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Abstract

The high U.S. unemployment rate after the Great Recession is usually considered as a result of changes in factors influencing either the demand side or the supply side of the labor market. However, no matter what factors have caused the changes in the unemployment rate, these factors should have influenced workers' and firms' decisions. Therefore, it is important to take into account workers' endogenous responses to changes in various factors when seeking to understand how these factors affect the unemployment rate. To address this issue, we estimate a Mortensen-Pissarides style labor-market matching model with endogenous separation decisions and stochastic changes in workers' human capital. We study how agents' endogenous choices vary with changes in the exogenous shocks and changes in labor-market policy in the context of human capital dynamics. There are four main findings. First, once workers have accounted for and are able to optimally

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respond to possible human capital loss, the unemployment rate in an economy with human capital loss during unemployment will not be higher than in an economy with *no* human capital loss. The reason is that the increase in the unemployment rate led by human capital loss is more than offset by workers' endogenous responses to prevent them from being unemployed. Second, human capital accumulation on the job is more important than human capital loss during unemployment for both the unemployment rate and output. Third, workers' endogenous separation rates will decline when job finding rates fall. Fourth, taking into account the endogenous responses, UI extensions contributed 0.5 percentage point to the increase in the aggregate unemployment rate in the 2008-2012 period.

JEL Classification Numbers: *E24; J08; J24; J45.*

Keywords: Unemployment, Unemployment Insurance (UI) Benefits, Matching Model, Human Capital, Labor Market

1 Introduction

The U.S. unemployment rate rose sharply in the 2007-2009 recession but fell only gradually after the end of the recession. The unemployment rate rose from 5% to 10%, peaking in the middle of 2010, and more than four years after the end of the recession (as officially dated by NBER), it was still above 7%. Researchers generally agree that the persistence in the high unemployment rate is due to the persistently low unemployment-to-employment transition rate (see, for example, Elsby, Hobijn, and Sahin (2010)). What is less agreed upon is whether this low job finding rate is mainly due to factors leading to weak demand for labor (literally, there are fewer job opportunities in the economy) or factors that influence the supply side, such as skill deterioration, a decline in job-search intensity, and extensions of Unemployment Insurance (UI) benefits.[1]

However, no matter which factors have changed, causing changes in the unemployment rate, these factors should be those that have influenced workers and firms' decisions. For example, intuitively, if there are fewer jobs in the economy, workers should be less willing to leave their current jobs; if there is skill deterioration, unemployed workers should respond by trying to leave the unemployment pool as soon as they can. In addition, when conditions in these factors have changed (such as when the number of job opportunities has increased or decreased, or when skill deterioration has become larger or smaller), workers and firms should re-optimize their decisions to account for these changes. Therefore, to understand how different factors affect the unemployment rate, it is important to account for the endogenous responses of key participants in the labor market to changes in these factors. These considerations become the main motivation of this paper.

In this paper, we construct and estimate a Mortensen-Pissarides style labor-market matching model with endogenous separation decisions and stochastic changes in workers' human capital as in Ljungqvist and Sargent (1998). To quantitatively investigate the points discussed above, we first use micro data to estimate the model to match the labor market dynamics and wage moments for different educational groups in the 2003-2007 period (a relatively stable period). We then conduct a series of experiments to study how agents' endogenous choices vary with changes in the exogenous shocks (which represent changes in economic conditions) and changes in labor-market policy (which capture the multiple extensions in UI benefits) in the context of human capital dynamics (which include possible human capital variations in the unemployment period and employment

[1] These discussions constitute the core part of the long-lasting debate on whether the increase in the U.S. unemployment rate in the past few years is cyclical or structural.

period).

Our key modeling elements are motivated by several observations from the data. First, the increase in the unemployment rate during the Great Recession was especially large for less-educated groups. The unemployment rate rose 2.8 percentage points for college graduates and rose 6.8 percentage points for non-college graduates. A similar pattern emerges for the employment-to-unemployment (E-U) transition rate. The E-U transition rate increased significantly for each educational group, and the increase was more dramatic for non-college graduates. The unemployment-to-employment (U-E) transition rate dropped from 50% to 20% and stayed low, but there was no significant difference between educational groups.

Second, the experience of a job loss is normally accompanied by a substantial earnings loss.[2] The wage decline after job loss may be due to the loss of human capital. Such human capital may be associated with a particular task, firm, industry, or occupation. On the other hand, the employment experience is associated with substantial wage gain. Using data from the Survey of Income and Program Participation (SIPP), we find that unemployed workers on average experience 4-5% of wage loss and employed workers on average experience 2-3% of wage increase in a year.

Motivated by these observations, we develop a model with human capital dynamics to study the aggregate and disaggregate (by education level) labor market dynamics in the Great Recession. The model builds on Ljungqvist and Sargent (2007). The economy is populated by a continuum of agents with different education levels who may either be employed or unemployed. When employed, workers can accumulate specific human capital, and when unemployed, workers may lose some of their specific human capital. The job markets are segmented by education. Firms can choose to post vacancies in different markets. There is a matching technology in each market to match unemployed workers with vacancies. A matched worker-and-job pair draws a match-specific productivity, and the productivity evolves over a match's life. The production value depends on both education and the specific human capital. Unemployed workers may be entitled to Unemployment Insurance (UI) benefits based on their past employment histories. The wage is determined by generalized Nash bargaining.

We estimate the steady state of this model to match the pre-crisis period labor market statistics using data from the Current Population Survey (CPS) and the Survey of Income and Program Participation (SIPP). We then simulate the estimated economy to match

[2]See, for example, Couch and Placzek (2010), von Wachter et al. (2011), Farber (2011), and Fujita (2012).

the labor market dynamics in the Great Recession taking into account the productivity shock, exogenous separation shock, matching efficiency shock and the extensions of UI benefits. To understand how workers respond to changes in different factors, we perform various experiments by shutting down the factors one at a time.

The key message from these experiments is that workers' human capital dynamics and endogenous responses are important in understanding U.S. labor market dynamics. Four main findings are summarized as follows. First, once workers have accounted for and are able to optimally respond to possible human capital loss, the unemployment rate in an economy with human capital loss during unemployment will not be higher than in an economy with *no* human capital loss. The reason is that the increase in the unemployment rate led by human capital loss is more than offset by workers' endogenous responses to prevent them from being unemployed. Second, compared to human capital loss during unemployment, human capital accumulation on the job is quantitatively more important for both the unemployment rate and output. Third, workers' endogenous separation rates will decline when job finding rates fall. Quantitatively, the decline in the job finding rates in the 2008-2012 period caused the endogenous separation rates to decline by almost 1 percentage point in the same period. Fourth, taking into account the endogenous responses, UI extensions in the 2008-2012 period contributed 0.5 percentage point to the increase in the aggregate U.S. unemployment rate, with the impact on highly-educated workers larger than on low-educated workers.

