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Decomposing the Ins and Outs of Cyclical Unemployment

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Ronald Bachmann and Mathias Sinning[1]

Decomposing the Ins and Outs of Cyclical Unemployment

Abstract

This paper analyzes the contribution of the socioeconomic and demographic composition of the pool of employed and unemployed individuals to the dynamics of the labor market in different phases of the business cycle. Using individual level data from the Current Population Survey (CPS), we decompose differences in employment status transition rates between economic upswings and downturns into composition effects and behavioral effects. We find that overall composition effects play a minor role for the cyclicality of the unemployment outflow rate, although the contribution of the duration of unemployment is significant. In contrast, composition effects dampen the cyclicality of the unemployment inflow rate considerably. We further observe that the initially positive contribution of composition effects to a higher unemployment outflow rate turns negative over the course of the recession.

JEL Classification: J63, J64, J21, E24

Keywords: Gross worker flows; unemployment duration; decomposition analysis; Blinder-Oaxaca

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1 Ronald Bachmann, RWI and IZA; Mathias Sinning, Australian National University, RWI and IZA. *– We gratefully acknowledge the support of the Leibniz Association. Participants of meetings of the European Association of Labour Economists, the European Economic Association, the European Society for Population Economics, the Scottish Economic Society and the Royal Economic Society provided valuable comments.* *All correspondence to: Ronald Bachmann, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, E-mail: ronald.bachmann@rwi-essen.de.*

1 Introduction

Starting with the contribution of Shimer (2007), the cyclicality of the U.S. labor market has attracted a great deal of attention recently. The main question in this debate concerns the relevance of the inflows into and the outflows from unemployment, which has typically been addressed by the analysis of aggregate time series of labor market transitions.[1] We contribute to the debate by exploiting the micro information available at the individual worker level to study the underlying composition and behavioral effects of inflows and outflows. Specifically, we use individual-level longitudinal data from the Current Population Survey (CPS) for the time period February 1976 - October 2009 to study the determinants of the transition probabilities from unemployment to employment and from employment to unemployment, respectively. A Blinder-Oaxaca decomposition is employed to decompose the estimated transition probabilities between economic upswings and downturns into a part that is due to "composition effects" (i.e., differences in observed characteristics that describe the socioeconomic and demographic composition of the underlying population) and a part that may be attributed to "behavioral effects" (i.e., different returns to observed characteristics).

The strong increase in long-term unemployment over the last years – especially during the recent recession – has become a serious concern among the public, policy-makers and economists alike (Mukoyama and Sahin, 2009, Elsby et al., 2010). One aim of our analysis is to study the contribution of long-term unemployment to the transition rate from unemployment to employment. More generally, we perform a detailed decomposition of composition effects because we are particularly interested in the contribution of specific single characteristics to the cyclicality of the labor mar-

[1] While earlier studies found inflows into unemployment to be the decisive factor for the cyclicality of unemployment (e.g., Darby et al., 1986, Hall, 2005, Shimer, 2007), more recent articles have established a more balanced role for inflows into and outflows from unemployment (e.g., Elsby et al., 2009, Yashiv, 2008, and Fujita and Ramey, 2009).

ket. Our empirical findings further provide new facts about the dynamic evolution of composition effects over the course of a recession. As spelt out in the final section of this paper, we believe that these facts should be taken into account in the modeling of labor market dynamics.

A strand of the economic literature that is closely related to our analysis explores the duration of unemployment. Most of this literature either focuses on trends in the duration of unemployment over the last decades (e.g., Abraham and Shimer, 2002, Portugal, 2007) or on the latest recession (e.g., Aaronson et al., 2010). Our analysis is closest to Baker (1992) and Elsby et al. (2010). The latter examine the effects of the recession of the late 2000s on unemployment and labor market flows, and compare it to previous recessions. We complement their analysis by focusing on the role of composition effects.

Using CPS data, Baker (1992) scrutinizes the (cyclical) determinants of the expected duration of unemployment of different worker groups as they enter unemployment. He concludes from his results that, during the 1980s, changes in unemployment duration (i.e., composition effects) are the major factor contributing to being unemployed. This finding has been challenged by Shimer (2007). Our empirical findings are in line with those of Baker (1992) for the 1980s and additionally show that the relevance of changes in the duration of unemployment seems to be a special feature of deep recessions.

The findings of a pooled decomposition analysis are as follows. First, our analysis confirms the well-known countercyclicality of the transition rate from employment to unemployment, and the procyclicality of the transition rate in the opposite direction. This has been established by, among others, Blanchard and Diamond (1990), Yashiv (2008) and Fujita and Ramey (2009). Second, the decomposition of the outflow rate reveals that composition effects contribute little to the cyclicality of transitions from unemployment to employment. In contrast, we find that composition effects have a dampening contribution to the unemployment inflow rate. Specifically, without composition effects, the cyclicality of the inflow rate would be about 30 percent higher than actually observed. Third, the composition effects of the inflow rate are driven by job tenure and educational attainment of employed workers, while the duration of unemployment is the most important determinant of the outflow rate, contributing almost nine percent to the difference between economic upswings and downturns.

