Decomposing the Ins and Outs of Cyclical Unemployment

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Abstract

The cyclicality of U.S. labor market dynamics has recently attracted a great deal of attention, following the paper by Shimer (2007). We contribute to this debate by analyzing the determinants of the transition rates into and out of unemployment. Particular attention is paid to job tenure and unemployment duration of those who change their employment status. Using individual-level data from the Current Population Survey, a detailed Blinder-Oaxaca decomposition is employed to decompose differences in transition rates between different phases of the business cycle into composition effects and behavioural effects. We find that, especially for unemployment outflows, behavioural effects drive the cyclicality of the labour market. Composition effects, by contrast, dampen labour market fluctuations. Without these composition effects, the differences in the unemployment outflow probability between recessions and cyclical upswings would be 50% larger.

JEL-Classification: J63, J64, J21, E24

Keywords: Unemployment Duration; Gross Worker Flows; Job Finding Rate; Decomposition Analysis

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1 Introduction

Starting with the contribution of Shimer (2007), the cyclicality of the U.S. labour market has attracted a great deal of attention recently.[1] The main question underlying this debate is the relative importance of the inflows into and the outflows from unemployment for the cyclicality of unemployment. This has major implications. First, it provides fundamental insights into the functioning of the labour market. In particular, it is informative about the nature of the job destruction process which plays a decisive role for the modelling of labour market and macroeconomic models. Second, it can help give advice to economic policy makers whether labour market policy can alleviate the unemployment problem by concentrating on either measures to increase job stability, or measures to help the unemployed find new jobs.

In this paper, we propose a new way of looking at this issue, exploiting the fact that the analysis of unemployment duration on the one hand, and the analysis of inflow and outflow rates on the other hand, are intimately linked. Longer unemployment durations go together with reduced outflows from unemployment. Conversely, higher inflows into unemployment imply a greater prevalence of short-term unemployment among the unemployed. We combine the two concepts by explicitly analysing the hazard of leaving unemployment to employment as a function of unemployment duration using monthly data from the Current Population Survey (CPS). This is done by estimating a regression model with the probability of transiting from unemployment to employment as the dependent variable, and unemployment duration among the explanatory variables. Furthermore, we estimate the same model for transitions from employment to unemployment. Using a Blinder-Oaxaca-type decomposition, we then decompose the difference in transition

[1]This debate goes back to the seminal article by Darby, Haltiwanger, and Plant (1986). Recent contributions include Elsby, Michaels, and Solon (2009), Yashiv (2008), and Fujita and Ramey (2009). The two former articles also provide overviews of the current state of the literature.

probabilities between economic booms and busts into a composition effect and a behavioural effect. This also allows an answer to the question which role unemployment duration plays for labour market dynamics over the cycle. In particular, we can make a statement about the importance of the increased number of unemployed workers with relatively high unemployment duration during recessions (the composition effect), compared to the greater difficulty workers of a given unemployment duration experience during recessions (the behavioural effect).

In our analysis, we explicitly take advantage of the fact that the CPS, the most widely used data set for analyzing labour market dynamics in the U.S., provides worker information at the level of the individuum. This stands in contrast to most of the related literature, which uses the micro information available to construct aggregated times series on different labour market transitions. Instead, we perform our regression and decomposition analysis using the panel data structure provided by the CPS. This allows us to take into account heterogeneity at the individual level. In this sense, our analysis is related to Baker (1992), who scrutinizes the (cyclical) determinants of the expected duration of unemployment of different worker groups as they enter unemployment. Our study takes matters further by examining completed spells of unemployment at the time an unemployed worker finds a new job.

The remainder of this paper is structured as follows. The next section describes the data used. Section 3 introduces the econometric methodology, and especially the decomposition analysis we apply. Section 4 contains the empirical results. The final section summarizes and concludes the analysis.