This paper is related to Nakajima (2012), who also investigates labor market dynamics in a structural model but focuses on the effect of UI extensions and does not explore the effect of human capital changes on labor market variables. And his model assumes that all separations are occurring exogenously thus cannot study how separation rates vary with changes in economic conditions. This paper is also related to Ljungqvist and Sargent (1998, 2007), who argue skill loss upon unemployment and the differences in the UI system can help explain the different unemployment rates in European countries and the U.S. Our model shares the same features on human capital dynamics as in Ljungqvist and Sargent (1998, 2007). But this paper is different from Ljungqvist and Sargent (1998, 2007) in three main dimensions. First, in addition to examining the steady-state effects of human capital, we also examine the cyclical effects of human capital transitions, including not only skill loss upon unemployment but also skill depreciation during unemployment and skill accumulation during employment. Second, we have used micro data to estimate the model parameters, including the information on wage changes conditional on unemployment and employment experience to identify human capital transition parameters. Third, we have applied the model to study the different labor-market dynamics between different educational groups, including the differences in human capital transitions in different educational groups. This paper is also related to Nie (2010), who uses German micro data to estimate a structural model with human capital dynamics. While Nie (2010) focuses on interactions between UI benefits and training programs, the two major labor-market policies used in European countries, this paper focuses on the U.S. labor market and introduces endogenous-separation decisions into Nie (2010).

There is also a literature that emphasizes the importance of human capital dynamics in affecting the cyclical dynamics of labor market variables. Laureys (2012) finds that the loss of skill during unemployment generates an externality in job creation. Chang, Gomes, and Schorfheide (2002) show that incorporating skill accumulation improves the ability of an RBC model to fit the dynamics of aggregate output and hours. Cairo and Cajner (2012) also explore the differences in labor market statistics of different educational groups and find that training, or human capital accumulation, is the main reason for the observed difference in statistical volatility of labor market variables for different educational groups. Since training can only increase human capital, their paper can not account for the wage loss after unemployment. In addition to modeling human capital accumulation, we also model human capital loss during an unemployment spell. Hence our treatment of human capital dynamics is richer and can account for both wage loss and wage growth. More importantly, in contrast to these papers, our focus differs in that we emphasize the effect of the endogenous response of agents to human capital transitions on the labor market dynamics in the business cycle.

The rest of the paper is organized as follows. Section 2 presents empirical evidence that motivates this paper. Section 3 develops a matching model with human capital transitions. Section 4 describes the calibration and estimation of the model and reports the results. Section 5 conducts a series experiments and provide discussions on the key findings. Section 6 concludes.

2 Data and Facts

This section documents the empirical evidence discussed in the introduction. We first investigate the labor market statistics using the Current Population Survey (CPS). We then explore the wage moments using the Survey of Income and Program Participation (SIPP).

2.1 Labor Market Statistics

This section explores several labor market statistics by education. We use monthly data from the Current Population Survey (CPS) to construct unemployment rate and transition rates between employment and unemployment.[3] The CPS has four rotation groups every month. Each group is in the survey for four month, out for eight month, and in again for another four month. Hence roughly there are three-quarters of the households are surveyed in the two consecutive months. We use these observations to construct the monthly transition rates between employment and unemployment. We restrict our sample to be individuals aged between 25 and 60. The lower bound is chosen because most of people have completed their education by age 25. The upper bound is chosen to exclude individuals who are close to the retirement age since these individuals' labor market behavior may be different from the younger groups. We apply the continuous-time correction for time aggregation bias developed by Shimer (2012) to each education group.[4] This correction takes into account that some workers who become unemployed managed to find a new job before the next CPS survey arrives. Please refer to the appendix for the details on constructing the labor market statistics.

Figure 1 plots the overall unemployment rate and the percentage of the unemployed who are long-term unemployed (unemployed for more than 26 weeks). The U.S. unemployment rate was roughly 5% in 2007 and then rose sharply after 2007 and peaked around 10% in early 2010 and decreased slowly since then. Meanwhile the long-term unemployment rate more than doubled after 2007. The job finding rate also declines with the unemployment length as shown in Figure 2. By contrast, after a sharp decline, GDP starts to grow in summer 2009 and the NBER officially announced the end of the recession. However the unemployment rate still remained above 9%.

Figure 3 plots the unemployment rates by education group. The trend in the unemployment rate for each education group closely follows the trend in the aggregate unemployment rate. The less educated workers have higher unemployment rates in both recessionary and expansionary periods. More importantly, the increase in unemployment rate during the Great Recession is more dramatic for low education group. The differences in the behavior of unemployment rate by education groups are mainly due to differences in separation rates, rather than job finding rates. Figure 4 and Figure 5 plot the E-U and

[3] The data can be obtained from http://www.nber.org/cps/.

[4] We also calculated the transition rates using the discrete-time correction method for time aggregation bias suggested by Elsby, Michaels, and Solon (2009). The differences between the two methods were quantitatively neglectable.

U-E transition rates by education group. Specifically, the less educated group has larger separation rate before the recession and also has larger increase in the separation rate during the Great Recession, while the difference in the job finding rate across education groups is small.

To simplify the computation, we restrict the model proposed in the next section to two education groups. To parameterize the model, we aggregate the data into two education group: less than college and college and above. Table 1 reports the average of the labor market statistics for these two groups between 2003 and 2007, which we use to estimating the model.

Table 1: Labor Market Statistics (2003-2007 average)

Statistics	Less than College	College and Above
Unemployment rate	6.0%	2.5%
Job finding rate	55%	46%
Separation rate	3.4%	1.1%
Employment share	69.9%	30.1%
Unemployment share	85.5%	14.5%

2.2 Wage Statistics

This section explores wage loss on unemployment as well as wage growth on employment. For this purpose, we analyze the wage data from SIPP. SIPP is a national representative panel that surveys each individual every four month but records labor market status, wage and other labor market information for each month. The SIPP also contains demographic information. The panel normally lasts 3-4 years since 1996 but lasts shorter before 1996. The high-frequency and longitudinal features of the SIPP make our analysis feasible because unemployment is a short-lived situation for most individuals, information at the monthly frequency is essential for comparing wages before and after unemployment.

For our analysis, we use the most recent 6 panels before the Great Recession.[5] We exclude the panel starts in 2008 because we will parameterize the wage loss and wage growth in the steady state of the model using estimates obtained from SIPP before the Great Recession. We include more than one panel to to increase the number of observations. We select individuals aged between 25 and 60 for the same reason as our selection

[5]The panels start at 1991, 1992, 1993, 1996, 2001, 2004.