A decomposition exercise, which takes into account the dynamic evolution of the observed mechanism, reveals that composition effects contribute to a higher unemployment outflow rate early on in a recession. This is mainly due to the fact that there are many people in the pool of the unemployed at the beginning of a recession who have been recently laid off and who are re-hired again relatively quickly. Later on in the recession, the share of long-term unemployed individuals rises, which contributes negatively to the unemployment outflow rate. Finally, we show that while the U.S. recessions since the 1970s exhibit noticeable heterogeneity, several stylized facts common to all recessions can be established with respect to composition effects.

The remainder of this paper is structured as follows. The next section includes a description of the CPS data and presents descriptive evidence. Section 3 explains the empirical approach and discusses methodological issues. Section 4 presents the empirical findings. The final section summarizes and concludes the analysis.

2 Data and Descriptive Analysis

2.1 Data

To analyze transitions from unemployment to employment, we use basic monthly data from the Current Population Survey (CPS) for the time period February 1976 - October 2009, 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.

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

We use an updated version of Shimer's program code to match observations over 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.[4] 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.[5]

To examine transitions from unemployment to employment, we only keep 16 - 65 year old individuals who are unemployed at an initial point in time $t-1$ and are either employed or unemployed at time t. After dropping observations with missing values on one of the variables used in our analysis, our sample of unemployment outflows contains 306,848 observations over the entire sample period. On average, we observe 783 individuals per month. The dependent variable of our analysis of this transition rate is an indicator variable that is equal to one if the observed (initially unemployed) individual has moved from unemployment at time $t-1$ to employment at time t, and zero otherwise.

Our analysis of unemployment inflows 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 labor 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 were collected 11 times in January or February of specific years of the sample period. We thus use this information on job tenure and combine it with information on transitions that are computed from the basic monthly files as described above.

We restrict the sample for the analysis of unemployment inflows to 16 - 65 year old individuals who are employed at an initial point in time $t-1$ and are either

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

[4]As a result of changes in household identifiers in the public-use files, there are several gaps in the time series (see Shimer, 2007 for details).

[5]Unfortunately, a non-representative sample of about 25% of the survey records may not be matched due to sample attrition (Shimer, 2007).

employed of unemployed at time t. After dropping observations with missing values on one of the variables of interest, our sample includes 129,109 observations. Our dependent variable for the analysis of unemployment inflows is an indicator variable that is equal to one if the observed (initially employed) individual has moved from employment at time $t-1$ to unemployment at time t, and zero otherwise.

The set of explanatory variables used in our analysis can be divided into the following groups: unemployment duration/job tenure, education, age, gender, and race. Specifically, we use unemployment duration (in weeks) in the sample of unemployment outflows and focus on job tenure (months with the current employer) in the sample of unemployment inflows. We are particularly interested in the contribution of these variables to the observed employment status transitions. We further control for a set of indicator variables to describe the remaining dimensions. Specifically, we consider the following levels of education: "Less than high school" (11 years or less), "High school" (12 years), "Some college" (13 years), "College" (14 or 15 years), and "Higher college" (16 years or more). Moreover, we generate indicator variables for different age groups (16 - 24 years, 25 - 44 years, and 45 - 65 years), gender (male/female), and race (white/non-white).

2.2 The Cyclicality of the U.S. Labor Market

Our definition of recession dates follows Elsby et al. (2009) who determine start and end dates by the respective minimum and maximum quarterly unemployment rates preceding and following the NBER recession dates. Instead of using the quarterly unemployment rate, we consider the closest local minimum or maximum unemployment rate as a boundary to obtain recession dates that coincide precisely with the lowest and highest unemployment rate of the relevant period.[6,7] Figure 1 displays the

[6]The recessionary periods defined by the NBER's Business Cycle Dating Committee are taken from `http://www.nber.org/cycles`. As noted by Elsby et al. (2009), the NBER recession dates are not suitable for the analysis of labor market dynamics because the NBER definition places a relatively high weight on GDP growth and a lower weight on employment.

[7]Due to the small number of time periods available, we deviate from this strict definition and also consider time periods within three months after a recession as recessionary periods when analyzing unemployment inflows. Specifically, we consider January 1983 and January 2010 as part of the

times of recession considered in our empirical analysis and the U.S. unemployment rate over the sample period.

< Figure 1 about here >

Descriptive evidence on the transitions between employment and unemployment over time is provided in Figures 2 - 4, as well as in Table 1.[8] Figure 2 shows that the transition rate from employment to unemployment is typically higher in a downturn than in an upswing, and average job tenure seems to be higher in recessions than in booms. In contrast, Figure 3 reveals a clear tendency of the unemployment outflow rate to decline in recessions. This pattern is mirrored by an increase in the average duration of unemployment displayed in Figure 4. Figure 4 also reveals that the duration of unemployment typically remains relatively constant or even continues to fall at the beginning of a recession but rises considerably at a later stage of a recessionary period.

