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Shigeru Fujita
Federal Reserve Bank of Philadelphia

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Effects of Extended Unemployment Insurance Benefits: Evidence from the Monthly CPS*

Shigeru Fujita†

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Abstract

This paper attempts to quantify the effects of extended unemployment insurance benefits in recent years. Using the monthly Current Population Survey, I estimate unemployment-to-employment (UE) hazard function and unemployment-to-inactivity (UN) hazard function for male workers. The estimated hazard functions for the period of 2004-2007, during which no extended benefits were available, exhibit patterns consistent with the expiration of regular benefits at 26 weeks. These patterns largely disappear from the hazard functions for the period of 2009-2010, during which large-scale extended benefits had become available. I conduct counterfactual experiments in which the estimated hazard functions for 2009-2010 are replaced by the counterfactual hazard functions whose patterns are inferred from those for the 2004-2007 period. The experiments suggest that extended benefits in recent years have raised male workers' unemployment rate by 1.2 percentage points with a 90% confidence interval of 0.8 to 1.8 percentage points. The increases in the unemployment rate largely come from the effects on the UE hazard function rather than the UN hazard function.

JEL codes: J08, J64, J65.
Keywords: Unemployment, unemployment insurance, and extended benefits.

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†Research Department, Federal Reserve Bank of Philadelphia. Ten Independence Mall, Philadelphia, PA 19106. E-mail: shigeru.fujita@phil.frb.org

1 Introduction

Whether or not the large-scale extensions of unemployment insurance (UI) benefits in recent years have contributed to raising the observed unemployment rate is an important policy question. There are only a few studies on this issue that directly use recent data, even though the effects of UI benefits on workers' search behavior in general have been studied extensively in the past. In this paper, I use the monthly Current Population Survey (CPS) data to estimate unemployment-to-employment (UE) transition rates and unemployment-to-inactivity (UN) transition rates by unemployment duration. I do this for all male workers.

Existing studies are often based on the UI administrative records and typically look at whether there is any spike in *exit* rates around the expiration dates, without distinguishing between job finding and dropping out of the labor force. It is, however, important to distinguish between the two outcomes, since a spike in the UN transition rate can occur without any changes in workers' search behavior.[1] Important studies based on the administrative records include Moffitt (1985), Katz and Meyer (1990), Meyer (1990), and Card and Levine (2000).

I use the monthly CPS to estimate the two exit rates. The information in the survey data such as the CPS may not be as precise as those in the administrative records. However, there are several advantages. First, the CPS allows me to calculate the UE and UN transition rates separately, since tracking workers' labor market status is one of the main purposes of the CPS. Second, it is pretty much the only publicly available data source that covers the most recent recession. Last, it is used for the Bureau of Labor Statistics' (BLS) official labor market statistics such as the unemployment rate. This allows me to easily translate the effects on transition rates into the unemployment rate. Fallick (1991) and McCall (1996) also use survey data, namely, the CPS Displaced Worker Survey (DWS), which covers a subset of workers in the CPS. The focus of their studies is to distinguish between transitions into part-time and full-time jobs. They do not consider transitions into inactivity.

I combine the information on duration of unemployment and transitions into employment and inactivity. First, I correct the measurement problem that creates inconsistency between the duration and transition information. Using the reconciled data, I then present UE and UN hazard functions by estimating a multinomial logit regression. The sample covers the period between January 2004 and July 2010, excluding the observations for 2008. The data prior to 2008 are used to infer the shape of the hazard functions when no UI benefits are available beyond 26 weeks, whereas the post-2008 data are used to estimate the hazard functions during the period of large extensions. Note that the first extension in response to the Great Recession is introduced in the middle of 2008. By excluding the 2008 data, I can clearly contrast the shapes of the hazard functions between the period with and without extensions. In the regression, UE and UN transitions depend on unemployment duration and the availability of extended benefits. The extension dummy is further interacted with unemployment duration so that the effect of the extensions can differ at different unem-

[1] Using high-quality administrative data in Austria, which can trace workers' labor market status after the exit, Card et al. (2007) find that the spike in the exit rate is often driven by dropping out of the labor force, and they call this effect the "reporting effect."

ployment durations. The regression also includes the aggregate job vacancy rate in order to control for the difference in the business cycle conditions as well as other variables that capture worker' individual characteristics.

I find that the fitted hazard functions for the two periods differ markedly. First, both UE and UN hazard functions for the earlier period are located above those for the latter period. Not surprisingly, job finding transition rates are lower, and transitions into inactivity are also less likely to occur at all unemployment durations in the latter period.[2] Second, the shapes of the hazard functions also differ between those two periods: The fitted UE hazard function for the 2004-2007 period exhibits a hump around the expiration of regular benefits, while the hump completely disappears from the fitted UE hazard function for the 2009-2010 period. The fitted UN hazard functions for both periods show a spike at the duration bin that includes 26 weeks, but the jump for the earlier period is much larger. These patterns are consistent with the fact that UI benefits expire at 26 weeks in the earlier sample, while the eligibility period is greatly expanded beyond 26 weeks in recent years.

The estimated regression is used to infer the counterfactual hazard functions for the 2009-2010 period that would have prevailed without the extensions. The shapes of the counterfactual hazard functions are inferred from those for the 2004-2007 period. However, the composition of the unemployment pool and the job vacancy rate are kept the same as in the 2009-2010 period. I find that the counterfactual UE transition rates are higher at almost all durations and that the differences between the counterfactual and actual transition rates are statistically significant. This means that without extended benefits, the unemployed workers would have found jobs more quickly, which in turn would have reduced the measured unemployment rate. On the other hand, the counterfactual UN hazard function is statistically indistinguishable from the actual hazard function.

I translate the effects on the hazard functions into the unemployment rate by comparing the steady-state unemployment rate under the actual and counterfactual hazard functions. I find that the effect on unemployment amounts to 1.2 percentage points. The 90% confidence interval around this point estimate is computed to be between 0.8 to 1.8 percentage points. Consistent with the previous finding that the counterfactual UN hazard function cannot be distinguished statistically from the actual one, the effect on the unemployment rate largely comes from the effects of the UE transition rates. My estimates are on the high side relative to recent two empirical studies by Valletta and Kuang (2010) and Aaronson et al. (2010). The approach of this paper differs significantly from those taken in these two papers. The main difference is that I directly use the information on the hazard functions.[3] A recent study by Nakajima (2011) uses a quantitative model of labor market search with wealth

[2]Note that the transition rate into inactivity is lower during recessionary periods in general. This is not inconsistent with the "discouraged worker effect." That is, even though the transition rate is lower, the number of unemployed workers who drop out of the unemployment pool is larger because the size of the unemployment pool is greater during recessions.

[3]Schmieder et al. (2010) estimate the effects of extended UI benefits in Germany. But the UI systems of the two countries are sufficiently different, and thus it is difficult to apply the implications of their study to the U.S. labor market. See also Barnichon and Figura (2010) who examine the effects of the extended UI benefits on the declines in matching efficiency inferred from estimating the aggregate matching function.

accumulation to estimate the effects on the unemployment rate. Nakajima's estimates are in line with the estimates of this paper.

In the next section, I discuss the data and present the econometric specification. Section 3 presents the estimation results, including the fitted hazard functions for the 2004-2007 period and 2009-2010 period, and discusses the differences between them. The counterfactual hazard functions are then discussed. Section 4 translates the effects on hazard functions into the effects on the unemployment rate. Section 4 concludes the paper. Appendix A discusses the inconsistency between the duration and worker transition data in the CPS and discusses the methodology to reconcile it. Appendix B presents the detailed descriptions of the explanatory variables used in the regressions. Appendix C provides a brief description of emergency unemployment insurance programs in recent years.