Table 2: Labor Market Statistics (2007-2012)

Statistics	2007	2008	2009	2010	2011	2012
			Total			
Unemployment rate	4.44%	5.45%	8.65%	8.96%	8.32%	7.53%
U-E rate	55.02%	46.61%	29.27%	25.94%	29%	30.46%
E-U rate	2.58%	2.95%	2.94%	2.47%	2.52%	2.43%
			Less than College			
Unemployment rate	5.47%	6.72%	10.58%	11.05%	10.34%	9.38%
U-E rate	56.15%	48%	29.82%	26.11%	29.41%	30.81%
E-U rate	3.28%	3.76%	3.73%	3.15%	3.23%	3.12%
			College and Above			
Unemployment rate	2.09%	2.62%	4.45%	4.51%	4.16%	3.87%
U-E rate	48.45%	38.71%	26.37%	24.97%	26.86%	28.64%
E-U rate	1.05%	1.23%	1.32%	1.13%	1.14%	1.13%

for CPS. For the purpose of exploring the change in human capital, it is important to have a precise measure for the price of labor. Measurement errors in hours and unrecorded overtime work that plague total earnings responses often contaminate wages computed for salaried workers. Hence we focus on hourly paid workers only. The hourly paid workers consist roughly half of all workers. We use the real wage data by deflating the nominal wage by monthly CPI.

To analyze the wage loss on unemployment, we select the episode in which an individual move from employment to unemployment and to employment again (EUE) with at least of one reported month as unemployed. The unemployment spell is measured as the number of month that an individual is unemployed and searching for jobs. We exclude the observations with an EUE spell but report the reason for unemployment as retirement, schooling and training, and quitting to take another job. Because these individuals are either not experiencing a real unemployment spell or are participating in activities to increase their human capital. We then run the following regression using the selected EUE spells for the two education groups defined earlier:

$$\triangle log(w) = cons + a * uspell + a_1 * controls + error \tag{1}$$

$\triangle log(w)$ is the log real wage change before and after an unemployment spell. uspell is the length of observed unemployment spell. The regression coefficient a denotes the monthly wage change during unemployment. The controls include panel dummy, age and unemployment rate. As demonstrated by Cooper (2013), the wage change might not be linear on unemployment spell. We estimate the monthly wage loss during unemployment because we do not model the nonlinear structure on human capital depreciation in the quantitative model developed next due to computational burden.

We run a similar regression with the length of employment as a regressor to analyze the wage growth on employment. In this regression, $\triangle log(w)$ is the wage change between the first and last wage on an employment spell. If the observation is employed at the beginning of the panel, the first wage is the first observed wage and if the observation is employed at the end of the panel, the last wage is the last observed wage. Table 3 reports the regression coefficients from the regressions. The regression results provide evidence that wages decline after unemployment and wages grow on employment. In particular, wage declines by about 4% a year and grows by about 3% a year. The more educated group has slightly larger wage changes both on unemployment and on employment.

There is a large literature that finds that workers experience earning losses after job losses.[6] Using longitudinal data from the Social Security Administration, Davis and von Wachter (2011) and von Wachter, Song, and Manchester (2011) find that workers experience substantial earning loss after job displacement. Farber (2011), using Displaced Workers Survey, finds that the average weekly earnings decline (upon reemployment) for displaced workers in the Great Recession. A key feature of these studies is that they consider earnings instead of wages. In addition, they explore the overall earning loss after job loss. In contrast, we explore the average monthly wage decline during unemployment using the SIPP, which is a relatively unexplored data set in this literature.

3 The Model

3.1 Economic Environment

This is an economy populated by infinite number of workers who differ in human capital levels and infinite number of firms which differ in their idiosyncratic productivity. Workers are either employed or unemployed. During employed periods, they earn a wage which determined by Nash bargaining with the associated firms. During unemployed periods,

[6] Please see Couch and Placzek (2010) for a literature review

Table 3: Wages (2003-2007)

Statistics	Less than College	College and Above
All, Average wage	12.97	18.05
	(0.005)	(0.022)
All, Standard deviation	6.5	10.51
Wage depreciation		
12*Monthly decline	-4.08%	-4.88%
Wage growth		
12*Monthly increase	2.7%	3.2%

they either receive unemployment insurance (UI) benefits if qualified, or supported by social welfare benefits which is the last resort if they are not qualified for UI benefits. In this model, both human capital and entitled UI benefits determine the unemployed workers' decision. These two factors together with the idiosyncratic productivity determine the wage level during the bargaining process.

Workers

Workers differ in their employment statuses and benefit entitlements. An unemployed worker entitled with UI benefit face a probability of δ to lose his UI benefit entitlement next period. This benefit expiration probability, δ, is calibrated to match the maximum length of entitled benefits an unemployed worker can receive. An unemployed worker who is not entitled with UI benefits will receive certain social welfare assistance, denoted by sa. For such an unemployed, in order to qualify for the UI benefits, he has to be employed for enough periods (so called "working requirements" in the literature). To capture this feature, we introduce another parameter, γ, which denotes the probability that an employed without UI benefit will be qualified for UI benefit in the next period. In other words, unemployed who are not entitled with UI benefits have to on average work $\frac{1}{\gamma}$ periods before they are eligible to receiving UI benefits. γ will also be calibrated to match the actual "working requirement" in the U.S. economy.

Human Capital

Workers' human capital consists of two parts, the general human capital, h^g, and the specific human capital, h^s. For example, a worker's degree of education can be thought as one kind of general human capital. It does not change with job tenure or the firm the worker works for. In contrast, the specific human capital is the skill related to the job the worker has. The longer a worker works on a job, the more likely the worker will become more familiar with the job and thus the specific human capital accumulates. It is reasonable to assume the general human capital complements the specific human capital as a worker who has more education may learn things faster than a worker receives less education. In particular, we assume the total human capital is jointly determined by these two types of human capital in the follow way.

$$h = h_g^{\epsilon} \cdot h_s^{1-\epsilon}, \tag{2}$$

where ϵ measures the importance of general human capital in determining total human capital.[7] From now on, we use subscript g to denote education.

Following Ljunqvist and Sargent (2007), an important feature of the model is that workers' human capital varies (stochastically) with the labor market status. It improves during the employment period, while depreciates at the layoff time and during unemployed periods. Specifically, we assume that an employed worker accumulates human capital according the transition function $\mu^e(h'|h)$, and an unemployed worker and laid off worker's human capital depreciates according to the transition function $\mu^u(h'|h)$ and $\mu^l(h'|h)$ respectively. Following Nie (2010), we will use Simulated Method of Moments to estimate these human capital transition processes.

Firms

Firms incur a cost of χ_g to post a vacancy, where g indexed education. When meeting with a worker, a firm draws a productivity from a distribution $Q_g^0(z)$. The productivity of a continuing match evolves according to the Markov process $Q_g(z'|z)$. Each period, a matched worker and job pair breaks up at a exogenous rate λ_g.

Matching

The job market are segmented by education. In each market, there is a match function $M(u_g, v_g)$that determine the number of new matches created each period, where u_g and v_g are total number of unemployed and vacancies indexed by the education level. Each worker meets with a vacancy at rate $\pi_g^w = \frac{M(u_g,v_g)}{u_g}$. Market tightness θ_g is defined as $\frac{v_g}{u_g}$. Each vacancy meets with a worker at rate $\pi_g^f(h_s, b) = \frac{M(u_g,v_g)}{v_g}\frac{f_g(h_s,b)}{u_g}$, where $f_g(h_s, 0) = \delta \sum_b u_g(h_s, b) + u_g(h_s, 0)$ and $f_g(h_s, b \neq 0) = (1-\delta)u_g(h_s, b)$.

