $E \rightarrow I \rightarrow U$. After we combine the parts that influence $U \rightarrow I \rightarrow E$ and $E \rightarrow I \rightarrow U$ together respectively as F_t^{UIE} and F_t^{EIU}, we rewrite Equation (E.1) as

$$F_t = F_t^{EU} + F_t^{EIU} + F_t^{UE} + F_t^{UIE} + \tilde{F}_t^{IE} + \tilde{F}_t^{IU} + \epsilon_t. \tag{E.2}$$

Here, for simplicity, we use F_t to represent the "total" log difference in unemployment target, $\ln u_t - \ln u_t^*$. In the main context, we use F^{tot} for total unemployment fluctuation and F^{gap} for total unemployment gap. This equation is totally same as Equation (E.1) but we just rearrange the component related to $U \rightarrow I \rightarrow E$ and $E \rightarrow I \rightarrow U$ flows. The factor F^k still describes the component that influence F_t through transition flow k. Here, we have six transition flows. The two depends on separation margins: $E \rightarrow U$ and $E \rightarrow I \rightarrow U$, and the two depends on hiring margins and $U \rightarrow E$ and $U \rightarrow I \rightarrow E$. The last two, $I \rightarrow E$ and $I \rightarrow U$, are related to labor force participation. Because $\tilde{F}^{IE}$ and $\tilde{F}^{IU}$ now only contains the factors related to the transition from I to E and U, we can clearly determine the "pure" impact of labor force participation margin on unemployment fluctuations or disadvantaged workers' unemployment gap. The part that cannot be accounted for by these components is residual ϵ_t, which is the same as that in Equation (E.1). Each component in Equation (E.2) can be explicitly written as below:

$$\begin{aligned}
F_t^{EU} &= a_t^U(\tilde{\lambda}_t^{IE}\tilde{\lambda}_t^{IU})\tilde{\lambda}_t^{EU}\hat{\lambda}_t^{EU,c}, \\
F_t^{UE} &= a_t^E(\tilde{\lambda}_t^{IE} + \tilde{\lambda}_t^{IU})\hat{\lambda}_t^{UE,c}, \\
F_t^{EIU} &= a_t^U\tilde{\lambda}_t^{IU}\tilde{\lambda}_t^{EI}\hat{\lambda}_t^{EI,c} + a_t^U\tilde{\lambda}_t^{EI}\tilde{\lambda}_t^{IU}\hat{\lambda}_t^{IU,c}, \\
F_t^{UIE} &= a_t^E\tilde{\lambda}_t^{IE}\tilde{\lambda}_t^{UI}\hat{\lambda}_t^{UI,c} + a_t^E\tilde{\lambda}_t^{UI}\tilde{\lambda}_t^{IE}\hat{\lambda}_t^{IE,c}, \\
\tilde{F}_t^{IE} &= \left(a_t^U\tilde{\lambda}_t^{EU} + a_t^E\tilde{\lambda}_t^{UE}\right)\tilde{\lambda}_t^{IE}\hat{\lambda}_t^{IE}, \text{ and} \\
\tilde{F}_t^{IU} &= \left(a_t^U\tilde{\lambda}_t^{EU} + a_t^E\tilde{\lambda}_t^{UE}\right)\tilde{\lambda}_t^{IU}\hat{\lambda}_t^{IU}.
\end{aligned} \tag{E.3}$$

Table E.1: β Coefficient: Unemployment Fluctuations, Overall

	Non-White	**Young**	**No College**	**All**
$E \to U$	0.167	0.158	0.213	0.206
	(0.014)	(0.013)	(0.012)	(0.010)
$E \to I \to U$	0.058	0.022	0.056	0.079
	(0.014)	(0.013)	(0.010)	(0.009)
$U \to E$	0.490	0.570	0.503	0.512
	(0.013)	(0.014)	(0.012)	(0.010)
$U \to I \to E$	0.289	0.242	0.232	0.204
	(0.012)	(0.010)	(0.009)	(0.007)
$I \to E$	0.005	0.021	0.008	0.008
	(0.000)	(0.001)	(0.001)	(0.001)
$I \to U$	-0.003	-0.006	-0.004	-0.006
	(0.000)	(0.001)	(0.000)	(0.000)
ϵ	-0.006	-0.006	-0.007	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)
	White	**Experienced**	**With College**	**All**
$E \to U$	0.218	0.246	0.216	0.206
	(0.011)	(0.012)	(0.012)	(0.010)
$E \to I \to U$	0.085	0.097	0.110	0.079
	(0.009)	(0.009)	(0.010)	(0.009)
$U \to E$	0.522	0.464	0.523	0.512
	(0.011)	(0.010)	(0.013)	(0.010)
$U \to I \to E$	0.177	0.197	0.155	0.204
	(0.007)	(0.008)	(0.008)	(0.007)
$I \to E$	0.008	0.004	0.007	0.008
	(0.001)	(0.000)	(0.001)	(0.001)
$I \to U$	-0.006	-0.003	-0.007	-0.006
	(0.000)	(0.000)	(0.001)	(0.000)
ϵ	-0.005	-0.005	-0.004	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)

Note: 95% Confidence Interval in brackets.