2 Data and Methodology

The CPS covers a large sample of individual U.S. workers each month, ascertaining whether they are employed and, if not employed, whether they engaged in active job search activities over the preceding month. After entering the sample, a household is surveyed for four consecutive months. Following an eight-month hiatus, it is surveyed again for four consecutive months. Month-over-month transitions between employment, unemployment, and not-in-the-labor-force (NILF) status can be measured by matching individual workers who are in the CPS sample for two consecutive months. Owing to the sample rotation and the eight-month gap, at most 75% of the individual workers in the sample can be matched. This study is based on this monthly matched CPS data.[4] Each two-period panel contains the information regarding workers' labor market transitions from the first month to the next month. It also includes unemployment duration (if the worker is unemployed) as well as other standard observable characteristics. I can thus calculate the unemployment-to-employment (UE) transition rates and unemployment-to-NILF transition rates (UN) by duration. The analysis in this paper focuses on the sample of male workers as in Moffitt (1985), Meyer (1990) and Katz and Meyer (1990) given that women are often secondary earners in a household, which may complicate the interpretation of the results.

I make an adjustment to the worker transition data. Remember that worker transitions are constructed by matching individual workers between the adjacent two months, whereas unemployment duration is asked directly to unemployed workers. When a worker is unemployed for two consecutive months, the CPS's dependent-interview procedure automatically assumes that the worker is continuously unemployed with no intra-month employment spell. I assume that this procedure is plausible.[5] However, when a worker reports that he/she is unemployed, transitioning from other labor market status in the previous month, or when he/she is in the incoming rotation group, the worker reports unemployment duration (in

[4]I use Robert Shimer's matching algorithm. I would like to thank him for posting the Stata code on his website.

[5]This technique is introduced at the time of the CPS redesign implemented in 1994, after the BLS's extensive research.

weeks). The adjustment is made on the first of these two cases: When a worker reported "employed" or "NILF" in the previous month's survey, the worker cannot logically be unemployed for more than 5 weeks. However, these logical conditions are often violated. This inconsistency happens more frequently when the worker's previous month labor market status is NILF. When this logical inconsistency is observed in the data (for example, a worker reports that his unemployment duration is 26 weeks even though he reported NILF in the previous month's survey), I assume that the previous month's labor market status was misreported. This means that in the corrected data, the worker with an inconsistent transition is assumed to be unemployed in the previous month. Since I use the duration data and worker transition data simultaneously in my analysis, it is important to ensure that the two sets of information are consistent with each other.[6] Appendix A presents the details of these adjustments.

2.1 Econometric Specification

I run the following multinomial logit regression using the sample of (male) unemployed workers in the first of the two months. There are three possible binary outcomes that occur in the second month: (i) stay unemployed, (ii) find a job, and (iii) drop out of the labor force. Let s_i be the labor market status in $t+1$ of an unemployed individual i in t. s_i takes one of the three outcomes $\{e, u, n\}$ (employed, unemployed, NILF, respectively). The probability of a transition into s is then modeled by:

$$\Pr(s_i) = \frac{\exp^{f_s(.)}}{\sum_s \exp^{f_s(.)}}. \tag{1}$$

I parameterize the $f_s(.)$ function as follows:

$$f_s(X_i, D_i, EB, v_t) \equiv \alpha_s' X_i + \beta_s' D_i + EB\Delta_s' D_i + \eta_s v_t, \tag{2}$$

where explanatory variables are partitioned into different groups. First, a vector X_i represents time-invariant individual characteristics, and their effects on outcome s are measured by a vector α_s. The variables included in this vector are (i) race, (ii) marital status, (iii) relationship to the reference person, (iv) educational attainment, (v) industry in the previous employment, and (vi) age and age squared. Details of each variable are presented in Appendix B. Second, the variable D_i is a vector of dummy variables, indicating which duration bin the worker is in and the coefficient vector β_s measures the effects on outcome s. In the CPS, unemployment duration is reported in weeks, but I group the reported durations into the following 12 categories: less than or equal to 4 weeks, $5-8$ weeks, $9-12$ weeks, $13-16$ weeks, $17-20$ weeks, $21-24$ weeks, $25-28$ weeks, $29-32$ weeks, $33-40$ weeks, $41-68$ weeks, $69-96$ weeks, and 97 weeks or more.[7] Third, a dummy variable EB

[6]Note that in empirical macro/labor literature, both duration data and worker transition data are used. However, they are used only separately. There is, however, little attempt to combine the two sets of information, as I do in this paper.

[7]The first duration bin (i.e., less than or equal to 4 weeks) is taken to be the base category.

takes 1 when extended benefits are available and 0 otherwise. In other words, if a worker is unemployed during the 2009-2010 period, then $EB = 1$ and 0 otherwise. Δ_s is a 12-by-1 vector that measures the effects of benefit extensions at each duration category. The second and third terms in Equation (2) allow me to capture the shape of the hazard functions in a flexible manner. For example, it allows for a jump in the transition rate at a certain duration bin. The effects of the extended benefits are also allowed to differ at different duration bins. Lastly, v_t represents the job vacancy rate in month t measured in the JOLTS, and its coefficient η_s captures the effects of the changes in v_t on outcome s. This variable serves to control for the availability of jobs at the aggregate level. Further discussion on this point follows.

Discussions on the specification choices. As already mentioned, the sample of the estimation consists of unemployed workers who are unemployed in two distinct periods: (i) between January 2004 and December 2007 and (ii) between January 2009 through July 2010 (Note, however, that all observations are included in one regression). During the former period, no benefit extensions were enacted. Therefore, the regular eligibility period of 26 weeks applies to those who are unemployed in this period. In the latter period, the eligibility period is extended a number of times in response to the severe recessions started in late 2007.I deliberately exclude the observations for 2008, because it them would make the identification of the effects of the extended benefits stronger. An important point to ensure in the estimation is that workers are certain that they receive benefits beyond 26 weeks. Note that the first extension beyond 26 weeks was enacted in the middle of 2008. It is, therefore, less clear whether workers who were unemployed in 2008 *knew* that they can receive extended benefits. It is however plausible to assume that by the beginning of 2009, workers expect to they receive extended benefits. Note that there are other possible cutoffs other than 26 weeks, because extensions were enacted sequentially over time.[8] However, identifying who is receiving extended benefits for how long at each point in time is simply not possible with the CPS data. Instead, what is certain is that workers who were unemployed in 2009 and 2010 knew that they could receive the benefits for more than 26 weeks.[9]

Note that those two periods differ significantly in terms of their business cycle conditions as well as the availability of the extended benefits. The aggregate job vacancy rate is used to control for the differences in the business cycle conditions. The idea is to see if there are any differences in the shape of the hazard functions attributable to the availability of extended benefits after controlling for the differences in the level of job vacancies. The implicit

[8] Appendix C provides an overview of UI benefit extensions. Fujita (2010) presents a more detailed chronology of the emergency unemployment compensation program (EUC08). See also Whittaker and Shelton (2009). For details of other extensions enacted in the previous recessions, refer to Whittaker (2008).

[9] The maximum entitlement period reached 99 weeks in November 2009 and has not been changed since. One may think that by using the data after November 2009, I can examine if exit rates increase around 99 weeks. However, the CPS data include fewer observations at such a long duration. Moreover, most of the observations are clustered at or around 104 weeks (2 years), which suggests that reported durations there are subject to serious measurement problems. This makes it difficult to distinguish workers based on the 99-week cutoff date.

assumption here is that job vacancies are exogenous to other variables, in particular, to the availability of extended benefits. In a standard search and matching model of Mortensen and Pissarides (1994) that features the endogenous job creation margin, this assumption is not true because the number of job seekers (which is influenced by the generosity of benefits) affects vacancy creation. However, ignoring this feedback only makes my estimates smaller and thus puts me on the conservative side.

It is well known that not all unemployed workers receive unemployment benefits. There are a number of reasons why a particular worker does not receive UI benefits. In particular, if a worker leaves his job voluntarily, he does not qualify for UI benefits, even though he can still be "unemployed" in the CPS. One way to proceed is to focus on those who are unemployed workers due to job loss. This sample selection would make it easier to infer the effects of UI benefits on their unemployment duration. In fact, Valletta and Kuang (2010) use the differences in unemployment duration between job losers and job leavers to infer the effects of the extended benefits.[10] The downside of focusing on this select group is that mapping into the aggregate unemployment rate becomes difficult. The treatment of labor market reentrants is also not clear, either. Thus I have chosen to look at all male unemployed workers instead of taking a particular stand on the benefit eligibility. However, I will also present the results based on the sample of job losers, since that exercise is more comparable to the analysis in the existing literature.