Timing

The sequence of events in a period evolves as follows. At the beginning of a period, the retirement shock realizes. It is at this point that the unemployed worker with UI benefits

[7] We also tried to use a more general human capital function which has a CES aggregation form. The key results are not changed.

loses the UI benefits with probability δ and the employed worker without UI benefits qualifies for UI benefits with probability γ. The new matches are then formed and the old matches are destroyed at the exogenous rate λ_g. Human capital evolves according to workers' labor market status and productivity evolves according the age of the match afterwards. If both the firm and the worker agree to form the match, the firm borrows the wage and repays it after production takes place.

The evolution of human capital happens after the meeting of workers and vacancies but before the match decision. As it will become clear next, this implies that the meeting probability depends on last period's rather than the current period's human capital level. This simplifies the computation process. This is not unreasonable. Employers in the real world normally select interviewee based on the resumes first, which reflects the past working experiences, and find out the ability of the candidate during the interview. The job offer, if made, is then based on the candidate's current ability.

3.2 Equilibrium

Worker's Problem

We assume that UI pays a fraction η of the average wage in the worker's skill category when last employed. Hence, to calculate benefit it is sufficient to keep track of a worker's human capital level when last employed, b. For some technical reason, we assume that when an employed worker's human capital changes, his benefit level will follow. Let $\bar{b}(b)$ be the UI payments to an unemployed worker. Let $U_b(h_g, h_s, b)$ and $U(h_g, h_s, 0)$ be the value functions for unemployed worker with benefits and without benefits respectively. Let $V_b(z, h_g, h_s, b)$ and $V(z, h_g, h_s, 0)$ be the value functions for employed workers with benefits and without benefits. Let $V_b^0(z, h_g, h_s, b)$ and $V^0(z, h_g, h_s, 0)$ be the value functions for newly matched workers with benefits and without benefits. All value functions are defined after the realization of human capital and match specific productivity and before the match decision is made.

The problem for an unemployed worker with human capital h and UI benefit entitlement $\bar{b}$ is given by:

$$\begin{aligned} U_b(h_g, h_s, b) \quad &= \quad \bar{b}(b) + \beta(1-\alpha)[\sum_{h'_s} \mu^u(h'_s|h_s)((1-\delta)(1-\pi_g^w)U_b(h_g, h'_s, b) + \delta(1-\pi_g^w)U(h_g, h'_s, 0)) \\ &\quad + \sum_{z', h'_s} \mu^u(h'_s|h_s)Q_g^0(z')((1-\delta)\pi_g^w V_b^0(z', h_g, h'_s, b) + \delta\pi_g^w V^0(z', h_g, h'_s, 0))], \end{aligned} \tag{3}$$

where π_g^w is the probability of finding a new job.

Similarly, for an unemployed worker without UI benefits, the value function is given by:

$$\begin{aligned} U(h_g, h_s, 0) &= sa + \beta(1-\alpha)[(1-\pi_g^w)\sum_{h_s'} \mu^u(h_s'|h_s)U(h_g, h_s', 0) \\ &\quad + \pi_g^w \sum_{z', h_s'} \mu^u(h_s'|h_s)Q_g^0(z')V^0(z', h_g, h_s', 0)] \qquad (4) \end{aligned}$$

The problem for an employed worker who is eligible to receive UI benefits once unemployed is given by:

$$\begin{aligned} V_b(z, h_g, h_s, h_s) &= \max\{U_b(h_g, h_s, h_s), w_b(z, h_g, h_s, h_s) + \beta(1-\alpha)[\lambda_g \sum_{h_s'} \mu^l(h_s'|h_s)U_b(h_g, h_s', h_s) \\ &\quad + (1-\lambda_g)\sum_{z', h_s'} \mu^e(h_s'|h_s)Q_g(z'|z)V_b(z', h_g, h_s', h_s')]\} \qquad (5) \end{aligned}$$

The problem for an employed worker who hasn't worked long enough to qualify UI benefits once unemployed is given by:

$$\begin{aligned} V(z, h_g, h_s, 0) &= \max\{U(h_g, h_s, 0), w(z, h_g, h_s, 0) \\ &\quad + \beta(1-\alpha)[\lambda_g \sum_{h_s'} \mu^l(h_s'|h_s)(\gamma U_b(h_g, h_s', h_s) + (1-\gamma)U(h_g, h_s', 0)) \\ &\quad + (1-\lambda_g)\sum_{z', h_s'} \mu^e(h_s'|h_s)Q_g(z'|z)(\gamma V_b(z', h_g, h_s', h_s') \\ &\quad + (1-\gamma)V(z', h_g, h_s', 0))]\} \qquad (6) \end{aligned}$$

The problem for a newly matched worker who is eligible to receive UI benefits is given by:

$$\begin{aligned} V_b^0(z, h_g, h_s, b) &= \max\{U_b(h_g, h_s, b), w_b^0(z, h_g, h_s, b) + \beta(1-\alpha)[\lambda_g \sum_{h_s'} \mu^l(h_s'|h_s)U_b(h_g, h_s', h_s) \\ &\quad + (1-\lambda_g)\sum_{z', h_s'} \mu^e(h_s'|h_s)Q_g(z'|z)V_b(z', h_g, h_s', h_s')]\} \qquad (7) \end{aligned}$$

The problem for a newly matched worker without UI benefits is given by:

$$
\begin{aligned}
V^0(z,h_g,h_s,0) \;=\; & \max\{U(h_g,h_s,0), w^0(z,h_g,h_s,0) \\
& +\beta(1-\alpha)[\lambda_g \sum_{h_s'} \mu^l(h_s'|h_s)(\gamma U_b(h_g,h_s',h_s)+(1-\gamma)U(h_g,h_s',0)) \\
& +(1-\lambda_g)\sum_{z',h_s'} \mu^e(h_s'|h_s)Q_g(z'|z)(\gamma V_b(z',h_g,h_s',h_s') \\
& +(1-\gamma)V(z',h_g,h_s',0))]\} \qquad (8)
\end{aligned}
$$

Firms' Problems

When a firm matches with a worker, they jointly decide whether to start the production process. If they decide to break up, firms have to pay a cost Ω for the matches lasted at least one period. But this cost does not apply to the new matches.

There are four value functions for firms depending on whether the match is new or old and whether the worker is eligible for UI or not. The firm's problem in a continued match with a worker eligible for UI benefits is given by:

$$
\begin{aligned}
J_b(z,h_g,h_s,h_s) \;=\; & \max\{-\Omega,(1-\tau)Azh - w_b(z,h_g,h_s,h_s) \\
& +\beta(1-\alpha)[(1-\lambda_g)\sum_{z',h_s'} \mu^e(h_s'|h_s)Q_g(z'|z)J_b(z',h_g,h_s',h_s') \\
& -\lambda_g\Omega]\} \qquad (9)
\end{aligned}
$$

where z is the idiosyncratic productivity shock and A is the aggregate productivity shock. We assume that the aggregate shock A does not change in the benchmark model which corresponds to the pre-crisis period. We will allow it to vary in the simulation part.