< Figures 2 - 4 about here >

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. We further observe that job tenure is countercyclical, while unemployment duration is procyclical. Moreover, the likelihood of changing the employment status (i.e., moving from employment to unemployment or from unemployment to employment) of highly educated individuals increases during recessions, while the corresponding likelihood of less educated individuals declines. The sample averages of the demographic characteristics reveal a similar pattern across the age distribution. Specifically, while the oldest age group is more strongly represented amongst both the employed and the unemployed in recessions, we observe the opposite for young and prime age workers. In contrast to age and education, there appears to be little variation in the gender and race distribution between upswings and downturns.

preceding recessions. Both months are characterized by high transition rates from employment to unemployment.

[8] We present weighted numbers throughout the paper, using weights provided by the basic monthly files of the CPS.

< Table 1 about here >

The linear probability estimates of unemployment inflows and outflows presented in Table 2 are in line with both the descriptive evidence and with the results generally found in the literature (e.g., Nagypál, 2008). Specifically, shorter job tenure and shorter unemployment duration are associated with a higher likelihood of changing the employment status. Moreover, a higher level of education reduces the probability of workers to lose their job and increases the job finding probability of unemployed individuals. Interestingly, the returns to education with regard to unemployment inflows are higher during recessions, i.e., highly educated workers are relatively more likely to keep their job in a downturn compared to an upswing. In contrast, the returns to education with regard to unemployment outflows are lower during recessions. We also find that older workers are significantly less likely to exit unemployment into employment than younger workers, and that the difference in the likelihood of finding a job between younger and older workers is twice as high in a downturn compared to an upswing. Men are more likely to change their employment status than women. We further observe significant differences in the unemployment outflow probability between white and non-white individuals, while racial differences in the inflow probability are not significant.

< Table 2 about here >

In sum, we observe considerable differences in observed characteristics and estimated parameters between upswings and downturns. Although the sample means confirm the countercyclicality of inflows and the procyclicality of outflows, we do not know whether the observed variations in transition probabilities over the business cycle are the result of variations in the socioeconomic and demographic composition of the underlying samples or of variations in behavioral effects (i.e., different returns to certain characteristics). The following sections address this issue in greater detail.

3 Methodology

We perform a decomposition analysis to examine the contribution of composition and behavioral effects to differences in transition probabilities between upswings and downturns. Our analysis uses the sample means and the estimated coefficients of the transition probabilities presented in Tables 1 and 2 as smallest elements of the decomposition equation. Formally, we consider the raw differential in the predicted probability of changing the employment status between recessionary periods (denoted by $d = 1$) and cyclical upswings (denoted by $d = 0$). Specifically, for a given employment status S_t at time t, we observe the outcome

$$Y_{id} = \begin{cases} 1 & \text{if } S_{t-1} \neq S_t \\ 0 & \text{if } S_{t-1} = S_t \end{cases}$$

and a set of characteristics $X_{id} = [X_{id1}, ..., X_{idK}]$ for each individual i in sample d. For simplicity, we assume that the conditional expectation of Y given X is linear[9] so that

$$p_{id} = Pr(Y_{id} = 1|X_{id}) = E(Y_{id}|X_{id}) = \beta_{d0} + \sum_{k=1}^{K} X_{idk}\beta_{dk}, \tag{1}$$

where the model parameters are given by the vector $\beta_d = [\beta_{d0}, \beta_{d1}, \beta_{d2}, ..., \beta_{dK}]'$. To isolate the part of the raw differential in the predicted probability of changing the employment status attributable to differences in composition effects (observed characteristics) from the part due to differences in behavioral effects (model parameters), we employ the decomposition proposed by Blinder (1973) and Oaxaca (1973) and generalized by Oaxaca and Ransom (1994), which can be written as follows:

$$\begin{aligned} \widehat{p}_{i1} - \widehat{p}_{i0} &= \underbrace{\sum_{k=1}^{K} (\overline{X}_{1k} - \overline{X}_{0k})\beta_k^*}_{\text{composition effects}} \\ &+ \underbrace{(\widehat{\beta}_{10} - \widehat{\beta}_{00}) + \sum_{k=1}^{K} \left[\overline{X}_{1k}(\widehat{\beta}_{1k} - \beta_k^*) + \overline{X}_{0k}(\beta_k^* - \widehat{\beta}_{0k}) \right]}_{\text{behavioral effects}}, \end{aligned} \tag{2}$$

[9]We use estimates of a linear probability model to avoid problems of non-linear decomposition methods, such as path dependency (see Fortin et al., 2011).

where hats denote estimated parameters, bars denote sample means, and the reference vector β^* is given by the linear combination $\beta^* = \Omega\widehat{\beta}_1 + (I - \Omega)\widehat{\beta}_0$.[10]

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 a different composition of the two samples with regard to observed characteristics. For example, a larger number of individuals with short unemployment duration in the pool of the unemployed during recessions would be associated with an increase in outflows from unemployment. The second term on the right-hand side of the equation may be interpreted as being due to "behavioral effects", i.e., differences in the returns to observable characteristics. For example, workers with a specific skill level may exhibit different transition probabilities during recessions and upswings, which would imply that the "pay-offs" to certain worker characteristics (in terms of transition probabilities) vary over of the business cycle.