With respect to the econometric methodology, I use a multinomial logit model as opposed to the survival model that is used somewhat more frequently in the literature. The conceptual difference between the two frameworks is that the former is a discrete choice model, whereas in the latter framework, the underlying events (e.g., exit from the unemployment pool in this paper's context) occur in continuous time.[11] In principle, a labor market transition occurs within a matter of days and thus the continuous time framework is more appropriate. In practice, however, there are important advantages to the discrete choice model. The main advantage is its flexibility and simplicity in terms of incorporating different types of covariates, whether categorical, continuous, time-invariant, or time-varying. In the context of the application of this paper, the duration data are recorded in weeks. On the other hand, labor market transitions can be traced only in monthly frequency. One can deal with such interval-censored data by making a certain assumption, say, the constant probability density within interval (e.g., Dolton and van der Klaauw (1999)). However, it certainly means dealing with a more complicated likelihood function. Moreover, one of the important covariates in my application, the vacancy rate, is time-varying and observed only at monthly frequency, even though it varies within each month. This would pose even more significant technical challenges. Given these costs, restricting the analysis within a discrete choice model appears to be a plausible compromise. For similar reasons, some of the previous work in fact have utilized the discrete choice framework to model labor turnover (e.g., Royalty (1998) and Card and Levine (2000)).[12] Therefore, I apply the discrete choice model to the CPS

[10] Fallick (1991) and McCall (1996) both use the CPS's Displaced Worker Survey (DWS), which in principle corresponds to a subset of job losers.

[11] See Jenkins (2005) for discussions regarding the differences between the two approaches.

[12] Note that setting aside technical issues regarding dealing with multiple data frequencies, there is nothing

Table 1: Average Marginal Effects

	UE Transition Coef.	UE Transition Robust Std. Err.	UN Transition Coef.	UN Transition Robust Std. Err.
Race (White)	(0.234)		(0.170)	
Black	−0.051**	0.004	0.033**	0.004
Asian	−0.024**	0.007	0.043**	0.008
Others	−0.024**	0.007	0.026**	0.007
Marital Status (Married)	(0.244)		(0.128)	
Separated	−0.047**	0.006	0.044**	0.006
Never Married	−0.039**	0.006	0.023**	0.006
Education (High School)	(0.220)		(0.161)	
< High School	−0.017**	0.004	0.046**	0.004
Some College or BA	−0.013**	0.003	0.009**	0.003
Advanced Degree	−0.011**	0.008	−0.013**	0.007
Relation to (Reference Person)	(0.234)		(0.135)	
Spouse	−0.008	0.004	0.019**	0.005
Child	−0.019**	0.005	0.033**	0.005
Others	0.016**	0.005	−0.004	0.005
Reason (Permanent Layoff)	(0.183)		(0.130)	
Temp. Layoff	0.147**	0.004	−0.034**	0.004
Job Leaver	0.033**	0.005	0.028**	0.005
Reentrant	−0.000	0.004	0.107**	0.004

Continued on the next page.

data throughout this paper.

2.2 Marginal Effects

Table 1 presents the marginal effects on UE and UN transition rates with respect to time-invariant covariates in the vector X_i. The second column presents the point estimates for the UE transition rate and the third column presents the standard errors. The fourth and fifth columns present the results for the UN transition rate. The coefficient estimate gives the change in the transition rate when a discrete change from a base category occurs, when it is a categorical variable. The base category chosen is indicated in the parentheses in the first

that keeps me from applying popular tools in the survival analysis to the CPS flow data that have the so-called "delayed entry" structure. In fact, I estimated the piecewise-constant exponential hazard model without the job vacancy data and obtained results similar to the ones presented below based on the logit regression. I will come back to this later.

Continued from the previous page.

Industry (Construction)	(0.271)		(0.132)	
New Entrant	-0.116^{**}	0.006	0.108^{**}	0.007
Agriculture/Mining	-0.004	0.009	0.012	0.082
Utilities	-0.057^{**}	0.020	0.026	0.022
Nondurable Goods Manuf.	-0.023^{**}	0.007	-0.003	0.006
Durable Goods Manuf.	-0.030^{**}	0.005	0.009^{*}	0.005
Wholesale Trade	-0.021^{**}	0.009	0.003	0.009
Retail Trade	-0.020^{**}	0.005	0.016^{**}	0.005
Transportation/Warehousing	-0.007	0.007	0.014^{**}	0.007
Information	-0.026^{**}	0.010	0.007	0.009
Financial Activities	-0.021^{**}	0.008	0.004	0.008
Professional and Business Serv.	-0.012^{**}	0.005	0.006	0.005
Education and Health Serv.	-0.008	0.007	0.019^{**}	0.007
Leisure and Hospitality	-0.010^{*}	0.005	0.015^{**}	0.005
Other Services	-0.008	0.008	0.018^{**}	0.007
Government	-0.033^{**}	0.010	0.041^{**}	0.010
Age	-0.002^{**}	0.000	-0.001^{**}	0.000
Job Vacancy Rate	0.023^{**}	0.006	0.020^{**}	0.006

Notes: Sample Size: 114,623, Pseudo R^2: 0.0790, Log likelihood:−100,172. The table reports the average change in the probability of each outcome with respect to a discrete change from the base category or a change by one unit if the variable is a continuous variable. The base categories are indicated in the parentheses in the first column. The (unconditional) average transition rates of the base category are presented in the parentheses along the same row. Seasonal dummies are also included in the regressions but the effects are omitted from the table. Standard errors for the marginal effects are calculated by the delta method applied to the robust standard errors in the multinomial logit regression. ** (*) indicates statistical significance at 5% (10%) level.

column. The (unconditional) average transition rates of the base category are also presented in the parenthesis along the same row. For example, with respect to race, white males are chosen to be the base category. Average UE and UN transition rates are 23.4% and 17.0%, respectively. The marginal effects presented below indicate that, relative to white male workers, other races have lower job finding rates. Black males have the largest difference of 5.1 percentage points. With respect to UN transition rates, other races are more likely to drop out of the labor force.

Married workers are more likely to find a job and less likely to drop out of the labor force relative to the workers in the other two categories. With respect to educational attainment, more education is not necessarily associated with higher job finding rates: relative to high school graduates, college graduates and those with advanced degrees have somewhat lower job finding rates. This result may reflect the differences in the type of jobs typically associated with each group (although this effect is at least, to some extent, controlled for by including the industry each worker used to work in). With respect to the relationship to the reference person in a household, children are less likely to find a job and more likely to drop out of the labor force, both of which make intuitive sense.

Next, observe that different reasons for unemployment result in large differences in transition rates. Not surprisingly, when workers are on temporary layoff, they are much more likely to be reemployed than those who are unemployed due to permanently layoffs. They are also less likely to drop out of the labor force. When workers voluntarily leave their job, their job finding rate is higher, but they are more likely to drop out of the labor force. Lastly, unemployed workers who have come from NILF (reentrants) have a higher chance of dropping out of the labor force again.[13]

The latter half of the panel presents the marginal effects with respect to the workers' industry prior to becoming unemployed. Including this variable a priori appears to be important in controlling for worker heterogeneities that are not captured by other time-invariant factors discussed above. Suppose that industries differ with respect to the extent of worker turnover. For example, the construction industry may be considered an industry with particularly large worker turnover. If there is a large cross-industry heterogeneity in this respect, changes in the industry composition of the unemployment pool can influence the shape of the hazard functions. In the table, I take construction as a based industry. As expected, all categories (including those with no experience, i.e., new entrants) show negative signs with respect to job finding: New entrants have particularly lower job finding rate relative to those who worked in construction prior to separating from their job. Apart from new entrants, those who worked in other industries have job finding rates that are 1-3 percentage points lower relative to those who worked in construction.