The firm's problem in a new match with a worker eligible for UI benefits is given by:

$$
\begin{aligned}
J_b^0(z,h_g,h_s,b) \;=\; & \max\{0,(1-\tau)Azh - w_b^0(z,h_g,h_s,b) \\
& +\beta(1-\alpha)[(1-\lambda_g)\sum_{z',h_s'} \mu^e(h_s'|h_s)Q_g(z'|z)J_b(z',h_g,h_s',h_s') \\
& -\lambda_g\Omega]\} \qquad (10)
\end{aligned}
$$

The firm's problem in a continued match with a worker not eligible for UI benefits is given by:

$$
\begin{aligned}
J(z,h_g,h_s,0) &= \max\{-\Omega,(1-\tau)Azh-w(z,h_g,h_s,0)+\beta(1-\alpha)[-\lambda_g\Omega \\
&+(1-\lambda_g)\sum_{z',h'_s}\mu^e(h'_s|h_s)Q_g(z'|z)(\gamma J_b(z',h_g,h'_s,h'_s) \\
&+(1-\gamma)J(z',h_g,h'_s,0))]\} \qquad (11)
\end{aligned}
$$

The firm's problem in a new match with a worker not eligible for UI benefits is given by:

$$
\begin{aligned}
J^0(z,h_g,h_s,0) &= \max\{0,(1-\tau)Azh-w^0(z,h_g,h_s,0)+\beta(1-\alpha)[-\lambda_g\Omega \\
&+(1-\lambda_g)\sum_{z',h'_s}\mu^e(h'_s|h_s)Q_g(z'|z)(\gamma J_b(z',h_g,h'_s,h'_s) \\
&+(1-\gamma)J(z',h_g,h'_s,0))]\} \qquad (12)
\end{aligned}
$$

Surplus Functions and Wage Determination

There are four types of standard surplus functions depending on if it is a new match or not and depending on if the worker is qualified for UI benefits or not.

$$
\begin{aligned}
S^0_b(z,h_g,h_s,b) &= J^0_b(z,h_g,h_s,b)+V^0_b(z,h_g,h_s,b)-U_b(h_g,h_s,b) \qquad (13)\\
S^0(z,h_g,h_s,0) &= J^0(z,h_g,h_s,0)+V^0(z,h_g,h_s,0)-U(h_g,h_s,0) \qquad (14)\\
S_b(z,h_g,h_s,h_s) &= J_b(z,h_g,h_s,h_s)+\Omega+V_b(z,h_g,h_s,h_s)-U_b(h_g,h_s,h_s) \qquad (15)\\
S(z,h_g,h_s,0) &= J(z,h_g,h_s,0)+\Omega+V(z,h_g,h_s,0)-U(h_g,h_s,0) \qquad (16)
\end{aligned}
$$

We assume wage is determined through the standard Nash Bargaining process. This implies that the surplus is split between the firm and the worker proportionally to their bargaining power. The surplus functions and wage functions are derived in the appendix.

Free Entry

The expected zero-profit condition pins down the two market tightness.

$$
\begin{aligned}
\chi_g &= \beta[\sum_{h_s,b}\pi^f_g(h_s,b)(\sum_{z',h'_s}\mu^u(h'_s|h_s)Q^0_g(z')J^0_b(z',h_g,h'_s,b)) \\
&+\sum_{h_s}\pi^f_g(h_s,0)(\sum_{z',h'_s}\mu^u(h'_s|h_s)Q^0_g(z')J^0(z',h_g,h'_s,0))] \qquad (17)
\end{aligned}
$$

where $\pi_f(h_g, h_s, b)$ is the probability that a firm meets a worker with states (h_g, h_s, b).

Distribution

Let $u_g(h_s, b)$ be the measure of unemployed workers with states (h_s, b) and $e_g(z, h_s, b)$ be the measure of employed workers with states (z, h_s, b) at the beginning of a period. Let $\bar{z}_g^0(h_s, b)$ be the cutoff value of z for a new match and $\bar{z}_g(h_s, b)$ be the cutoff value of z for a continued match. Let $\xi(h_g)$ be the fraction of population with education level h_g and let $I(h_s' = h_{s1}) = 1$ if $h_s' = h_{s1}$ and zero otherwise, where h_{s1} is the lowest level of specific human capital. The next period's measure of individuals with different states is given by:

$$\begin{aligned} u_{g,t+1}(h_s', 0) = {} & (1-\alpha)\Big(\sum_{h_s, b\neq 0} u_{g,t}(h_s, b)\delta(1-\pi_{g,t}^w)\mu^u(h_s'|h_s) \\ & + \sum_{h_s, b\neq 0} u_{g,t}(h_s, b)\delta\pi_{g,t}^w\mu^u(h_s'|h_s)Q_g^0(z' \leq \bar{z}_g^0(h_s', 0)) \\ & + \sum_{h_s} u_{g,t}(h_s, 0)(1-\pi_{g,t}^w)\mu^u(h_s'|h_s) \\ & + \sum_{h_s} u_{g,t}(h_s, 0)\pi_{g,t}^w\mu^u(h_s'|h_s)Q_g^0(z' \leq \bar{z}_g^0(h_s', 0)) \\ & + \sum_{z, h_s} e_{g,t}(z, h_s, 0)\lambda_g(1-\gamma)\mu^l(h_s'|h_s) \\ & + \sum_{z, h_s} e_{g,t}(z, h_s, 0)(1-\lambda_g)(1-\gamma)\mu^e(h_s'|h_s)Q_g(z' \leq \bar{z}_g(h_s', 0)|z) \\ & + \alpha\xi(h_g)I(h_s' = h_{s1}), \end{aligned} \tag{18}$$

$$\begin{aligned} u_{g,t+1}(h_s', b' \neq 0) = {} & (1-\alpha)\Big(\sum_{h_s} u_{g,t}(h_s, b')(1-\delta)(1-\pi_{g,t}^w)\mu^u(h_s'|h_s) \\ & + \sum_{h_s} u_{g,t}(h_s, b')(1-\delta)\pi_{g,t}^w\mu^u(h_s'|h_s)Q_g^0(z' \leq \bar{z}_g^0(h_s', b')) \\ & + \sum_{z} e_{g,t}(z, b', b')\lambda_g\mu^l(h_s'|b') \\ & + \sum_{z, h_s} e_{g,t}(z, h_s, h_s)(1-\lambda_g)\mu^e(h_s' = b'|h_s)Q_g(z' \leq \bar{z}_g(h_s', h_s')|z) \\ & + \sum_{z} e_{g,t}(z, b', 0)\gamma\lambda_g\mu^l(h_s'|b') \\ & + \sum_{z, h_s} e_{g,t}(z, h_s, 0)\gamma(1-\lambda_g)\mu^e(h_s' = b'|h_s)Q_g(z' \leq \bar{z}_g(h_s', h_s')|z)\Big) \end{aligned} \tag{19}$$