2 The Data

To analyze transitions from unemployment to employment, we use basic monthly data from the Current Population Survey (CPS) for the time period January 1976 through December 2008, which also constitute the basis of the "gross flow data" employed by Fujita and Ramey (2009) and Yashiv (2008). The data are readily available from the website of the National Bureau of Economic Research (NBER)[2] The CPS is a rotating panel, which follows individuals who enter the survey for four consecutive months, then leave the sample for eight months, re-enter the sample for another four consecutive months, and then leave the sample altogether. We use an extended version of Shimer's program code to match observations across time.[3] In particular, we match individual records from one month to the next using the household identification number, the serial suffix when household identification numbers are not unique, the person's line number within the household, and the person's age, race, and sex. Exact matches are required for all of the variables except age, where we accept cases in which age increased by no more than one year.

The analysis of transitions from employment to unemployment is complicated by the fact that information on job tenure is not available in the basic monthly data of the CPS. This is a severe data restriction, because in any econometric analysis of labour market transitions, it is of paramount importance to control for the duration an individual has spent in the state of origin before making a transition. However, information on job tenure is available in the Job Tenure and Occupational Mobility Supplements, which are collected in January or February of specific years (see Figure 1. We thus use this information on job tenure and combine it with the information on transitions which are computed from the basic monthly files as described above.

The recessionary periods defined by the NBER's Business Cycle Dating Committee are taken from `http://www.nber.org/cycles`.

[TO BE COMPLETED]

3 Econometric Methodology

The econometric analysis proceeds in two steps. First, we estimate the determinants of the probabilities of transiting from employment to unemployment, and from unemployment to employment, using a linear probability model. This is done

[2] See `http://www.nber.org/data/cps_basic.html`.

[3] The original program files are available at `http://sites.google.com/site/robertshimer/`.

separately for recessionary periods (denoted by $j = 1$) and for cyclical upswings (denoted by $j = 0$). The model thus reads as follows:

$$Y_{ijt} \quad = \quad \beta_0 + \sum_k X_{ijkt}{}'\beta_{jk} + \varepsilon_{ijt}, \tag{1}$$

where $i = 1, ..., N_j$, $\sum_j N_j = N$, $t = 1, ..., T$, and Y_{ijt} indicates the change in employment status of individual i between time $t-1$ and time t. The vector X_{ijt} includes a set of individual-specific characteristics. We assume that the error term ε_{ijt} is conditionally independent of these characteristics, i.e. $E(\varepsilon_{ijt}|X_{ijt}) = 0$. We thus obtain two sets of results for the determinants of the transition rates of interest, one for recessions and one for upswings.

In the second step of the analysis, we analyse the differences between these two sets of results in detail. The aim of this step is to find out whether these differences are driven by differences in characteristics (composition effects) or differences in coefficients. In order to do so, a conventional Blinder-Oaxaca decomposition is employed, departing from the estimates of the pooled linear probability model.[4] Given the parameter estimates of this model, we may decompose the overall difference in average transition rates between economic downturns and economic upswings using the decomposition method proposed by Blinder (1973) and Oaxaca (1973) and generalized by Oaxaca and Ransom (1994). Specifically, we may isolate the part of the overall difference between the two subsamples attributable to differences in observed characteristics from the part due to differences in coefficients:

$$\begin{aligned} \overline{Y}_1 - \overline{Y}_0 \quad &= \quad \underbrace{\sum_{k=1}^{K} (\overline{X}_{1k} - \overline{X}_{0k})'\beta_k^*}_{=\text{explained}} \\ &+ \quad \underbrace{(\widehat{\beta}_{10} - \widehat{\beta}_{00}) + \sum_{k=1}^{K} \left[\overline{X}_{1k}{}'(\widehat{\beta}_{1k} - \beta_k^*) + \overline{X}_{0k}{}'(\beta_k^* - \widehat{\beta}_{0k}) \right]}_{=\text{unexplained}}, \end{aligned} \tag{2}$$

where the reference vector β^* is given by the linear combination $\beta^* = \Omega\widehat{\beta}_1 + (I - \Omega)\widehat{\beta}_0$.

[4] Approximate decomposition results for Logit and Probit models can be derived by employing the decomposition method proposed by Fairlie (2003). These results do not differ qualitatively from the results presented in our paper.