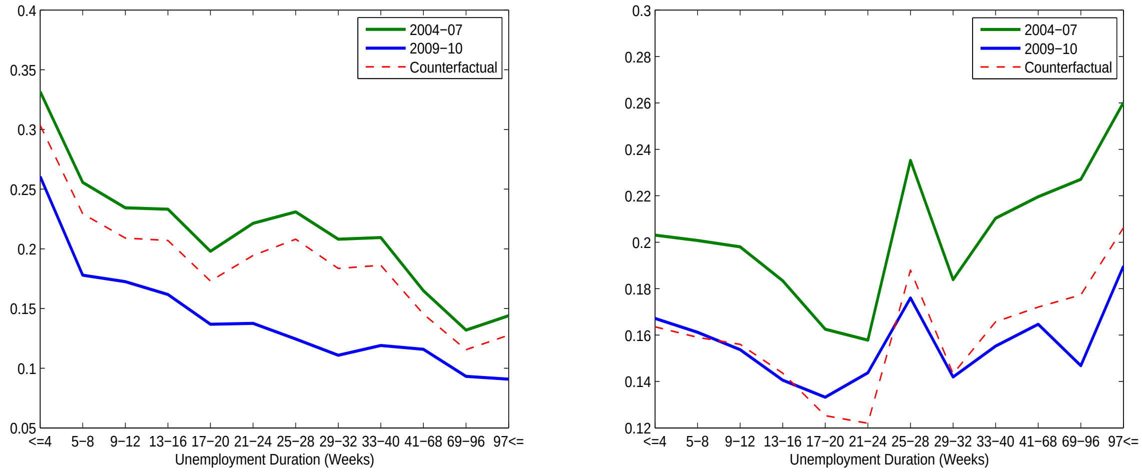
A worker's age is negatively related to exit rates from the unemployment pool. This is consistent with the previous finding that younger workers have higher labor turnover in general (e.g., Fujita and Ramey (2006)). The last row presents the elasticity of exit rates with respect to the job vacancy rate. It indicates that a 1-percentage-point decline in the vacancy rate lowers the UE and UN transition rates by 2.3 percentage points and 2.0 percentage points on average, respectively.[14] The information necessary for the counterfactual experiments below is how much of the declines in the exit rates during the most recession are attributed to the changes in cyclical conditions. The elasticities with respect to the vacancy rate estimated here capture this effect.

2.3 Predicted Transition Rates

This paper's main focus is on the comparison of the hazard functions between the period with and without extended UI benefits, namely between 2004-2007 and 2009-2010. The estimated model can be used to calculate the average predicted transition rates at each duration bin for the two periods. Let me partition the full sample into these two periods.

[13] Another category for reasons for unemployment is "new entrants." This category is collinear to those who do not report their prior industry. I thus talk about this category together with the industry effects.

[14] Note that the fact that the UN rate declines when the vacancy rate is lower does not necessarily contradict the "discouraged worker effect." See footnote 2.



(a) UE Transition Rates

(b) UN Transition Rates

Figure 1: Predicted Exit Rates from Unemployment: All Male Workers

Notes: Average predicted probabilities are based on the estimated multinomial logit regression specified in Equation (1) and calculated by Equations (3) and (4). The counterfactual hazard functions are calculated by Equation (5).

Let H^B represent the set of workers who are in the earlier sample. Similarly, H^R is defined as a set of individuals who are in the later sample. Let me denote the size of each sample as I^B and I^R, respectively. The average predicted transition rate into state s at duration bin j for individual $i \in H^B$ is calculated by:

$$\widehat{\Pr}(s, |j, EB = 0, i \in H^B) = \frac{1}{I^B} \sum_{i \in H^B} \frac{\exp^{\hat{\alpha}'_s X_i + \hat{\beta}_{sj} + \hat{\eta}_s v_{it}}}{\sum_s \exp^{\hat{\alpha}'_s X_i + \hat{\beta}_{sj} + \hat{\eta}_s v_{it}}} \tag{3}$$

where $\hat{\beta}_{sj}$ is an estimated coefficient on the dummy variable for the corresponding duration bin j for outcome s. The first duration category (duration of less than or equal to 4 weeks) is taken to be the base duration bin and thus $\hat{\beta}_{s1} = 0$ for normalization. Similarly, the average predicted transition rate into the state s at duration bin j for individual $i \in H^R$ is calculated by:

$$\widehat{\Pr}(s, |j, EB = 1, i \in H^R) = \frac{1}{I^R} \sum_{i \in H^R} \frac{\exp^{\hat{\alpha}'_s X_i + \hat{\beta}_{sj} + \hat{\Delta}_{sj} + \hat{\eta}_s v_{it}}}{\sum_s \exp^{\hat{\alpha}'_s X_i + \hat{\beta}_{sj} + \hat{\Delta}_{sj} + \hat{\eta}_s v_{it}}}, \tag{4}$$

where $\hat{\Delta}_{sj}$ is an estimated coefficient on the dummy variable indicating the availability of the extended benefits and capturing its effect at duration bin j. Again, $\hat{\beta}_{s1} = 0$ for normalization. Note also that whenever predicted probabilities are calculated, $\exp^{f_e(.)} = 1$ is assumed for normalization.

The green and blue lines in Figure 1 represent the average predicted hazard functions for the 2004-2007 period and the 2009-2010 period, respectively. I discuss the red dashed lines,

Table 2: Predicted Exit Rates by Unemployment Duration: All Male Workers

Duration (weeks)	2004−2007			2009−2010		
	UE Transition Rates					
0 − 4	0.332	[0.326	0.337]	0.261	[0.253	0.268]
5 − 8	0.256	[0.248	0.263]	0.178	[0.169	0.187]
9 − 12	0.234	[0.225	0.244]	0.173	[0.163	0.182]
13 − 16	0.233	[0.221	0.245]	0.162	[0.151	0.172]
17 − 20	0.198	[0.183	0.213]	0.137	[0.124	0.149]
21 − 24	0.221	[0.205	0.238]	0.138	[0.125	0.150]
25 − 28	0.231	[0.215	0.247]	0.125	[0.113	0.136]
29 − 32	0.208	[0.189	0.228]	0.111	[0.098	0.124]
33 − 40	0.209	[0.192	0.227]	0.119	[0.109	0.123]
41 − 68	0.165	[0.155	0.175]	0.116	[0.109	0.123]
69 − 96	0.132	[0.107	0.157]	0.093	[0.077	0.109]
97+	0.144	[0.130	0.158]	0.091	[0.080	0.102]
	UN Transition Rates					
0 − 4	0.203	[0.198	0.208]	0.167	[0.161	0.174]
5 − 8	0.201	[0.194	0.208]	0.161	[0.153	0.170]
9 − 12	0.198	[0.189	0.207]	0.154	[0.145	0.163]
13 − 16	0.183	[0.172	0.195]	0.141	[0.130	0.151]
17 − 20	0.162	[0.147	0.178]	0.133	[0.120	0.146]
21 − 24	0.158	[0.144	0.172]	0.144	[0.131	0.157]
25 − 28	0.235	[0.220	0.250]	0.176	[0.163	0.189]
29 − 32	0.184	[0.166	0.202]	0.142	[0.128	0.156]
33 − 40	0.210	[0.193	0.227]	0.155	[0.143	0.167]
41 − 68	0.220	[0.209	0.230]	0.165	[0.157	0.172]
69 − 96	0.227	[0.196	0.258]	0.147	[0.128	0.166]
97+	0.260	[0.245	0.276]	0.190	[0.176	0.203]

Notes: Average predicted probabilities for 2004-2007 and 2009-2010 are based on the estimated multinomial logit regression specified in Equation (1) and calculated by Equations (3) and (4). The 90% confidence intervals are in brackets. See Table 1 for marginal effects and other information about the underlying regression.

labelled as "counterfactual" later. Panel (a) plots UE transition rates by duration. Observe first that there is some indication of duration dependence for both periods. In particular, the decline in the UE transition rate between the first and second duration bins is considerable. Note that the predicted UE hazard function controls for the differences in observable worker characteristics, and therefore the downward sloping hazard function cannot be attributed to the differences in the worker characteristics.[15] Of course, it is possible that unobservable heterogeneity is behind the duration dependence as is often argued in the literature, but it appears difficult to eliminate the duration dependence at least in the monthly CPS data.[16] While neither of the UE hazard functions shows a clear "spike," one can observe a significant hump around the 23-29 week bin for the 2004-2007 hazard function. On the other hand, job finding rates steadily decline all the way to the longest duration category during the recent years.