To understand the factors that contribute to differences in transition probabilities between economic upswings and downturns, we also perform a detailed decomposition of the raw differential into components describing the contribution of single (groups of) characteristics.[11] A detailed decomposition is not unproblematic because arbitrary scaling of continuous variables may affect the components of the gap attributable to different coefficients (Jones, 1983; Jones and Kelley, 1984; Cain, 1987; Schmidt, 1998). Consequently, we focus on overall behavioral effects and do not perform a detailed decomposition of this component.

A problem related to the detailed decomposition of dummy variables is the arbitrary choice of reference categories that are omitted from the regression model due to collinearity (Schmidt, 1998; Oaxaca and Ransom, 1999; Horrace and Oaxaca, 2001; Gardeazabal and Ugidos, 2004; Yun, 2005). Although a normalization may avoid

[10]Numerous studies have addressed the problem of the particular choice of the weighting matrix Ω and the resulting reference vector (Blinder, 1973; Oaxaca, 1973; Reimers, 1983; Cotton, 1988; Neumark, 1988). We employ an approach proposed by several recent studies (Fortin, 2008; Jann, 2008; Elder et al., 2010) and estimate the reference vector through a pooled regression model over both samples, including a sample-specific intercept.

[11]Jann (2008) describes the calculation of standard errors of all components of the decomposition equation.

having omitted reference categories (Gardeazabal and Ugidos, 2004; Yun, 2005), it complicates the economic interpretation of the decomposition results (Gelbach, 2002; Fortin et al., 2011). Our detailed decomposition analysis focuses on groups of dummy variables, which are not affected by the choice of reference categories.

In addition to a pooled decomposition analysis of complete upswing and downturn periods, we are also interested in the evolution of the quantitative relevance of composition effects for the transition probability from unemployment to employment from the beginning to the end of each recession. In order to do so, we compare every upswing in our sample with specific data from the following recession. For every such comparison, we use the data on the entire upswing and a "slice" of the following recession, which is gradually extended, and perform the decomposition analysis outlined above on these data.

For example, when taking the first boom-recession pair in our sample, we start by selecting the data on the entire upswing (1976:2 - 1979:4) as well as the first recessionary month (1979:5) to obtain the decomposition results for the change in transition probabilities between these two time periods. We obtain a second set of results by comparing the entire upswing (1976:2 - 1979:4) with the first two recessionary months which follow (1979:5 - 1979:6). We gradually extend the recessionary period considered until the end of the recession is reached. In sum, we compare the period 1976:2 - 1979:4 with the time periods {1979:5, 1979:5 - 1979:6, 1979:5 - 1979:7, ..., 1979:5 - 1980:7}. We perform this exercise separately for each of the five upswings that were followed by a recession over the time period 1976:2 - 2009:10. The decomposition results obtained from this analysis allow us to trace the dynamic evolution of the role of composition effects for the recessions in our sample.

4 Results

The decomposition method described in the previous section allows us to examine the contribution of composition and behavioral effects to business cycle variations. We begin by studying the raw differential in transition probabilities between downturns and upswings, using a pooled sample. Since job tenure is only available for a few years during the period 1983:1 - 2010:1, we limit our analysis of unemployment inflows to a pooled sample.

To study unemployment outflows, we also use a pooled sample of the period 1976:2 - 2009:10. Additionally, we perform a separate analysis of unemployment outflows for different pairs of booms and recessions and further examine the extent to which composition effects evolve over the business cycle by comparing entire upswings with cumulative parts of the following recessions. Since we are primarily interested in the contribution of the socioeconomic and demographic composition of the underlying populations to the raw differential in transition probabilities between downturns and upswings, a number of relevant (observable and unobservable) factors are not considered in our analysis. Consequently, we expect that a sizeable part of the observed cyclicality may be attributed to behavioral effects, i.e., changes in transition probabilities that apply to all workers with certain (observed or unobserved) characteristics. Our main objective is to gain a better understanding of the impact of the composition of specific groups (such as individuals with a certain level of education) on overall transitions.

4.1 Composition Effects and Labor Market Flows

The results of the decomposition analysis of the pooled samples of unemployment inflows and outflows are presented in Table 3. The observed difference in unemployment inflow probabilities between downturns and upswings is relatively small but significantly positive, reflecting the countercyclicality of transitions from employment to unemployment. We find that overall composition effects have a negative sign, indicating that they have a dampening impact on the cyclicality of unemployment inflows. Specifically, overall composition effects reduce the cyclicality of the unemployment inflow rate by 27.3 percent. This result is mainly driven by the composition of workers with regard to job tenure and educational attainment in different phases of the business cycle.

The contribution of job tenure to the raw differential is negative because jobs with shorter tenure are more likely to be destroyed in a recession than jobs with longer tenure. Since the latter jobs are generally more stable, changes in job tenure reduce unemployment inflows in recessions. Composition effects with regard to education have a similar dampening impact. In particular, the educational composition of workers reduces unemployment during recessions because highly educated workers are more likely to keep their jobs in a recession than less educated workers. We find that the dampening impact of job tenure accounts for 10.4 percent of the increase in unemployment inflows during recessions, while the negative contribution of education even makes up 18.2 percent.