We interpret the first term on the right-hand side of equation (2) as the part of the overall difference due to "composition effects" because it results from differences in the composition between the two groups with respect to observed characteristics. For example, one may expect that during recessions, there are more individuals with short unemployment durations in the pool of the unemployed, which increases outflows from unemployment, relative to economic upswings. The second term on the right-hand side of the equation may be interpreted as being due to "behavioural effects", i.e. differences in transition probabilities that exist for given observable characteristics. For example, workers with a specific skill level may display transition probabilities that differ between recessions and upswings. This would imply that the "pay-offs" to certain worker characteristics (in terms of transition probabilities) vary over the business cycle.

4 Results

4.1 Evidence on transitions

The descriptive evidence on the transitions between employment and unemployment is displayed in Figures 1 and 2, as well as in Table 1. As one can see from Figure 2, there is a clear tendency of the unemployment outflow rate to decline in recessions. The summary statistics in Table 1 confirm the countercylicality of the transitions from employment to unemployment, and the procyclicality of the transitions in the opposite direction. Furthermore, job tenure is countercyclical, and unemployment duration is procyclical. As for the demographic characteristics, the largest differences arise for workers belonging to different age groups. In particular, while the oldest age group is more strongly represented amongst both the employed and the unemployed in recessions, the opposite is true for middle-aged workers. As for the different levels of education, the largest differences can be observed for workers with very low or very high levels of education.

The results for the regression for the two transitions are in Table 2, and are in line with the descriptive evidence and with the results generally found in the literature: male workers have a higher probability of exiting unemployment to employment, as do younger workers. By contrast, older workers and workers without a degree have a lower probability of making such a transition. Most importantly for our purposes, workers with shorter job tenure and with shorter unemployment durations are more likely to transit from unemployment to employment than workers who have been unemployed for some time. Furthermore, important differences between economic upswings and downturns emerge. These are analysed in detail in the next section.

4.2 Decomposition results

In order to analyse what drives the differences between booms and recessions in unemployment inflow and outflow rates, we employ the decomposition methodology discussed in Section 3. In doing so, we first decompose these differences for groups of variables, e.g. for age in general (i.e. all age group variables taken together), and then for specific variables, e.g. for all the age groups, separately.

Table 3 displays the results from the decomposition analysis by groups of variables for both unemployment inflows and unemployment outflows. For unemployment inflows, the difference is positive, reflecting the countercylicality of transitions from employment to unemployment, but it is not statistically significant. Looking at composition effects (explained part of the raw gap), one can see that tenure plays a dampening role, i.e. it reduces the procyclicality of EU transitions. This can be rationalized by the fact that in recessions, average job tenure rises (cf. Table 1). As jobs with longer tenure are generally more stable, this effect leads to lower unemployment inflows in recessions. The same is true for the composition effect with respect to education. These results imply that without composition effects, unemployment inflows would be more procyclical than observed in practice. Overall, however, the impact of the composition effect is limited, as it is not statistically significant overall.

As for unemployment outflows, the difference is significantly negative, which reflects the fact that the transition rate from unemployment to employment is lower in a recession than it is in a boom. Furthermore, the composition effect is positive, which means that, by itself, it would lead to a *higher* transition rate during a recession. In particular, the difference between booms and recessions would be nearly 50% higher without the composition effect. This, however, is overcompensated by the coefficients effect, which therefore explains more than 100% of the raw difference.

As for the variable groups, three of them have a significant impact on the raw gap. First, unemployment duration is positively significant, and it is most important quantitatively. As shown by the regression results, short-term unemployed workers have a higher probability of transiting from unemployment to employment. As the number of short-term unemployed workers in the pool of the unemployed rises during a recession, the composition effect due to unemployment duration raises the transition rate. Second, the overall effect of the age composition of the pool of the unemployed on the raw gap is negative, i.e. it lowers the transition probability during a recession. Third, the effect of the skill composition is positive. The coefficients effects, on the other hand, are insignificant if analysed separately.

In the second step of the decomposition analysis, we are interested in which individual variables can account for the group effects found in the first step. Looking at unemployment inflows, one can see that the composition effect of education levels is driven by those with a very low (11 years or less) or very high (higher than college degree) levels of education (cf. Table 4). Bearing in mind the results from the regression analysis, which showed that higher levels of education reduce the probability of transiting from employment to unemployment, this means that during recessions the composition of employees shifts towards workers with higher education levels, which leads to the dampening effect described above. The coefficients effects ("unexplained"), by contrast, are all insignificant.