Panel (b) presents the predicted UN transition rates by duration. First, consider the one for the recent years (green line). While it shows some spiking (about 3 percentage points) around the 25-28 week bin, it is roughly constant until the second-from-the-last (69-96 week) bin before it jumps up at the last bin. On the other hand, the hazard function for 2004-2007 shows a much larger spike at the 25-28 week bin, which amounts to 7.7 percentage points. After a part of the spike is reversed in the following bin, it continues to be on the upward trend until the last bin. It seems plausible to interpret this spike as being induced by the expiration of regular benefits, although a part of the observed jump may have to do with other factors, such as measurement errors, given that the 2009-2010 hazard function also shows a spike at the same bin. However, note that the magnitude of the spike in the earlier period is much larger, and the fact that the UN transition rates increase to a permanently higher level seems to suggest that the jump is driven by the expiration of regular benefits. Below I will assess this point statistically.

Table 2 presents the underlying numbers together with 90% confidence intervals. One can see that all of the predicted probabilities are fairly tightly estimated. Also note that the two hazard functions, whether UE or UN transitions, are statistically significantly different from each other as suggested by the fact that there is little overlap between the confidence intervals of the two hazard functions. This is not surprising given that the business cycle conditions differ greatly between the two periods.

2.4 Counterfactual Hazard Functions

There are two main reasons why the fitted hazard functions for the two periods are misleading for the purpose of inferring the effects of extended benefits. The first reason is, of course, the difference in the business cycle conditions as I mentioned earlier. The vacancy rate included in the regression is meant to control for this effect. Second, the composition of the unemployment pool may also be different. In general, Table 1 showed that different observable characteristics of workers are associated with different speeds of exits from the unemployment pool. Thus, to the extent that the composition of the unemployment pool differs across the two periods, observed exit rates can also differ. For example, a much larger

[15]As can be seen in formulas (3) and (4), the average effects of being in a certain duration bin are determined by calculating predicted probabilities for everybody in each sample (either H^B or H^R), which ensures that the composition of workers at each bin stays the same across different duration bins.

[16]When I estimated a piecewise-constant exponential survival model with Gamma-distributed unobserved heterogeneity as in Meyer (1990), duration dependence similar to the ones in panel (a) was still present.

Table 3: Effects of Extended Benefits on Hazard Functions (All Males)

Duration (weeks)	Job Finding Actual (1)	Job Finding Counter-factual (2)	Job Finding (1)−(2)	Dropout Actual (1)	Dropout Counter-factual (2)	Dropout (1)−(2)
0 − 4	0.261	0.304	0.043**	0.167	0.164	−0.004
5 − 8	0.178	0.229	0.051**	0.161	0.159	−0.002
9 − 12	0.173	0.209	0.036**	0.154	0.156	0.002
13 − 16	0.162	0.207	0.045**	0.141	0.144	0.003
17 − 20	0.137	0.173	0.036**	0.133	0.125	−0.008
21 − 24	0.138	0.194	0.057**	0.144	0.122	−0.022
25 − 28	0.125	0.208	0.084**	0.176	0.188	0.012
29 − 32	0.111	0.184	0.073**	0.142	0.143	0.001
33 − 40	0.119	0.186	0.067**	0.155	0.166	0.010
41 − 68	0.116	0.145	0.030**	0.165	0.172	0.007
69 − 96	0.093	0.116	0.022	0.147	0.177	0.031
97+	0.091	0.128	0.037**	0.190	0.206	0.017

Notes: Actual average predicted probabilities for 2009-2010 are based on the estimated multinomial logit regression specified in Equation (1) and calculated by Equation (4). Counterfactual predicted probabilities are calculated by turning off the extended-benefit dummy for those who are unemployed between January 2009 and July 2010 (Equation (5). The fourth and seventh columns present the difference between actual and counterfactual transition rates at each duration bin. ** indicates statistical significance at the 5% level. Standard errors for the differences are based on the delta method applied to the robust standard errors of estimated coefficients of the multinomial logit regression.

fraction of workers are unemployed because of job losses in the 2009-2010 period.[17] Table 1 showed that workers who are unemployed due to permanent layoffs have lower exit rates than job leavers. This by itself pushes down the hazard functions for the latter sample period. Another relevant example is the difference in the industry compositions: In the most recent recession, certain industries (such as construction) might have been hit harder than other industries. Again, the results in Table 1 suggest that the industry of the worker's previous job has statistically significant impacts on exit rates.

I therefore calculate the average predicted transition rates at each duration, controlling for the differences in the composition of the unemployment pool and the level of job vacancies:

$$\widehat{\Pr}(s|j, EB = 0, i \in H^R) = \frac{1}{I^R} \sum_{i \in H^R} \frac{\exp(\hat{\alpha}_s' X_i + \hat{\beta}_{sj} + \hat{\eta}_s v_{it})}{\sum_s \exp(\hat{\alpha}_s' X_i + \hat{\beta}_{sj} + \hat{\eta}_s v_{it})}. \tag{5}$$

Observe that the expression inside the outer summation is identical to the corresponding ex-

[17] The share of permanent layoffs out of all unemployed workers was around 35% over the 2004-2007 period and went up to a level higher than 50% in the 2009-2010 period.

pression for predicted transition rates for 2004-2007, Equation (3)), where extended benefits are not available ($EB = 0$). However, the average predicted transition rates are calculated for those who are observed in the 2009-2010 period. With respect to the predicted transition rates for 2009-2010, Equation (4), the job vacancy rates are at the same levels and the composition of workers is also identical.

The red dashed lines in Figure 1 present the counterfactual hazard functions. First, notice that the counterfactual hazard functions can be obtained by shifting the hazard functions for 2004-2007 downward. The idea is that under the counterfactual scenarios, the vacancy rate and the composition of workers correspond to those during the 2009-2010 period, but no extended benefits are available ($EB = 0$). The blue solid line and red dashed line are now comparable. Table 3 presents this comparison, including the statistical significance. The fourth and seventh columns present the point estimate of the difference between the actual and counterfactual transition rates at each duration bin, defined as $D(s|j)$:

$$D(s|j) \equiv \Pr(s|j, EB = 0, i \in H^R) - \Pr(s|j, EB = 1, i \in H^R). \tag{6}$$

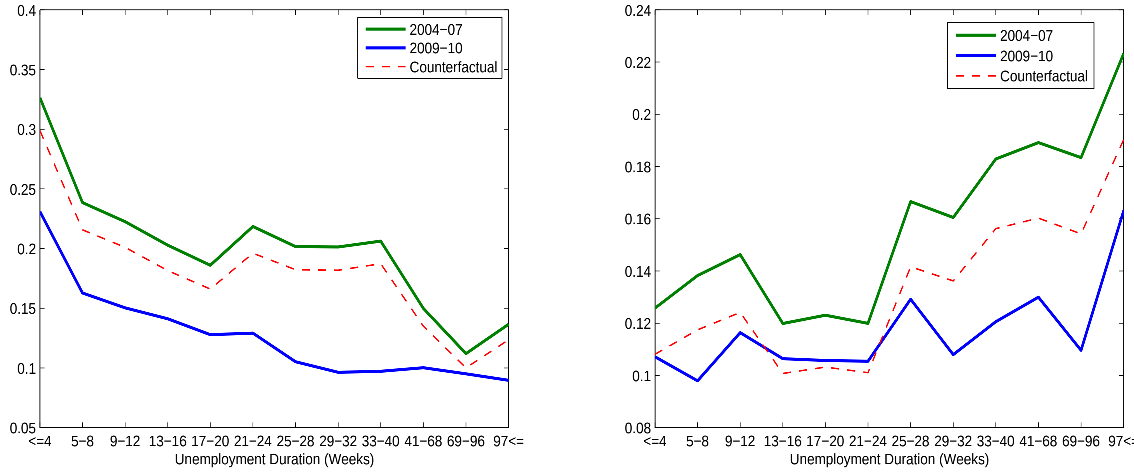
First consider UE transition rates. All of the entries in the fourth column show statistically significant positive signs. That is, the fitted transition rates for the 2009-2010 period are lower than the counterfactual ones by statistically significant margins. In other words, the observed UE transition rates during the most recent recession cannot be accounted for by the lower job vacancy rate and the differences in the composition of the unemployment pool.