< Table 3 about here >

The raw differential of unemployment outflows is significantly negative, reflecting that the transition rate from unemployment to employment is lower during recessions. We find that overall composition effects are also negative, i.e., they contribute to the general labor market development in a recession, although the overall contribution of observed characteristics to the raw differential is only 1.9 percent.

The small contribution of composition effects may be attributed to varying signs of the contributions of the underlying groups of variables, which partly cancel each other out. Above all, the contribution of unemployment duration is significantly negative, accounting for almost nine percent of the raw differential in unemployment outflows between booms and recessions. The negative composition effect with regard to age contributes an additional 2.3 percent to the raw differential. In contrast, the components of the remaining variable groups have a positive sign and therefore exert a dampening effect on the cyclicality of unemployment outflows. Most notably, the education level of the unemployed in a recession changes in such a way that unemployment outflows would (all else equal) actually increase during a recession. This result may be attributed to the positive impact of education on unemployment outflows and a decline in the share of less educated individuals in the pool of the unemployed during a recession.

The pooled decomposition analysis of the cyclicality of transitions between employment and unemployment could hide important differences between downturns and upswings. To address this issue, we perform a separate decomposition analysis for each upswing and the following downturn in the sample period. Due to data limitations, our analysis focuses on unemployment outflows. We further pay particular attention to the duration of unemployment, which turned out to have the strongest contribution to the raw differential (see Table 3).

The numbers in Table 4 show that the unemployment outflow rate is significantly lower in recessions than in booms for virtually all cases considered, with the first time period being the only exception. While the contribution of behavioral effects to the raw differential is positive in all cases, the estimates point to substantial heterogeneity in the contribution of composition effects over time. Specifically, overall composition effects of recessions in the early 1980s and 1990s are positive, while they are insignificant for the remaining time periods. The estimates suggest that the contribution of the duration of unemployment to the raw differential may be either positive or negative, while the composition effects due to "remaining factor" are either significantly positive or insignificant.

< Table 4 about here >

On balance, the estimates presented in Table 4 reveal some commonalities and considerable heterogeneity with regard to the contribution of composition effects. The strong variation across time periods could be due to the fact that booms and recessions are different with respect to their length and magnitude, which could generate differing dynamics. The next section explores this possibility.

4.2 The Dynamics of Composition Effects

To examine the evolution of the contribution of composition effects to the raw differential from the beginning to the end of a recession, we compare every upswing in our sample with cumulative parts of the following recession. This approach allows us to study the contribution of the changing duration of unemployment as the economy slides deeper into recession. Figures 5 - 9 depict the results of this exercise for the raw differential and the duration of unemployment. The data points presented for each point in time are obtained from a separate decomposition analysis of the entire upswing and a cumulative part of the following recession. Therefore, the last set of data points displayed in each figure is a graphical representation of the raw differential and the part that is due to changes in the duration of unemployment reported in Table 4.

< Figures 5 - 6 about here >

Two facts that are common to the last four recessions under investigation become apparent from Figures 6 - 9.[12] First, the raw differential quickly increases at the beginning of a recession before starting a gradual but sustained decline, turning negative before the end of all four recessions. Second, the contribution of the composition effect with regard to unemployment duration is positive at the beginning of each recession, but then gradually falls, taking on a negative sign at the end of two of the four recessions.

These two stylized facts are intimately related. At the beginning of a recession, there are many people in the pool of the unemployed who recently lost their jobs, and whose chances of being re-hired quickly are relatively high. In addition, firms might use this opportunity to engage in worker churning to improve the quality of their workforce (Burda and Wyplosz, 1994). Compared to the preceding upswing, this process leads to a relatively high outflow rate from unemployment. Therefore, the composition effect with regard to unemployment duration is positive at this stage of the recession.

< Figure 7 - 9 about here >

As the recession continues, the share of short-term unemployed individuals in the pool of the unemployed gradually falls, as does the outflow rate from unemployment. At the end of two of the four recessions considered – the recession in 1981/1982 and

[12] The recession of the early 1980s does not share either of these two facts. This is in all likelihood due to the double-dip nature of the two recessions at the beginning of the 1980s.

the last “Great Recession” – , both the raw differential and the part attributable to the duration of unemployment are negative. This result implies that the duration of unemployment contributes to a reduced unemployment outflow rate at the end of these two recessions, which were particularly severe (see, e.g., Romer, 2006, Table 4.1).

In the middle of a recession, the outflow rate is typically lower than in the preceding upswing, but the share of short-term unemployed persons is still relatively high. Therefore, the composition effect with regard to unemployment duration exerts a dampening role on the outflow rate at this intermediate stage of a recession. This feature can be observed in the middle of the two severe recessions of the 1981/1982 and of the late 2000s, as well as at the end of the recession of the early 1990s, which was relatively shallow.

5 Conclusions

The recent “Great Recession” has further increased the interest in the cyclical nature of both labor market transitions and the duration of unemployment. We contribute to the debate by investigating the underlying composition and behavioral effects of unemployment inflows and outflows. A Blinder-Oaxaca decomposition is employed to decompose the differential in employment status transition rates between economic downturns and upswings into a part that is attributable to changes in the socioeconomic and demographic composition of the underlying population and a part that is due to changes in the returns to characteristics. The decomposition analysis allows us to establish several stylized facts regarding the role of composition effects for labor market dynamics.