With respect to unemployment outflows, the first step of the decomposition analysis showed that there is not much heterogeneity when looking at coefficients. This picture is confirmed by the detailed decomposition of unemployment outflows, as the results in Table 5 show. As for the endowment effects the age and education variables are of particular interest. With respect to the age effects, middle-aged and older workershave a significantly negative impact. Given that these workers have a lower transition rate (as shown by the linear regression), one can conclude that there are more of these workers in the pool of the unemployed during a recession, which exerts a negative influence on the transition rate to employment. As for the education variables, the lowest category ("less highschool") exerts the strongest effect. Given the lower transition probability of workers without a degree, this implies that there are relatively fewer workers with low education in the pool of the unemployed during recessions. This increases the overall outflow rate and therefore reduces the difference in outflow rates to employment between booms and recessions.

5 Robustness Checks

In this section, we conduct several robustness checks. In particular, we are interested in whether the effects we found also hold when we looking at different sub-periods, or whether the importance of worker heterogeneity for the cyclicality of labour market dynamics has changed over time.

[RESULTS: TO BE COMPLETED]

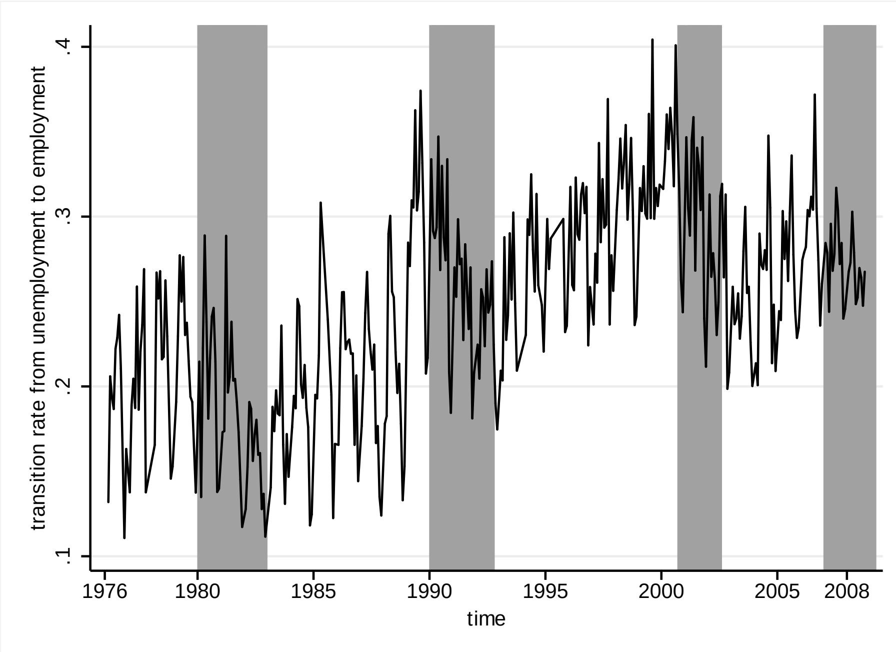
6 Conclusions

In this paper, we analyse the evolution of the transitions between unemployment and employment over the cycle. In doing so, we estimate regression models including unemployment duration and job tenure, respectively, as explanatory variable. A Blinder-Oaxaca-type decomposition allows us to decompose differences in determinants of these transition rates between business cycle upswings and downturns. Our results indicate that such differences are entirely due to behavioural effects. Composition effects, by contrast, play a dampening role. Put differently, without composition effects, both unemployment inflows and outflows would be much more cyclical than observed in reality. While this dampening effect is modest for unemployment inflows, it amounts to 50% of the observed difference for unemployment outflows.