The fifth through seventh columns compare UN transition rates. Recall from panel (b) in Figure 1 that the shape of the hazard function for the 2004-2007 period was significantly different from that for the 2009-2010 period, particularly with respect to the jump at the 25-28 week bin. However, the results here suggest that once the differences in the level of the job vacancy rate and the composition of the pool are adjusted, the two hazard functions are not distinguishable. After the 25-28 week bin, the differences are always positive (as intuitively expected) but are not statistically significant.[18] These results suggest that the effects of extended benefits are largely concentrated to the job finding margin. Section 3 examines this proposition more closely by mapping the effects on the hazard functions into the unemployment rate.

2.5 Results for Job Losers

So far my analysis has focused on all male unemployed workers. However, some of the past research focused on a subset of unemployed workers, namely, job losers mainly because job leavers (or quitters) in principle do not qualify for UI benefits. I would like to take the results for all male unemployed workers as a benchmark for aforementioned reasons. Nevertheless, it is still useful to see if I obtain results similar to those for all male unemployed workers even when I restrict the sample to (male) job losers. In addition to excluding job leavers and labor market entrants, I exclude those who are on temporary layoffs because recalls

[18] I also tested the null hypothesis that $\Pr(s|j, EB = 0, i \in H^R) - \Pr(s|j, EB = 1, i \in H^R) = 0$ for $j = 7, ..., 12$, but could not reject the hypothesis at the 10% level.



(a) UE Transition Rates

(b) UN Transition Rates

Figure 2: Predicted Exit Rates from Unemployment: Male Job Losers

Notes: Average predicted probabilities are based on the estimated multinomial logit regression specified in Equation (1) and calculated by Equations (3) and (4). The sample is restricted to job losers (excluding those who are on temporary layoffs).

to previous jobs that coincide with benefit expirations can create a spurious hump or spike around the 25-28 week bin.

The same multinomial logit regression is estimated with this restricted sample. The green and blue lines in Figure 2 give the fitted hazard functions for the same two periods. In general, the results here are stronger than those for all male unemployed workers. The hump in the UE hazard function for the 2004-2007 period becomes even clearer, whereas no discernible hump can be observed for the 2009-2010 hazard function. With respect to the UN hazard function, the upward jump for the 2004-2007 period is again clearer. Although the size of the jump at the 25-28 week bin is now smaller (4.7 percentage points instead of 7.7 percentage points), there is no large subsequent drop at the next duration bin. It is also easier to observe that it increases to a permanently higher level after the 25-28 week bin. In contrast, the UN hazard function for the 2009-2010 period is flat all the way until the last bin, when it jumps up.

Counterfactual hazard functions are also calculated for this restricted sample and plotted in Figure 2 as red dashed lines. Table 4 presents the statistical examination of the differences between the predicted transition rates for the 2009-2010 period and the corresponding counterfactual transition rates. As in the case for all males, the counterfactual UE hazard function lies above the actual hazard function. The difference is quite large and highly statistically significant except at the 69-96 week bin. As for the UN hazard function, the differences become clearer than before. In particular, the counterfactual hazard function is positioned significantly higher and the differences are sometimes statistically significant

Table 4: Effects of Extended Benefits on Hazard Functions (Male Job Losers)

	Job Finding			Dropout		
Duration bin (weeks)	Actual (1)	Counter-factual (2)	(2)−(1)	Actual (1)	Counter-factual (2)	(2)−(1)
0 − 4	0.231	0.299	0.068**	0.107	0.108	0.001
5 − 8	0.163	0.216	0.053**	0.098	0.117	0.019*
9 − 12	0.150	0.201	0.051**	0.116	0.124	0.008
13 − 16	0.141	0.182	0.040**	0.106	0.101	−0.006
17 − 20	0.128	0.166	0.038**	0.106	0.103	−0.003
21 − 24	0.129	0.196	0.067**	0.105	0.101	−0.004
25 − 28	0.105	0.182	0.077**	0.129	0.142	0.012
29 − 32	0.096	0.182	0.086**	0.108	0.136	0.028
33 − 40	0.097	0.187	0.090**	0.121	0.156	0.036**
41 − 68	0.100	0.135	0.035**	0.130	0.160	0.030**
69 − 96	0.095	0.100	0.005	0.110	0.154	0.045*
97+	0.090	0.124	0.034**	0.163	0.190	0.027

Notes: ** (*) indicates statistical significance at the 5% (10%) level. Standard errors are based on the delta method applied to the robust standard errors of estimated coefficients of the multinomial logit regression.

(particularly after the 25-28 week bin).[19]

3 Mapping into the Unemployment Rate

This section maps the differences between the actual and counterfactual hazard functions into the differences in the steady-state unemployment rate. First, I describe the derivation of the steady-state labor market quantities, when UE and UN transition rates vary by unemployment duration. I define the frequency distribution of unemployment over duration by $U(m)$. This function gives the number of unemployed at duration m, which is measured in months. The duration in the CPS is measured in weeks, but I convert the reported information into months because the labor flow series I need to use are available only at a monthly frequency. Let w be the unemployment duration measured in weeks. I convert w into m by the floor function $m = \lfloor w/4 \rfloor$. Let $f(m)$ and $d(m)$ be UE and UN transition rates, respectively. Note that the following relationship holds for $m > 1$:

$$U(m) = [1 - f(m-1) - d(m-1)]U(m-1). \quad (7)$$

For $m = 0$, the following relationship holds:

$$U(0) = p^{eu}E + p^{nu}N, \quad (8)$$

[19]Other results for job losers, including marginal effects, are available upon request.

where p^{lk} represents the transition rate from state l to state k, and E and N are the stocks of employed workers and those who are out of the labor force, respectively. Equation (8) simply equates the number of unemployed workers whose duration is less than a month and the inflows into the unemployment pool from the two possible sources. The recursion in equation (7) together with equation (8) can be expressed as:

$$U(m) = (p^{eu}E + p^{nu}N) \prod_{i=1}^{m+1} [1 - f(m+1-i) - d(m+1-i)], \tag{9}$$

for all $m \geq 0$ with $f(0) \equiv 0$ and $d(0) \equiv 0$. The total number of unemployment (U) can be calculated by

$$U = \sum_{m=0}^{\infty} U(m) = (p^{eu}E + p^{nu}N) \sum_{m=0}^{\infty} \prod_{i=1}^{m+1} [1 - f(m+1-i) - d(m+1-i)]. \tag{10}$$

Note also that hires from unemployment (H) and the flow from unemployment to out-of-the-labor force (G) are calculated by

$$H = \sum_{m=0}^{\infty} f(m)U(m), \tag{11}$$

and

$$G = \sum_{m=0}^{\infty} d(m)U(m). \tag{12}$$

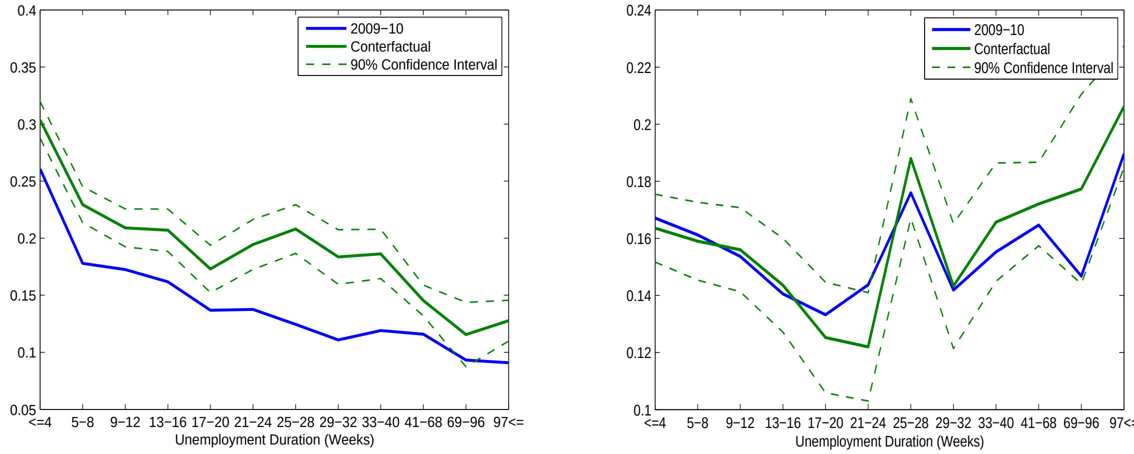
The stock-flow balance equations for employment, unemployment, and not-in-the-labor force are written as:

$$(p^{eu} + p^{en})E = H + p^{ne}N, \tag{13}$$
$$H + G = p^{nu}N + p^{eu}E, \tag{14}$$
$$(p^{nu} + p^{ne})N = p^{en}E + G, \tag{15}$$
$$\bar{P} = E + U + N, \tag{16}$$

where $\bar{P}$ is the working-age population. Note that Equation (14) is equivalent to Equation (10). Also note that one of the first three equations above is not independent. By dropping one of the three and adding the last equation for normalization, I can solve this system for E, U, N, H, G and $U(m)$, taking all transition rates as given.

3.1 Calibration

First, I have to set the four transition rates p^{eu}, p^{en}, p^{nu}, and p^{ne}. I use the BLS research series on labor force status flows from the CPS. The BLS releases all labor market flows for males and females separately. I calculate the four monthly transition rates based on the



(a) UE Transition Rates

(b) UN Transition Rates

Figure 3: Counterfactual Hazard Functions

Notes: Upper and lower bounds around the point estimates of the counterfactual hazard functions are translated from the 90% confidence intervals on the difference between the fitted and counterfactual hazard functions.

seasonally adjusted data for all males. Note that as I mentioned in the second paragraph of Section 2, I made an adjustment on worker transition data to make them consistent with duration data. Incorporating this adjustment into the published BLS data results in the following values: $p^{eu} = 0.0195, p^{en} = 0.0180, p^{nu} = 0.0216,$ and $p^{ne} = 0.0393$.[20]

I specify $f(m)$ and $d(m)$ as follows. Up to 32 weeks, duration originally reported in the CPS is classified into 8 four-week bins. After that, the widths of the bins are set longer than 4 weeks to accommodate smaller sample sizes at longer duration ranges in the CPS. Thus, for $m \leq 8$, I directly apply the estimated UE and UN transition rates to $f(m)$ and $d(m)$. For $9 \leq m \leq 10$, $11 \leq m \leq 17$, $18 \leq m \leq 24$, and $25 \geq m$, the same transition rates are applied within each bin.[21]

Having assigned numerical values to all parameters, I solve the system of equations for all quantities as follows. I first set an initial guess for $U(0)$ denoted by $U^{(1)}(0)$, then I can use (3) through (10) to solve for E, U, N and all $U(m)$ for $m \geq 1$. I can then calculate $U^{(2)}(0)$ from (2). Let $U^{(i)}(0)$ be the guess of $U(0)$ in the ith iteration. When $|U^{(i)}(0) - U^{(i-1)}(0)| > \kappa$ where κ is some small number, I set a new guess by $U^{(i+1)}(0) = \frac{1}{2}[U^{(i)}(0) + U^{(i-1)}(0)]$. If $|U^{(i)}(0) - U^{(i-1)}(0)| \leq \kappa$, then the algorithm stops.

[20] The original average transition rates over the period between January 2009 and July 2010 are $p^{eu} = 0.0212, p^{en} = 0.0220, p^{nu} = 0.0470,$ and $p^{ne} = 0.0472$. These original transition rates are converted into the ones above by using reporting error probabilities discussed in Appendix A.

[21] The largest number of m I consider is 100. There are virtually no unemployed workers at $m = 100$.

3.2 Counterfactual Experiments

I can now calculate the effects on the unemployment rate by calculating the two unemployment rates that come out under the actual hazard functions and the counterfactual hazard functions. I can use the 90% confidence intervals on the differences between the fitted hazard function and the counterfactual hazard function at each bin to set the bounds on the effects on the unemployment rate. Figure 3 visually shows what this means for my calculations. In the figure, the blue solid lines and green solid lines correspond to the point estimates of actual and counterfactual hazard functions, respectively. The dashed lines around the point estimates of each counterfactual hazard function set the bounds around them[22] Let $D^L(s|j)$ and $D^U(s|j)$, respectively, be the lower and upper bound of the differences between the counterfactual and actual transition rates at duration bin j. The upper and lower bound around each counterfactual hazard function are calculated by:

$$\widehat{\Pr}(s|j, EB = 0, i \in H^R) + D^U(s|j) \text{ and } \widehat{\Pr}(s|j, EB = 0, i \in H^R) + D^L(s|j),$$

respectively. The experiments entail calculating the unemployment rates corresponding to those three counterfactual hazard functions and comparing them with the unemployment rate under the fitted hazard functions. I perform this experiment for UE and UN transition rates separately, which allows me to calculate the contribution from each hazard function.

It is clear from Panel (a) of Figure 3 that the differences between the counterfactual and actual UE transition rates are statistically significant at almost all duration bins. According panel (a), the effects of extended benefits can be observed in two respects. The first effect comes from the hump in the hazard function around the 25-28 week bin. The second effect comes from the downward shift in the entire hazard function. The latter effect plays an important role in estimating the effects on the unemployment rate. If the effects of extended benefits exist only around the 25-28 week duration bin, a large number of workers would have found a job before reaching the hump.[23] Theoretically speaking, the idea that the effects show up only around the expiration data does not appear plausible. Rather, standard search theory would predict that not only does an extension alter the shape around the expiration date, but it also shifts the hazard function downward, given that job seekers are forward looking.[24]

In contrast to UE transitions, empirical and counterfactual hazard functions for UN transitions are not statistically distinguishable. Theoretically speaking, the fact that counterfactual UN hazard function comes below the empirical one at any duration bin does not make much economic sense, given that the benefit level is strictly lower under the counterfactual hazard functions. Statistically speaking, however, this type of anomalistic relationship could happen. As a result, it is possible that the unemployment rate can be lower under

[22]Note that equivalently, I could put the bounds around the actual hazard functions, keeping the counterfactual functions at the point estimates. The two approaches are equivalent.

[23]According the estimated hazard function for the 2009-2010 period, the survival probability at the 17-20 week bin is 0.36.

[24]Nakajima (2011)'s recent study based on a quantitative search model confirms this prediction.

Table 5: Effects on the Unemployment Rate

Due to	Lower bound	Point estimates	Upper bound
UE transitions	0.78	1.17	1.52
UN transitions	0.00	0.00	0.29
Total	0.78	1.17	1.79

Notes: Each row gives the increase in the (male) unemployment rate (in percentage points) due to the effects of extended benefits on UE or UN hazard function.

the counterfactual scenario. Whenever this happens, I assume that the effect of extended benefits on the unemployment rate is zero.

Table 5 presents the increases in the unemployment rate due to extended benefits. The point estimate of the counterfactual UE hazard function implies that extended unemployment benefits raise the (male) unemployment rate by 1.2 percentage points with 90% confidence interval of 0.8 to 1.5 percentage points. In contrast, as panel (b) of Figure 3 implies, the effects through UN transition rates are mostly negligible. Applying the point estimates of the counterfactual UN hazard function results in a small negative effect on the unemployment rate. Even at the upper bound, the effect on the unemployment rate through UN transition rates is relatively small (0.29 percentage point). The total effect, which comes largely from the effects through the UE hazard function amounts to 0.8 to 1.8 percentage points.

4 Conclusion

This paper has estimated the effects of UI benefit extensions in recent years on the two exit rates from the unemployment pool. The results are based on the monthly CPS data. I find large differences in the shape of UE and UN hazard functions between the 2004-2007 period and the 2009-2010 period. The estimation results allowed me to infer counterfactual hazard functions for the 2009-2010 period under the absence of extended benefits. I then translated the effects on the hazard functions into the effects on the unemployment rate. I find that UI benefit extensions have raised the male unemployment rate by around 1.2 percentage points. The effects on the unemployment rate largely come from the job finding margin.