The decomposition of the unemployment inflow rate reveals that composition effects exert a dampening impact on unemployment inflows during recessions. Specifically, without composition effects, the cyclicality of the inflow rate would be about 30 percent higher than actually observed. The results of a detailed decomposition indicate that composition effects of the inflow rate are mainly driven by the composition of workers with regard to job tenure and educational attainment in different phases of the business cycle.

While composition effects have a considerable contribution to the cyclicality of unemployment inflows, they contribute little to the cyclicality of unemployment outflows. However, the small contribution of overall composition effects to the raw differential of unemployment outflows are the result of varying signs of the contributions of underlying variables. In particular, our detailed decomposition results reveal that the duration of unemployment contributes almost nine percent to the overall difference in the unemployment outflow rate between economic downturns and upswings.

We further observe that composition effects contribute to a higher unemployment outflow rate early on in a recession. At this point, the unemployment outflow rate even rises relative to the preceding upswing. This is mainly due to the fact that at the beginning of a recession, there are many people in the pool of the unemployed who have been recently laid off and who are re-hired again relatively quickly. Later on in the recession, the share of long-term unemployed individuals rises, which exerts a negative impact on the unemployment outflow rate. This result is consistent with Elsby et al. (2010) who find that while unemployment inflows are more important at an early stage of a recession, outflows take over later on.

Our results have two main implications for the modeling of labor market dynamics. First, worker heterogeneity seems crucial for an explanation of the stylized facts uncovered. This is especially true for the fact that the unemployment inflow rate first rises and then declines in a recession (see, e.g., Pries (2008) and Bils et al. (2011) for extended versions of the Mortensen and Pissarides (1994) model). Second, the sorting of workers over the business cycle seems to play an important role, as highlighted by the fact that the composition effect with regard to unemployment duration gradually turns negative over the course of a recession. In this context, heterogeneity on both sides of the labor market – , i.e., business cycle variations in the type of firms that hire specific types of workers (Bachmann and David, 2010; Moscarini and Postel-Vinay, 2011) – is likely to have an impact. However, the relevance of two-sided heterogeneity for the dynamics of the role of composition effects is left to future research.

Tables and Figures

Figure 1: The U.S. Unemployment Rate

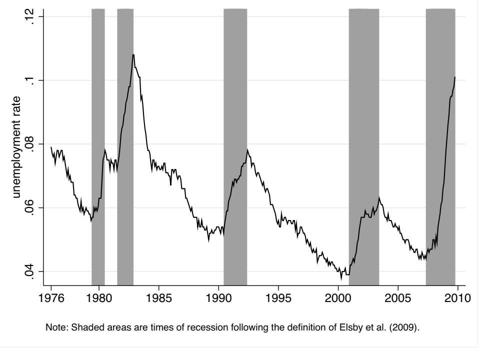


Figure 2: The Transition Rate from Employment to Unemployment and Tenure

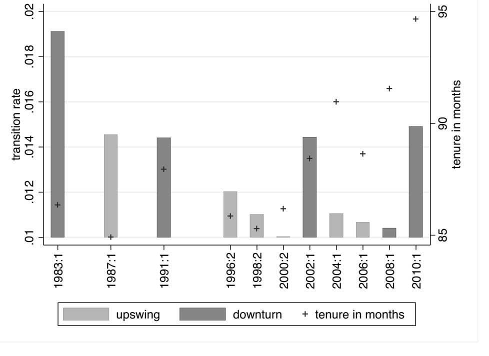


Figure 3: The Transition Rate from Unemployment to Employment

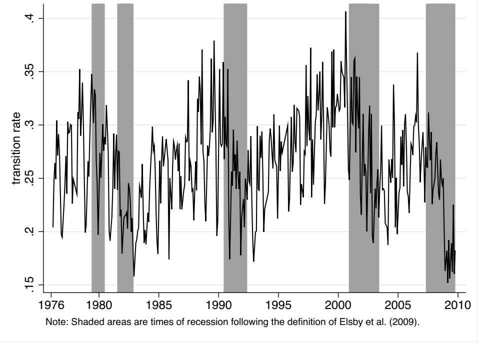
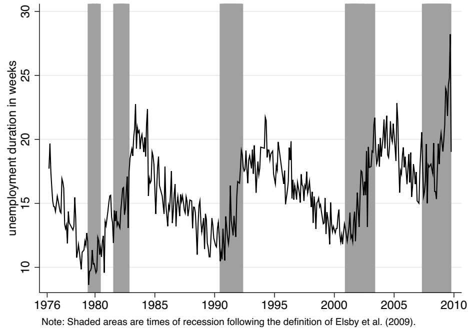


Figure 4: Unemployment Duration



Note: Shaded areas are times of recession following the definition of Elsby et al. (2009).