[TO BE COMPLETED]

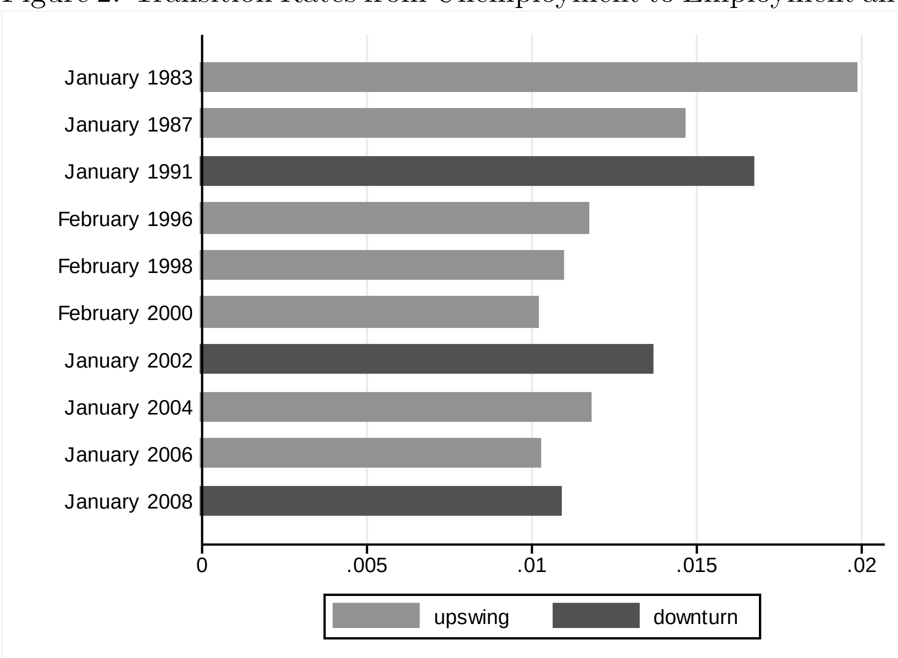
A Tables and Figures

Figure 1: Transition Rates from Employment to Unemployment



Source: Authors' calculations based on the CPS basic monthly files.
Note: Shaded areas are times of recession following the NBER definition.

Figure 2: Transition Rates from Unemployment to Employment and Recession Dates



Source: Authors' calculations based on the CPS basic monthly files.

Table 1: Summary Statistics

	Inflows Sample		Outflows Sample	
	Upswing	Downturn	Upswing	Downturn
Transition rate from employment to unemployment	1.10	1.24		
	(10.41)	(11.05)		
Transition rate from unemployment to employment			27.78	26.72
			(44.79)	(44.25)
Tenure in months	87.39	90.01		
	(95.91)	(98.17)		
Unemployment duration in months			17.34	16.12
			(23.00)	(21.03)
Demographic Characteristics (In per cent)				
Male	52.77	52.63	53.45	54.56
	(49.92)	(49.93)	(49.88)	(49.79)
White	85.57	84.37	73.14	73.53
	(35.14)	(36.32)	(44.32)	(44.12)
Age 16-24 years	13.23	12.52	33.37	33.33
	(33.88)	(33.09)	(47.16)	(47.14)
Age 25-44 years	50.61	47.08	43.28	40.29
	(50.00)	(49.92)	(49.55)	(49.05)
Age 45-65 years	36.16	40.40	23.34	26.38
	(48.05)	(49.07)	(42.30)	(44.07)
Levels of Education (In per cent)				
11 years or less	11.11	10.08	29.01	26.94
	(31.42)	(30.11)	(45.38)	(44.36)
High school	29.62	28.92	33.74	34.08
	(45.66)	(45.34)	(47.28)	(47.40)
Some college	20.35	20.16	18.38	18.56
	(40.26)	(40.12)	(38.73)	(38.88)
Higher college	29.44	31.18	13.04	14.04
	(45.58)	(46.32)	(33.67)	(34.74)
College	9.47	9.65	5.83	6.38
	(29.29)	(29.53)	(23.44)	(24.43)
N	81,748	36,383	135,715	70,383

Note: Weighted numbers based on weights provided by the CPS. Standard deviations reported in parentheses.