The purpose of this paper was *not* to provide any normative conclusions regarding the welfare implications of the extended UI benefits but to conduct a statistical analysis using the currently available information. It is possible that longer duration is welfare improving, for example, due to the liquidity effect (Chetty (2008)) and the job creation effect (Acemoglu and Shimer (2000)). A recent paper by Landais et al. (2010) in fact argues that UI benefits

Table 6: Inconsistency between Duration and Flow Data

Status in month 1	Duration in month 2 (weeks) 5 or less	6 or more	Total	Error rates (%)
Employed	11,694	3,129	14,823	7.9
	(78.9)	(21.1)	(100.0)	
Unemployed	2,494	27,036	29,530	–
	(8.5)	(91.6)	(100.0)	
NILF	5,544	6,947	12,491	17.5
	(44.4)	(55.6)	(100.0)	
Total	19,732	37,112	56,844	25.4
	(34.7)	(65.3)	(100.0)	

Notes: Distribution of unemployment duration by labor market status in the previous month's survey. Fractions within the previous month's labor market status are in parentheses. The last column reports the classification error rates calculated as the probabilities of misreporting given that the true state is unemployed. Sample period: 2004-2007.

should be more generous during recessionary times. I hope that the estimates given in this paper provide useful information for those normative discussions.

A Reconciliation of Duration and Flow Data

As I mentioned in the main text, the data on unemployment duration and worker transitions across labor market status exhibit some inconsistencies. Table 6 presents the distribution of unemployed workers by duration. The first row looks at employed (E) workers in the previous month's survey, the second row looks at those who previously report "unemployed" (U), and the third row looks at those who report "not-in-the-labor force" (N). If the labor market status in the previous month's survey is correctly reported, unemployment duration for those who report E or N in the previous month's survey needs to be less than 4 or 5 weeks by construction. However, a large fraction of workers give unemployment durations inconsistent with the previous month's labor market status. The first row shows that more than 20% of the individuals who report being employed in month 1 report that they are "unemployed" in month 2 *and* give an unemployment duration of more than 5 weeks in month 2. The problem is more severe for those who report being out of the labor force in month 1. Roughly 55% of these workers who say that they are "unemployed" in month 2 report durations inconsistent with the previous month's labor market status. The approach I use is to take the duration information as given and renew the labor market status in the previous month. That is, if the duration is greater than or equal to 4 or 5 weeks, I replace the previous month's labor market status with "unemployed" and calculate the

Table 7: Effects of Reconciliation

Duration	UE		UU		UN	
	before	after	before	after	before	after
$\leq$ 5 weeks	0.38	0.33	0.41	0.49	0.22	0.19
>5 weeks	0.22	0.19	0.56	0.63	0.22	0.19
Total	0.28	0.24	0.50	0.58	0.22	0.19

Notes: "before": transition rates with no correction of the labor market status. "after": transition rates with correction. Sample period: 2004-07.

associated duration by subtracting 5 from the unemployment duration reported in month 2. An alternative approach would be to take the labor market status as truth, overwriting the duration information, in which case, the reported duration information is overwritten as "0-4" or "0-5 weeks." However, I follow the first approach. The reason is that it is well known in the literature that unemployed individuals often misreport their labor market status. For example, a seminal paper by Poterba and Summers (1986) estimate that the error reporting rate that unemployed workers are misclassified as being out of the labor force is greater than 11%. Similarly, the error rate that unemployed workers are misclassified as having a job is around 4%.

I can also calculate error reporting rates using the data presented in Table 6 under the assumption that the duration information is correctly reported.[25] They can be calculated by

$$\Pr(S_R = E|S_T = U) = \frac{3,129}{3,129 + 29,530 + 6,947} = 0.079$$

$$\Pr(S_R = N|S_T = U) = \frac{6,947}{3,129 + 29,530 + 6,947} = 0.175$$

where S_T is the true labor market status and S_R is the reported labor market status. These error rates are somewhat higher than those reported by Poterba and Summers (1986). However, other more recent studies that use different methodologies and data from different sample periods estimate the error rates that are close to my estimates.[26]

The reporting error that creates the spurious flow from NILF to unemployment is particularly an intuitively understandable phenomenon given the difficulty in drawing a clear line between unemployment and NILF. For example, it is easy to imagine a situation in which an individual has been looking for a job for a long time yet reports being out of the labor force in one particular survey. This situation is consistent with the data shown in Table 6.

[25]More precisely, the only necessary assumption is that a worker knows whether he or she has been looking for a job (i.e., unemployed) for more than one month. I do not need to assume that workers are reporting exactly how many weeks they are unemployed.

[26]See Table 3 in a recent paper by Feng and Hu (2010), which lists the error reporting rates estimated by seven different studies, including Poterba and Summers (1986).

A consequence of this adjustment is the reduction in exit rates from the unemployment pool. The adjustment adds unemployed workers to month 1 based on the duration information observed in month 2. In the adjusted data, these workers are recorded as unemployed in both months. Table 7 shows the magnitude of the adjustment. Observe that making the adjustment makes the exit rates from unemployment lower by 8 percentage points. The largest effect is observed for the UE transition rate for those who are unemployed for less than or equal to 5 weeks (5 percentage points).

B Explanatory Variables in the Regressions

The multinomial logit regressions include the following explanatory variables. The number of categories is in parenthesis.

- 11 seasonal dummies.
- Race (4): Asian, Black, White, and other races.
- Marital status (3): married, separated, and never married (single).
- Age: age and age^2.
- Relationship to the reference person (3): self, spouse, child, and others (incl. relatives).
- Education (4): high school diploma, less than high school, some college and college degree, and advanced degree.
- Reason for unemployment (4): permanent layoff, temporary layoff, reentrant, and new entrant.
- Duration of Unemployment (12): less than or equal to 4 weeks, 5-8 weeks, 9-12 weeks, 13-16 weeks, 17-20 weeks, 21-24 weeks, 25-28 weeks, 29-32 weeks, 33-40 weeks, 41-68 weeks, 69-96 weeks, and 97 weeks or more.
- Industry (16) : no experience, agriculture and mining, utilities, construction, nondurable-goods manufacturing, durable-goods manufacturing, wholesale trade, retail trade, transportation and warehousing, information, financial activities, professional and business services, education and health services, leisure and hospitality, other services, and government. “No experience” is equivalent to “new entrant” in reason for unemployment above.
- Job vacancy rate: Monthly series for total nonfarm sector taken from the BLS Job Openings and Labor Turnover Survey (JOLTS).

Recall that each matched CPS data set takes the form of a two-month panel. Each panel consists of those who are unemployed in the first mont and includes their characteristics in that month. These characteristics are regressed on three transitions into the following month:

(i) stay unemployed, (ii) find a job, and (iii) drop out of the labor force. The aggregate job vacancy rate is also associated with the first month.

C Emergency Unemployment Compensation Programs

Regular unemployment insurance benefits run by state governments typically last 26 weeks. The federal government, however, often enacts extensions of UI benefits during economic downturns. There are two types of federal emergency programs. The first is called the extended benefit (EB) program, which is permanently authorized, meaning that the extension is triggered automatically whenever the state unemployment rate reaches a certain level. It provides additional weeks of unemployment benefits up to a maximum of either 13 weeks or 20 weeks, depending on the state.

The second type is a federal program that Congress enacts temporarily during downturns. The latest program of this type, the Emergency Unemployment Compensation program (EUC08), represents the eighth time Congress has created such a program. EUC08 was signed into law in June 2008. Initially, the maximum entitlement period under this program was 13 weeks, but it has been extended several times since then. As of the end of 2010, EUC08 provides extended benefits for up to 53 weeks. This means that, combining the regular benefit and the two emergency programs, an unemployed worker is entitled to UI benefits for up to 99 weeks. Fujita (2010) provides a chronology of the EUC08. See also Whittaker and Shelton (2009) for details of the EUC08.

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