$$
\begin{aligned}
e_{g,t+1}(z', h_s', 0) &= (1-\alpha)(\sum_{h_s, b\neq 0} u_{g,t}(h_s, b)\delta\pi^w_{g,t}\mu^u(h_s'|h_s)Q_g^0(z' \geq \bar{z}_g^0(h_s', 0)) \\
&+ \sum_{h_s} u_{g,t}(h_s, 0)\pi^w_{g,t}\mu^u(h_s'|h_s)Q_g^0(z' \geq \bar{z}_g^0(h_s', 0)) \\
&+ \sum_{z, h_s} e_{g,t}(z, h_s, 0)(1-\lambda_g)(1-\gamma)\mu^e(h_s'|h_s)Q_g(z' \geq \bar{z}_g(h_s', 0)|z), \quad (20)
\end{aligned}
$$

and

$$
\begin{aligned}
e_{g,t+1}(z', h_s', b' \neq h', b' \neq 0) &= 0, \quad (21) \\
e_{g,t+1}(z', h_s', h_s') &= (1-\alpha)(\sum_{h_s, b\neq 0} u_{g,t}(h_s, b)(1-\delta)\pi^w_{g,t}\mu^u(h_s'|h_s)Q_g^0(z' \geq \bar{z}_g^0(h_s', b)) \\
&+ \sum_{z, h_s} e_{g,t}(z, h_s, h_s)(1-\lambda_g)\mu^e(h_s'|h_s)Q_g(z' \geq \bar{z}_g(h_s', h_s')) \\
&+ \sum_{z, h_s} e_{g,t}(z, h_s, 0)(1-\lambda_g)\gamma\mu^e(h_s'|h_s)Q_g(z' \geq \bar{z}_g(h_s', h_s')), \quad (22)
\end{aligned}
$$

The aggregate unemployment and employment can be derived as follows.

$$u_{g,t} = \sum_{h_s, b} u_{g,t}(h_s, b) \quad (23)$$

$$e_{g,t} = \sum_{z, h_s} e_{g,t}(z, h_s, h_s) \quad (24)$$

Government Budget

In this economy, the government collects income tax and firing tax from the firms and use the revenues to provide UI benefits provided to unemployed workers (who are qualified) and the social welfare assistance to unemployed workers who are not qualified for receiving UI benefits. The government balances budget each period:

$$\sum_{z, h_g, h_s, b} \tau e_g(z, h_s, b)Azh + \sum_{z, h_g, h_s, b} e_g(z, h_s, b)\lambda_g\Omega = \sum_{h_g, h_s} u_g(h_s, 0)sa + \sum_{h_g, h_s, b\neq 0} \bar{b}(b)u_g(h_s, b) \quad (25)$$

Equilibrium

A ***Recursive Stationary Equilibrium*** consists of a set of government policies $(\tau, \kappa, \delta, \gamma, \eta, sa)$, workers' decisions on match formation (at different labor market status), firms' decision rules on match formation and vacancy posting, wage functions, and time-invariant distribution, such that:

- Given the government's policies and wages functions, workers' and firms' decision rules solve workers' and firms' problems.
- Wage functions solve the Nash Bargaining problem.
- The associated time-invariant distribution is consistent with workers' and firms' optimal decisions.
- The government's budget constraint holds for every period.

4 Calibration and Estimation

The model parameters are pinned down in two ways. For those parameters which we can directly calibrate, we chose the proper target to match. For those parameters which are difficult to separately calibrate, we jointly estimate them to match a set of moments which are informative to identify them.

The calibrated parameters and the corresponding targets are reported in Table 4. We set the model period to be one month. The monthly interest rate is chosen so that the implied annual rate is 4%. The implied β is 0.9967. The retiring probability α is chosen so that workers on average work about 40 years. Following Ljungqvist and Sargent (1998), the UI expiration probability δ is set to be $\frac{1}{6}$ so that an unemployed worker is expected to receive UI benefits for 6 months. The replacement ratio η is set to 0.45, a value commonly used in the literature. γ is set to be $\frac{1}{6}$ which captures the condition that an unemployed worker needs to have 2 quarters of employment experience before unemployment to qualify for UI benefits. The SA parameter sa is chosen to match the average welfare benefits as a fraction of the average wage level. The Nash Bargaining weight is set to be 0.5, a value commonly used in the literature. The exogenous separation rates for the two educational groups are chosen in the benchmark economy so that 60% of total separations are due to exogenous separations, which is the ratio of the layoff and discharge rate in the JOLTs data to the total separation rate calculated from the CPS data. There is no good estimates for the shares of the two types of human capital. We set $\epsilon = 0.5$ which implies that both human capital are equally important in the production.

Table 5 reports the values of the parameters we jointly estimate using the Simulated Method of Moments (SMM).[8] In total, there are 18 parameters: 3 parameters on the

[8]To circumvent the computational difficulty of the optimization problem with nonsmooth and local optima, we apply a recent approach proposed by Chernozhukov and Hong (2005). They develop a class of

levels of human capital (note that we normalize the low specific human capital level to be 1), 6 parameters on the human capital transitional probabilities, 5 parameters on the processes of idiosyncratic productivity z (note that we normalize the mean of the productivity process for the low-educational group), and 4 parameters on the matching efficiency and vacancy-posting cost.

We next discuss how the parameters are identified. First, three wage ratios are used to help identify the 3 parameters on human capital levels. They are the ratio of the average wage for the high-educational group to the average wage for the low-educational group, the ratio of the average wage for experienced workers (approximated by the workers between age 45 and 50) to the average wage for unexperienced workers (represented by the workers between age 25 and 30) in the low-educational group, and the ratio of the average wage of workers who are age 25 in the high-educational group to the average wage of workers who are age 25 in the low-educational group. Age 25 is chosen to represent those workers with relatively less labor market experience. Second, wage changes conditional on employment and unemployment experience are used to identify the human capital accumulation rate, the human capital loss at the layoff time, and the human capital depreciation rate during the unemployment period. As explained in the empirical analysis in Section 2.2, a wages change is measured as the difference between the new wage and the old wage for a worker. Third, (endogenous) separation rates and wage dispersions are used to identify the parameters on the z processes. Fourth, the U-E transitional rates are used to identify matching efficiency parameters. Vacancy-posting cost parameters are chosen to match the vacancy costs-to-GDP ratio. We set this ratio to be 4 percent, which is in the range of values used in the literature.

4.1 Model Fit

Table 6 reports the values of the moments predicted by the model and compares them with the counterparts in the data. Overall, the model-generated moments match the data pretty well. In particular, the model is able to match the unemployment rates, E-U transitional rates, and U-E transitional rates for both educational groups. The model also does a great job in matching the wage declines at layoff times and during the unemployment period for the two educational groups. The main statistic that the model could not match well is the wage dispersion. Specifically, the model predicts a

Laplace Type Estimators (LTE) which can be implemented by Markov Chain Monte Carlo simulations. In the appendix, we describe the details about the estimation method.