Table 2: Determinants of Transitions from Employment to Unemployment (Inflows) and from Unemployment to Employment (Outflows)

	Inflows		Outflows	
	Upswing	Downturn	Upswing	Downturn
Tenure in months	-0.00006***	-0.00006***		
	(0.00001)	(0.00001)		
Unemployment duration in months			-0.00288***	-0.00292***
			(0.00007)	(0.00013)
Demographic Characteristics				
Male	0.00196***	0.00228**	0.01583***	0.01570***
	(0.00050)	(0.00081)	(0.00176)	(0.00297)
Female	-0.00196***	-0.00228**	-0.01583***	-0.01570***
	(0.00050)	(0.00081)	(0.00176)	(0.00297)
White	-0.00122	0.00053	0.03930***	0.03410***
	(0.00081)	(0.00118)	(0.00197)	(0.00334)
Non-White	0.00122	-0.00053	-0.03930***	-0.03410***
	(0.00081)	(0.00118)	(0.00197)	(0.00334)
Age 16-24 years	0.00292*	0.00302	0.00284	0.00744
	(0.00143)	(0.00244)	(0.00276)	(0.00466)
Age 25-44 years	-0.00223**	-0.00264	0.01301***	0.00942*
	(0.00085)	(0.00143)	(0.00239)	(0.00408)
Age 45-65 years	-0.00069	-0.00038	-0.01585***	-0.01686***
	(0.00093)	(0.00162)	(0.00278)	(0.00453)
Levels of Education				
11 years or less	0.01062***	0.01472***	-0.03926***	-0.03554***
	(0.00192)	(0.00346)	(0.00346)	(0.00600)
High school	0.00169	0.00044	-0.00041	-0.01126*
	(0.00099)	(0.00166)	(0.00316)	(0.00527)
Some college	-0.00158	-0.00254	0.01540***	0.00198
	(0.00107)	(0.00172)	(0.00389)	(0.00647)
Higher college	-0.00637***	-0.00692***	0.01234**	0.01674*
	(0.00078)	(0.00135)	(0.00439)	(0.00728)
College	-0.00437***	-0.00569**	0.01193*	0.02807**
	(0.00117)	(0.00193)	(0.00599)	(0.00999)
Constant	0.01859***	0.01956***	0.31226***	0.30329***
	(0.00115)	(0.00180)	(0.00281)	(0.00472)
R^2	0.007	0.007	0.036	0.031
N	81,748	36,383	135,715	70,383

Note: Weighted regression based on weights provided by the CPS. Robust standard errors (reported in parentheses) were adjusted to take repeated observations of individuals into account. The outflows regression further includes month indicators. $^{*}p < 0.10$,$^{**}\ p < 0.05$,$^{***}\ p < 0.01$..

Table 3: Decomposition Analysis by Groups of Variables

	Raw gap	Explained		Unexplained	
Unemployment inflows					
Difference	0.00141				
	[0.00095]				
Tenure		-0.00015**	-10.5%	0.00005	3.6%
		[0.00005]		[0.00087]	
Gender		-0.00001	-0.4%	0.00002	1.2%
		[0.00002]		[0.00005]	
Race		0.00002	1.2%	0.00121	85.7%
		[0.00002]		[0.00099]	
Age		0.00004	2.5%	-0.00006	-4.5%
		[0.00004]		[0.00087]	
Education		-0.00025***	-17.6%	-0.00043	-30.7%
		[0.00005]		[0.00058]	
Months		0.00029	20.6%	-0.00025	-17.5%
		[0.00059]		[0.00050]	
Constant				0.00094	66.4%
				[0.00213]	
Total		-0.00006	-4.2%	0.00147	104.2%
		[0.00060]		[0.00111]	
N	118,131				
Unemployment outflows					
Difference	-0.01053**				
	[0.00349]				
Unemployment duration		0.00352***	-33.5%	-0.00070	6.7%
		[0.00050]		[0.00232]	
Gender		0.00035**	-3.3%	-0.00001	0.1%
		[0.00013]		[0.00030]	
Race		0.00030	-2.9%	-0.00244	23.1%
		[0.00027]		[0.00182]	
Age		-0.00085***	8.1%	-0.00020	1.9%
		[0.00014]		[0.00066]	
Education		0.00103***	-9.8%	-0.00354	33.6%
		[0.00019]		[0.00228]	
Months		0.00066*	-6.3%	0.00031	-2.9%
		[0.00030]		[0.00041]	
Constant				-0.00897	85.1%
				[0.00549]	
Total		0.00501***	-47.6%	-0.01555***	147.6%
		[0.00071]		[0.00345]	
N	206,098				