Table 1. Summary Statistics

	Inflows Sample		Outflows Sample	
	Upswing	Downturn	Upswing	Downturn
Transition rate from employment to unemployment	1.09	1.32		
	(10.40)	(11.41)		
Transition rate from unemployment to employment			28.20	23.50
			(45.00)	(42.40)
Tenure in months	87.39	91.51		
	(95.90)	(98.58)		
Unemployment duration in weeks			17.15	18.56
			(23.04)	(22.56)
Education (Percentages)				
11 years or less	11.11	9.51	29.56	24.92
	(31.43)	(29.33)	(45.63)	(43.25)
High school	29.72	28.57	33.92	34.35
	(45.70)	(45.18)	(47.34)	(47.49)
Some college	20.27	19.77	18.01	19.00
	(40.20)	(39.82)	(38.43)	(39.23)
College	9.46	9.81	5.77	6.72
	(29.26)	(29.74)	(23.33)	(25.04)
Higher college	29.44	32.35	12.73	15.01
	(45.58)	(46.78)	(33.34)	(35.72)
Demographics (Percentages)				
Age 16-24 years	13.22	12.10	33.64	30.91
	(33.87)	(32.62)	(47.25)	(46.21)
Age 25-44 years	50.61	46.20	43.28	41.27
	(50.00)	(49.86)	(49.55)	(49.23)
Age 45-65 years	36.17	41.70	23.08	27.82
	(48.05)	(49.31)	(42.13)	(44.81)
Male	52.77	52.44	53.31	55.96
	(49.92)	(49.94)	(49.89)	(49.64)
White	85.57	84.41	73.28	73.80
	(35.14)	(36.28)	(44.25)	(43.97)
N	69,110	59,999	204,481	102,367

Note: Standard deviations are reported in parentheses.

Table 2. Determinants of Transition 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 weeks			-0.00290***	-0.00273***
			(0.00007)	(0.00009)
Education				
High school	-0.00891***	-0.01347***	0.04121***	0.01811**
	(0.00256)	(0.00392)	(0.00461)	(0.00575)
Some college	-0.01225***	-0.01621***	0.05947***	0.02479***
	(0.00258)	(0.00394)	(0.00556)	(0.00671)
College	-0.01500***	-0.02081***	0.05717***	0.03816***
	(0.00268)	(0.00399)	(0.00834)	(0.00969)
Higher college	-0.01697***	-0.02162***	0.05995***	0.03757***
	(0.00242)	(0.00375)	(0.00637)	(0.00746)
Demographics				
Age 25-44 years	-0.00516*	-0.00736*	0.01271**	-0.00213
	(0.00217)	(0.00317)	(0.00446)	(0.00554)
Age 45-65 years	-0.00359	-0.00554	-0.01464**	-0.02791***
	(0.00226)	(0.00332)	(0.00513)	(0.00601)
Male	0.00390***	0.00625***	0.03538***	0.01901***
	(0.00100)	(0.00138)	(0.00362)	(0.00432)
White	-0.00244	-0.00052	0.07942***	0.06101***
	(0.00161)	(0.00211)	(0.00406)	(0.00485)
Constant	0.03137***	0.03745***	0.17043***	0.18655***
	(0.00329)	(0.00481)	(0.00782)	(0.00969)
R^2	0.007	0.008	0.037	0.031
N	69,110	59,999	204,481	102,367

Note: $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Robust standard errors are reported in parentheses. The regression model further includes month indicators.

Table 3. Decomposition Analysis

	Unemployment Inflows		Unemployment Outflows	
Raw differential	0.00227**	100.0%	-0.04696***	100.0%
	[0.00086]		[0.00285]	
Composition effects				
Tenure	-0.00024***	-10.4%		
	[0.00005]			
Unemployment duration			-0.00402***	8.6%
			[0.00044]	
Education	-0.00041***	-18.2%	0.00226***	-4.8%
	[0.00006]		[0.00022]	
Age	0.00002	1.1%	-0.00109***	2.3%
	[0.00005]		[0.00017]	
Gender	-0.00002	-0.7%	0.00076***	-1.6%
	[0.00002]		[0.00012]	
Race	0.00002	0.9%	0.00038*	-0.8%
	[0.00002]		[0.00022]	
Seasonal Trend			0.00081***	-1.7%
			[0.00024]	
Total	-0.00062***	-27.3%	-0.00089	1.9%
	[0.00009]		[0.00062]	
Behavioral effects				
Total	0.00289***	127.3%	-0.04607***	98.1%
	[0.00086]		[0.00282]	
N	129,109		306,848	

Note: $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$. Robust standard errors are reported in brackets.