We report the results (β and γ) based on the decomposition approach in Equation (E.2) as we did in Table 4 and Table 5.

Table E.1 reports the estimated β based on Equation (E.2) for unemployment fluctuations. In Table E.1, some important information can be found this table by comparing the confidence intervals. The estimated β of all different types of workers share common features. First, the contribution of hiring margins ($F^{UE} + F^{UIE}$ or F^{UE} only) is significantly larger than that of separation ($F^{EU} + F^{EIU}$ or F^{EU} only) to workers' unemployment fluctuations. Second, the role of direct inflows from U to E (F^{UE}) is more important than that of indirect inflows from U to I to E (F^{UIE}). The same story applied to the two separation margins components F^{EU} and F^{EIU}. Third, the direct inflows from I to E or from I to U play trivial roles in unemployment fluctuations. Therefore, in the comparison with separation or hiring margins, the **pure** impact of labor force participation (directly from I to U or E) in explaining unemployment fluctuations is

Table E.2: Compositions of Unemployment Gap, Overall

	Non-White	**Young**	**No College**
$E \to U$	0.35	0.776	0.616
	(0.005)	(0.008)	(0.004)
$E \to I \to U$	0.433	1.237	0.196
	(0.006)	(0.013)	(0.004)
$U \to E$	0.436	-0.188	0.116
	(0.006)	(0.007)	(0.006)
$U \to I \to E$	-0.142	-0.746	0.064
	(0.005)	(0.013)	(0.003)
$I \to E$	-0.009	-0.048	0.035
	(0.001)	(0.003)	(0.001)
$I \to U$	-0.021	-0.029	0.001
	(0.001)	(0.002)	(0.000)
ϵ	-0.048	-0.002	-0.027
	(0.002)	(0.001)	(0.001)

Note: 95% Confidence Interval in brackets.

really minor. Our analysis shows that out-of-the-labor-force I is just a transient status when workers move between employment and unemployment in a given month. Our results about I actually complement the findings in Elsby et al. (2015b) which emphasize the role of transition between I and U in unemployment rate fluctuations. We show that IU or UI transition flows are important only when I is a transient status between E and U.

Table E.2 reports the estimated fraction of the factor which depend on a specific flows in total unemployment gap and the corresponding confidence interval. First, we can see that for all disadvantaged workers, the main factor of unemployment gap is F^{EU}. In particular, the component F^{UE} only accounts for 10 percent in total unemployment gap for workers without any college education, and its contribution is even smaller than zero for young workers. This finding for young workers is not surprising. It is consistent with the estimated parameter in Table 2, which shows that young workers have higher job finding rate compared to experienced workers. However, for non-white workers, 40 percent of total unemployment gap can be attributed to the contribution from F^{UE}. Particularly, non-white workers' ratio of F^{UE} to total unemployment gap is significantly higher than that of F^{EU} in total. Second, the impact of F^{EIU} and F^{UIE} on unemployment gap is different. For non-white and young workers, the unemployment gap is mainly caused by F^{EIU}, a component that belongs to separation margin. However, F^{UIE}, a component in hiring margin, did not contribute to unemployment gap for all disadvantaged workers. Third, as the estimated results we report in Table E.1, the pure labor force participation component F^{IE} and F^{IU} did not account for any fraction of unemployment gap. Transition flows related to not-in-the-labor-force I are important only when I is a transient status when workers transit from E to U. In overall, hiring margins contributes to the unemployment gap for non-white workers, while separation margins are the most crucial factors in explaining the unemployment gap for all disadvantaged workers.

Appendix F Robustness Check: Sample Average

In this section, we report the estimation results based on sample average as the trend component, rather than HP-filter trend. Based on Table F.1, the main results hold: workers' unemployment fluctuation is mainly attributed to hiring margin rather than separation margin. In addition, even though we use sample average as trend, small magnitude of β^{ϵ} shows again the accuracy of our decomposition approach.

Given sample average as trend, we show separation margin to non-white workers may contribute to their unemployment changes during normal time. When we use HP-filter trend in the main context, we find that the contribution of separation margin to unemployment fluctuations of non-white and young workers decline. Therefore, contribution of separation margin to non-white workers' unemployment fluctuation is not significantly larger than that of other workers now.