Note: Weighted numbers based on weights provided by the CPS. Robust standard errors reported in brackets. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Table 4: Detailed Decomposition of Unemployment Inflows

	Raw gap	Explained		Unexplained	
Difference	0.00141				
	[0.00095]				
Tenure		-0.00015**	-10.5%	0.00005	3.6%
		[0.00005]		[0.00087]	
Male		-0.00000	-0.2%	0.00017	12.1%
		[0.00001]		[0.00050]	
Female		-0.00000	-0.2%	-0.00015	-10.9%
		[0.00001]		[0.00045]	
White		0.00001	0.6%	0.00148	104.6%
		[0.00001]		[0.00121]	
Non-White		0.00001	0.6%	-0.00027	-18.8%
		[0.00001]		[0.00022]	
Age 16-24 years		-0.00002	-1.5%	0.00001	0.9%
		[0.00001]		[0.00036]	
Age 25-44 years		0.00008**	5.8%	-0.00020	-14.5%
		[0.00003]		[0.00080]	
Age 45-65 years		-0.00003	-1.8%	0.00013	9.1%
		[0.00003]		[0.00073]	
11 years or less		-0.00012***	-8.5%	0.00042	29.9%
		[0.00004]		[0.00041]	
High school		-0.00001	-0.7%	-0.00037	-26.1%
		[0.00001]		[0.00056]	
Some college		0.00000	0.3%	-0.00019	-13.8%
		[0.00001]		[0.00041]	
Higher college		-0.00011***	-8.0%	-0.00017	-11.9%
		[0.00003]		[0.00048]	
College		-0.00001	-0.6%	-0.00013	-8.9%
		[0.00001]		[0.00022]	
Months		0.00029	20.6%	-0.00025	-17.5%
		[0.00059]		[0.00050]	
Constant				0.00094	66.4%
				[0.00213]	
Total		-0.00006	-4.2%	0.00147	104.2%
		[0.00060]		[0.00111]	
N	118,131				

Note: Weighted numbers based on weights provided by the CPS. Robust standard errors reported in brackets. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 5: Detailed Decomposition of Unemployment Outflows

	Raw gap	Explained		Unexplained	
Difference	-0.01053**				
	[0.00349]				
Unemployment duration		0.00352***	-33.5%	-0.00070	6.7%
		[0.00050]		[0.00232]	
Male		0.00017**	-1.7%	-0.00007	0.6%
		[0.00006]		[0.00187]	
Female		0.00017**	-1.7%	0.00006	-0.5%
		[0.00006]		[0.00158]	
White		0.00015	-1.4%	-0.00382	36.3%
		[0.00014]		[0.00284]	
Non-White		0.00015	-1.4%	0.00138	-13.1%
		[0.00014]		[0.00103]	
Age 16-24 years		-0.00000	0.0%	0.00153	-14.5%
		[0.00001]		[0.00181]	
Age 25-44 years		-0.00036***	3.4%	-0.00147	14.0%
		[0.00008]		[0.00194]	
Age 44-65 years		-0.00049***	4.6%	-0.00026	2.5%
		[0.00009]		[0.00136]	
11 years or less		0.00080***	-7.6%	0.00102	-9.7%
		[0.00015]		[0.00190]	
High school		-0.00001	0.1%	-0.00369	35.0%
		[0.00002]		[0.00209]	
Some college		0.00002	-0.2%	-0.00248	23.6%
		[0.00004]		[0.00140]	
Higher college		0.00014**	-1.3%	0.00061	-5.8%
		[0.00005]		[0.00117]	
College		0.00009*	-0.8%	0.00100	-9.5%
		[0.00004]		[0.00073]	
Months		0.00066*	-6.3%	0.00031	-2.9%
		[0.00030]		[0.00041]	
Constant				-0.00897	85.1%
				[0.00549]	
Total		0.00501***	-47.6%	-0.01555***	147.6%
		[0.00071]		[0.00345]	
N	206,098				

Note: See note to Table 4. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

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