TABLE 4. Decomposition of Outflows by Time Period

	Upswing followed by Downturn				
	1976:2 – 1980:7	1980:8 – 1982:12	1983:1 – 1992:6	1992:7 – 2003:6	2003:7 – 2009:10
UNEMPLOYMENT OUTFLOWS					
Raw differential	0.01955***	-0.04062***	-0.01115***	-0.03071***	-0.05222***
	[0.00516]	[0.00544]	[0.00378]	[0.00414]	[0.00409]
Composition effects	0.01658***	-0.00258	0.00876***	-0.00040	0.00067
	[0.00145]	[0.00170]	[0.00083]	[0.00090]	[0.00095]
	(84.8)	(6.4)	(-78.6)	(0.0)	(-1.3)
Unemployment duration	0.01047***	-0.00368***	0.00440***	-0.00035	-0.00454***
	[0.00068]	[0.00065]	[0.00047]	[0.00058]	[0.00063]
	(53.5)	(9.1)	(-39.5)	(1.1)	(8.7)
Remaining factors	0.00611***	0.00110	0.00436***	-0.00005	0.00521***
	[0.00130]	[0.00157]	[0.00068]	[0.00067]	[0.00071]
	(31.3)	(-2.7)	(-39.2)	(0.2)	(-10.0)
Behavioral effects	0.00297	-0.03804***	-0.01991***	-0.03031***	-0.05290***
	[0.00520]	[0.00551]	[0.00375]	[0.00411]	[0.00407]
	(15.2)	(93.6)	(178.6)	(98.7)	(101.3)
N	40,890	33,218	95,520	82,321	54,899

Note: $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$. Robust standard errors are reported in brackets. Percentages in parentheses.

Figure 5: Decomposition of Outflow Rate: 1976:2 - 1979:4 vs. {1979:5, 1979:5 - 1979:6, 1979:5 - 1979:7, ..., 1979:5 - 1980:7}

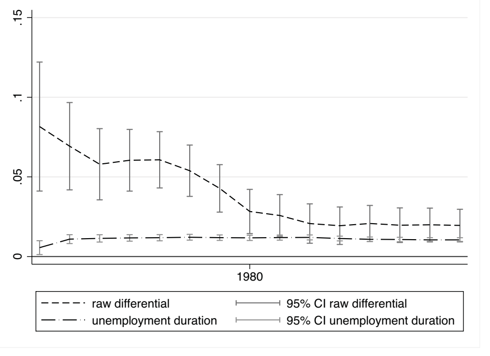


Figure 6: Decomposition of Outflow Rate: 1980:8 - 1981:6 vs. {1981:7, 1981:7 - 1981:8, 1981:7 - 1981:9, ..., 1981:7 - 1982:12}

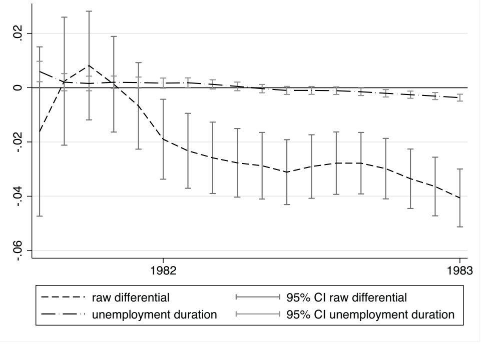


Figure 7: Decomposition of Outflow Rate: 1983:1 - 1990:5 vs. {1990:6, 1990:6 - 1990:7, 1990:6 - 1990:8, ..., 1990:6 - 1992:6}

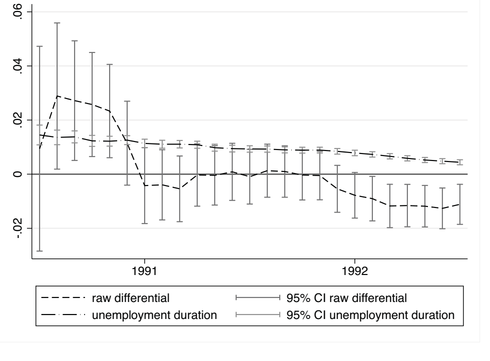


FIGURE 8: Decomposition of Outflow Rate: 1992:7 - 2000:10 vs. {2000:11, 2000:11 - 2000:12, 2000:11 - 2001:1, ..., 2000:11 - 2003:6}

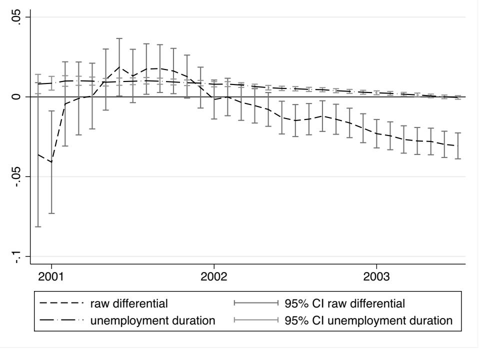
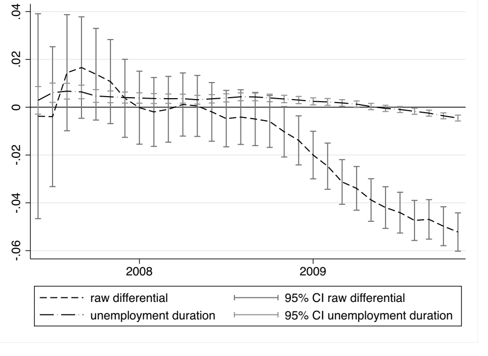


FIGURE 9: Decomposition of Outflow Rate: 2003:7 - 2007:4 vs. {2007:5, 2007:5 - 2007:6, 2007:5 - 2007:7, ..., 2007:5 - 2009:10}



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