Moreover, based on HP-filter trend, the contribution of hiring margin to young workers' unemployment fluctuations is significantly larger than that of experienced workers. Because using HP-filter trend will increase the contribution of hiring margin, based on mean as trend component, we have lower bound for the contribution of hiring margin to non-white and young workers' unemployment fluctuations. Fujita and Ramey (2009) also addressed that contribution of hiring (separation) margin to unemployment fluctuation is higher (lower) when we use HP-filter trend. In sum, out conclusion that hiring influence disadvantaged workers' unemployment fluctuations do not change even when we use HP-filter trend.

Table F.1: β Coefficient: Sample Average

	Non-White	**Young**	**No College**	**All**
λ^{EU}	0.31	0.209	0.207	0.245
	(0.014)	(0.016)	(0.012)	(0.013)
λ^{EI}	-0.004	-0.016	-0.029	-0.004
	(0.006)	(0.009)	(0.006)	(0.006)
λ^{UE}	0.339	0.499	0.52	0.473
	(0.015)	(0.02)	(0.014)	(0.016)
λ^{UI}	0.105	0.124	0.133	0.13
	(0.006)	(0.007)	(0.007)	(0.005)
λ^{IE}	0.105	0.109	0.096	0.064
	(0.006)	(0.009)	(0.005)	(0.004)
λ^{IU}	0.151	0.082	0.083	0.097
	(0.009)	(0.012)	(0.006)	(0.006)
ϵ	-0.006	-0.007	-0.01	-0.005
	(0.002)	(0.002)	(0.001)	(0.001)

	White	**Experienced**	**With College**	**All**
λ^{EU}	0.248	0.246	0.2	0.245
	(0.014)	(0.011)	(0.012)	(0.013)
λ^{EI}	0.003	-0.004	0.015	-0.004
	(0.006)	(0.005)	(0.006)	(0.006)
λ^{UE}	0.49	0.475	0.562	0.473
	(0.016)	(0.012)	(0.015)	(0.016)
λ^{UI}	0.12	0.138	0.089	0.13
	(0.005)	(0.005)	(0.006)	(0.005)
λ^{IE}	0.05	0.052	0.059	0.064
	(0.004)	(0.004)	(0.007)	(0.004)
λ^{IU}	0.094	0.099	0.087	0.097
	(0.005)	(0.006)	(0.008)	(0.006)
ϵ	-0.006	-0.006	-0.011	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)

Note: Standard Error in parentheses.

Appendix G β for Unemployment Gap

In the main context, we use Equation (4.2) to derive ratio of each factor to total unemployment gap so we are able to determine the contribution of each factor to unemployment gap. The β coefficients in Equation (3.4) can only reveal the importance of these factors to variation of unemployment gap, rather than the level of the gap. Therefore, we do not use β coefficient for analysis of unemployment gap in the main context. This appendix reports the results for the β coefficients when we apply Equation (3.4) to unemployment gap.

As we can see in Table G.1, the variation of unemployment gap is still mainly caused by the fluctuations in the separation factors F^{EU} and F^{EIU} for non-white and young workers. For workers without any college education, 60 percent of unemployment gap variation is accounted for by the hiring margin, which only contribute around 20 percent to unemployment gap. Table G.2 reports the β coefficients for the different recession periods. As in Table G.1, variation in unemployment gap is determined by separation margin. Particularly, the importance of hiring margin for workers without any college education decline during the recessions (especially the Great Recession). Therefore, hiring margin only explains the fluctuations in the normal time for workers without any college education, rather than for recession.

Although Figure 7 shows that hiring margin contribute trivially to unemployment gap, the β coefficients for hiring margin factors are even positive for young workers. Moreover, β coefficient for hiring margin is even much larger than that of separation margin for those without any college education. Because β means the contribution of the fluctuations of a factor to variation, rather than level, of unemployment gap, β coefficients are inconsistent with the features in Figure 7. This is the reason that we do not use β in the main context for unemployment gap.