Table 4: Calibration

Parameter	Target
$\beta = 0.9967$	
sa	Median welfare benefits
$\alpha = \frac{1}{40*12}$	40 years working life
$\delta = 1/6$	Maximum UI length of 6 months
$\eta = 0.45$	Average replacement ratio of UI
$\gamma = 1/6$	6-month employment requirement to gain UI
$\lambda_L = 1.4\%$	60% of total separations for the low edu. group
$\lambda_H = 0.4\%$	60% of total separations for the high edu.group
$\psi = 0.5$	Nash Bargaining weight
$\epsilon = 0.5$	Cobb-Douglas parameter in human capital fun.

Table 5: Estimated Values of the Model Parameters

		High edu. group	Low edu. group
Parameters on the human capital level			
general component	h^g	1.637	1.058
specific component	h^s	2.755	1.000
Parameters on human capital transitions			
skill depreciation rate during unemp. periods (%)	μ^u	0.000	1.444
skill loss probability at layoffs (%)	μ^l	34.101	2.806
skill accumulation rate on the job (%)	μ^e	1.606	1.004
Parameters on the z process (AR(1))			
persistence	ρ_z	0.311	0.317
mean	μ_z	-0.008	0.000
standard deviation	ϵ_t	0.062	0.083
Other labor market parameters			
vacancy-posting cost	χ	1.353	0.236
matching efficiency	ρ	2.279	1.344

Table 6: Moments Matched

Moments	*Model*	*Data*
Unemployment Rates and Transitional Rates (%)		
High edu. group:		
unemployment rate	2.5	2.5
E-U transitional rate	1.1	1.1
U-E transitional rate	43.7	45.8
Low edu. group:		
unemployment rate	5.9	6.0
E-U transitional rate	3.4	3.4
U-E transitional rate	54.6	54.7
Wage Moments Conditional on U/E Length (%)		
High edu. group:		
annual wage growth	2.3	3.2
initial wage decline	−1.9	−1.9
6-month wage decline	−4.9	−4.9
Low edu. group:		
annual wage growth	3.2	2.7
initial wage decline	−1.3	−1.3
6-month wage decline	−4.1	−4.0
Other Wage Statistics		
$\frac{wage^{H-edu}}{wage^{L-edu}}$	1.4	1.5
$\frac{wage^{L-edu}(age{:}45-50)}{wage^{L-edu}(age{:}25-30)}$	1.7	1.7
$\frac{wage^{H-edu}(age{:}25)}{wage^{L-edu}(age{:}25)}$	1.3	1.3
wage dispersion (High edu. group)	0.2	0.6
wage dispersion (Low edu. group)	0.2	0.5
vacancy costs-GDP ratio (%)	3.9	4.0

wage dispersion that is significantly lower than that in the data. This is probably because workers are heterogenous in more dimensions than what includes in the model.

Some comments on the estimated values of the key parameters are also delivered here. First, on the human capital loss at the layoff time, the estimated values for μ^l show that the human capital loss for highly-educated workers is much larger than for low-educated workers. This is probably because in reality highly-educated workers own more specific human capital or are more specialized in skills associated with their jobs. Second, during unemployment periods, the depreciation of human capital for highly-educated workers is almost zero. For low-educated workers, the estimated value for μ^u is 1.44% per month, which suggests an 8-percent loss of human capital per month.[9] Third, the human capital accumulation rate is a little bit higher for highly-educated workers than for low-educated workers. This seems to suggest some complementarity between education and specific human capital, meaning that highly-educated workers may be able to learn relevant skills on the job faster than low-educated workers. These differences will help explain the results reported in the next section for various policy experiments.

5 Applications and Policy Experiments

This section reports several applications of the estimated model which quantify the effects of endogenous separation, human capital dynamics, and exogenous shocks (TFP shocks, matching efficiency shocks, exogenous separation shocks) on the labor market variables and other macroeconomic variables.

5.1 Calibrated Transitional Dynamics

The transitional dynamics between 2008 and 2012 are driven by three shocks: TFP shocks, shocks to exogenous separation rates, and shocks to matching efficiency. In particular, quarterly TFP series are constructed using the standard approach in the literature. The matching efficiency and exogenous separation rates series are chosen to match the E-U transitional rates and U-E transitional rates for the two educational groups.

In addition, during the 2008-2012 period, UI benefits were extended multiple times. This leads to an increase in the maximum weeks of UI benefits from 26 to 99.[10] As described in Nakajima (2012), there are multiple tiers of benefit extensions. As there

[9] Using the estimated values of the parameters in Table 5, this is calculated as $\frac{2.755-1.0}{2.755} * 1.444\% = 8\%$.
[10] See Nakajima (2012) for a detailed description on the timeline of UI extensions.

exists a large amount of heterogeneity at both the state level and the individual level on when workers started to be eligible for the next tier of UI benefits extension, we assume the UI benefits were gradually extended during the period from July 2008 to July 2010. Specifically, we assume that the UI expiration rate δ declines smoothly in the period of the 2008-2010 from the value in the benchmark economy to the corresponding value after all UI extensions.[11] Table 7 reports the details on the calibrated transitional dynamics (i.e., our benchmark case).

5.2 The Effects of UI Extensions

To quantify the effects of the 2008-2010 UI extensions, we compare the transitional dynamics without UI extensions to those with actual UI extensions. The dynamics with UI extensions refer to the transitional dynamics we described in Section 5.1 (we will call these the benchmark transitional dynamics hereafter). The transitional dynamics without UI extensions were generated by simulating the model under the assumption that the UI benefit policy was unchanged in the period of 2008-2012. The differences in the main variables from the benchmark case are reported in Table 8.

The main findings are summarized as follows. First, the contribution of UI extensions to the increase in the aggregate unemployment rate is about 0.5 percentage point. More precisely, without UI extensions, the unemployment rate during the 2010-2012 period would have been 0.5 percentage point lower than the actual level.

Second, the UI extensions had a larger impact on the high-educational group than on the low-educational group. The reason is as follows. Highly-educated workers are more afraid of losing UI benefits because the transition from UI to SA represents a larger loss to highly-educated workers than to low-educated workers. Therefore, highly-educated workers have more incentives to leave unemployment before their UI benefits run out. Correspondingly, when UI benefits were extended, highly-educated workers became more "relaxed" and more patient in selecting jobs. As a result, the job finding rates (U-E transitional rates) declined more for highly-educated workers than for low-educated workers. This led the unemployment rate for the high-educational group to increase more than that for the low-educational group.

Third, UI extensions had different implications for output and labor productivity. The benefit extensions lowered output by about 0.35 percent in each year in the 2010-2012 period. This is a result of two effects. First, as the unemployment rate increased by

[11] All UI extensions took place between July 2008 and July 2010 (see again, Nakajima (2012)).

0.41 percentage point, fewer people were working after UI benefits were extended, which lowered total output. Second, UI extensions slightly increased the labor productivity, by an average annual rate of 0.13 percent in the period of 2010-2012. The increase in the labor productivity is due to the fact that benefit extensions allowed unemployed workers to be more patient in selecting jobs, which increased average productivity (as measured by the average level of z). This finding is consistent with the view that extra UI benefits help improve the matching quality and thus productivity (Acemoglu (1999)).