Table G.1: β Coefficient: Unemployment Gap, Overall

	Non-White	**Young**	**No College**
λ^{EU}	0.402	0.421	0.375
	[0.368, 0.436]	[0.377, 0.465]	[0.339, 0.411]
λ^{EI}	0.002	0.095	0.016
	[-0.017, 0.021]	[0.069, 0.12]	[-0.006, 0.038]
λ^{UE}	0.400	0.187	0.424
	[0.359, 0.441]	[0.142, 0.232]	[0.376, 0.471]
λ^{UI}	0.014	0.12	0.086
	[-0.003, 0.032]	[0.098, 0.142]	[0.066, 0.106]
λ^{IE}	0.100	-0.075	0.111
	[0.08, 0.119]	[-0.107, -0.042]	[0.088, 0.133]
λ^{IU}	0.156	0.27	0.023
	[0.134, 0.178]	[0.234, 0.305]	[-0.007, 0.054]
ϵ	-0.074	-0.018	-0.035
	[-0.086, -0.062]	[-0.029, -0.007]	[-0.043, -0.028]

Note: 95% Confidence Interval in brackets.

Table G.2: β Coefficient: Unemployment Gap, Recessions

Non-White	1980s	1990s	2000s	Great Recession
λ^{EU}	0.365	0.292	0.512	0.199
	[0.178, 0.551]	[0.168, 0.416]	[0.273, 0.75]	[0.039, 0.36]
λ^{EI}	0.165	0.065	0.009	0.099
	[0.078, 0.252]	[-0.001, 0.13]	[-0.117, 0.134]	[0.012, 0.186]
λ^{UE}	0.374	0.466	0.346	0.3
	[0.207, 0.541]	[0.258, 0.674]	[0.107, 0.585]	[0.142, 0.458]
λ^{UI}	0.094	0.106	0.121	0.13
	[0.041, 0.147]	[0.044, 0.168]	[0.012, 0.229]	[0.028, 0.232]
λ^{IE}	0.051	0.026	0.089	0.079
	[-0.065, 0.167]	[-0.055, 0.107]	[-0.029, 0.207]	[-0.008, 0.167]
λ^{IU}	-0.024	0.097	0.008	0.134
	[-0.057, 0.104]	[0.008, 0.185]	[-0.161, 0.177]	[0.027, 0.242]
ϵ	-0.073	-0.051	-0.084	0.058
	[-0.127, -0.019]	[-0.106, 0.004]	[-0.148, -0.019]	[-0.007, 0.124]
Young	1980s	1990s	2000s	Great Recession
λ^{EU}	0.287	0.265	0.319	0.418
	[0.154, 0.42]	[0.124, 0.406]	[0.142, 0.497]	[0.289, 0.548]
λ^{EI}	0.158	0.13	0.113	0.165
	[0.086, 0.23]	[0.053, 0.207]	[0.042, 0.184]	[0.095, 0.236]
λ^{UE}	0.353	0.195	0.244	0.073
	[0.178, 0.528]	[0.016, 0.374]	[0.063, 0.425]	[-0.079, 0.225]
λ^{UI}	0.066	0.162	0.142	0.141
	[0.014, 0.117]	[0.067, 0.257]	[0.048, 0.237]	[0.079, 0.203]
λ^{IE}	-0.139	0.024	-0.093	-0.138
	[-0.263, -0.015]	[-0.115, 0.163]	[-0.202, 0.016]	[-0.215, -0.061]
λ^{IU}	0.301	0.195	0.279	0.327
	[0.158, 0.445]	[0.04, 0.351]	[0.152, 0.406]	[0.234, 0.42]
ϵ	-0.026	0.029	-0.004	0.013
	[-0.059, 0.007]	[-0.017, 0.075]	[-0.058, 0.051]	[-0.029, 0.055]
No College	1980s	1990s	2000s	Great Recession
λ^{EU}	0.412	0.37	0.245	0.496
	[0.295, 0.529]	[0.252, 0.489]	[0.108, 0.382]	[0.327, 0.664]
λ^{EI}	0.053	0.094	0.043	0.138
	[-0.017, 0.124]	[0.026, 0.162]	[-0.022, 0.109]	[0.059, 0.217]
λ^{UE}	0.399	0.41	0.474	0.217
	[0.232, 0.565]	[0.215, 0.605]	[0.287, 0.661]	[0.028, 0.406]
λ^{UI}	0.004	0.07	0.174	0.047
	[-0.055, 0.063]	[0.008, 0.132]	[0.112, 0.237]	[-0.036, 0.13]
λ^{IE}	0.135	0.034	0.026	0.098
	[0.075, 0.195]	[-0.046, 0.114]	[-0.028, 0.079]	[0.003, 0.193]
λ^{IU}	0.036	0.049	0.053	0.027
	[-0.047, 0.119]	[-0.064, 0.162]	[-0.039, 0.145]	[-0.098, 0.151]
ϵ	-0.040	-0.028	-0.015	-0.022
	[-0.066, -0.013]	[-0.055, -0.001]	[-0.045, 0.015]	[-0.051, 0.007]

Note: 95% Confidence Interval in brackets.