5.3 The Effects of Changes in TFP

The model can also be used to quantify the effects of changes in TFP in the period of 2008-2012. This is done by comparing the transitional dynamics in the benchmark case with the simulated paths assuming no changes in TFP levels. As a reminder, TFP declined by about 5 percent through 2008 and the first half of 2009 before it started to increase in late years. The general message from this exercise is that changes in TFP had larger effects on output and labor productivity than on labor market variables. The results are reported in Table 9.

Compared to the benchmark, the decline in TFP in the first two years caused the unemployment rate to increase by an average of 0.13 percentage point and 0.12 percentage point in 2009 and 2010, respectively, while the improvement in TFP in the following years reduced the unemployment rate by an average of 0.11 percentage point in 2012. In addition, TFP affects the unemployment rate mainly by influencing the job finding rates. This is because a decline in TFP reduces the matching surplus and thus reduces the vacancies posted. Fewer vacancies lead to a lower probability for an unemployed worker to meet with a firm and result in a lower job finding rate. Finally, as Table 9 clearly shows the effects of TFP on output and labor productivity are much larger than on unemployment rates.

5.4 The Effects of Changes in Matching Efficiency

In the benchmark case, changes in matching efficiency are used to match the U-E transitions. As Figure xx shows, matching efficiency declines significantly during the recession period, which can be interpreted as the result of deteriorations in economic conditions causing workers to be less successful in finding jobs. We can quantify the effects of such changes on the unemployment rate and other key macroeconomic variables by comparing the transitional paths in the benchmark case with those under the assumption that matching efficiency did not change. The resulting differences from the benchmark case are reported in Table 10.

The main findings are summarized as follows. First, the changes in matching efficiency had very large effects on job finding rates. This is not surprising as, in the benchmark case, matching efficiency was chosen to generate the variations in the U-E transitions in each period. As Table xx shows, the decline in matching efficiency after 2008 caused the negative difference in the job finding rate in the 2010-2011 period to reach 22 percentage points and 15 percentage points for the low-educational group and the high-educational group, respectively. The differences slightly diminished in 2012 to 19 percentage points and 13 percentage points, respectively.

Second, though it is not surprising that changes in matching efficiency had large impacts on job finding rates, it is interesting to investigate how changes in matching efficiency influenced the separation rate. Intuitively, when there are fewer job opportunities in the economy, workers should be less willing to separate. Thus, the (endogenous) separation rate should fall. This intuition has been confirmed in our exercise. As Table 10 shows, the separation rate declined by almost 1 percentage point during the 2008-2012 period, with the decline being larger in the first two years than in late years. Remember that these changes were solely caused by the changes in matching efficiency, not by changes in exogenous separation rates, the effects of which will be quantified in the next section. This finding suggests that endogenous responses of workers to economic conditions account for a significant part of variations in the labor market dynamics.

Third, the decline in separation rates is mainly concentrated in the low-educational group. Some explanations follow. In normal times, low-educated workers are more willing to separate for two reasons. First, on average, low-educated workers accumulate less specific human capital and thus have less to lose. Second, as the estimation result indicates, the human capital accumulation rate is lower for low-educated workers, which implies that low-educated workers have larger incentives to look for new jobs with higher productivity z. Put differently, the opportunity cost for low-educated workers to separate to look for new jobs is lower. Following the same logic, when the outside opportunity (of finding a good z) is severely reduced, as represented by a large decline in matching efficiency, low-educated workers are more influenced than highly-educated workers.

5.5 The Effects of Changes in Exogenous Separation Rates

As in the previous section, we can also quantify the effects of changes in exogenous separation rates on the unemployment rate and other macroeconomic variables. This can be achieved by simulating the transitional paths under the assumption that there were no changes in exogenous separation rates and comparing them with the benchmark transitional paths. The differences represent the effects of changes in exogenous separation rates, which are reported in Table 11.

It is not surprising that, without the increases in *exogenous* separation rates in the 2008-2012 period, the total separation rates were lower than in the benchmark case. However, it is worth noting how job finding rates responded to the changes in exogenous separation rates. In general, in our model, an increase in the exogenous separation rate may influence the job finding rate through two channels. First, it reduces the market tightness (that is, $\frac{v}{u}$ declines) and thus lowers the probability for an unemployed worker to meet with a firm. Second, it may change the skill distribution (i.e., the ratio of high-skilled workers to low-skilled workers) in the pool of unemployed workers, which may influence the aggregate job finding rate. Specifically, as Table 11 shows, without increases in exogenous separation rates, the job finding rates increased for the low-educational group. For the high-educational group, the general pattern is the same.

5.6 The Effects of Human Capital Loss

To quantify the effects of human capital loss (which includes both the initial loss and the following human capital depreciation), we have simulated the transitional dynamics under the assumption that there was no human capital loss. We compare the outcome with the benchmark case. The differences in the key variables are reported in Table 12.

We summarize the main findings as follows. First, when there was no human capital loss, the aggregate unemployment rate increased, which was mainly driven by the increase in the unemployment rate for the low-educational group, which was slightly offset by the small decline in the unemployment rate for the high-educational group.

Second, the increase in the unemployment rate in the low-educational group is completely due to the decline in the job finding rates. This is because, without human capital loss, workers become more patient in selecting jobs.

Third, the job finding rate for the high-educational group increased because, without the large human capital loss at layoff time, the fraction of high-skilled unemployed workers increased in the high-educational group. As high-skilled workers have a higher

U-E transitional rate, it raised the overall job finding rate for the high-educational group. This effect dominates the effect of lowering the job finding rate mentioned in the previous paragraph. Thus, the job finding rate for the high-educational group increased. This also explains why the unemployment rate for the high-educational group slightly declined.

Fourth, it is straightforward to understand that, without human capital loss, output and labor productivity both increased, as the ratio of high-skilled workers increased.

5.7 The Effects of Human Capital Depreciation

The key findings in the previous section seem to contradict the common wisdom that skill deterioration will increase the unemployment rate. However, as discussed in that section, the key explanation of why the unemployment rate will increase when there is no human capital loss relies on workers' endogenous responses to skill deterioration. That is, if workers understand the possible skill deterioration and are allowed to make their best choices, they will respond to the skill deterioration by taking low-wage offers to leave the unemployment pool.

To further illustrate this point, we conduct an experiment in which workers' decision rules are based on the actual human capital transitional dynamics (as shown in the estimation results) while we assume no human capital depreciation actually occurred in the transitional paths. In other word, the decision rule is the same as in the benchmark case, while in the simulation, we shut off the actual human capital depreciation. By comparing the outcome in this simulation with the outcome in the benchmark case, we isolate the "pure" effect of human capital depreciation. The details are shown in Table 13.

The results show that the "pure" effect of human capital depreciation on increasing the unemployment rate is only about 0.08 percentage point in the 2010-2012 period. Furthermore, this is completely driven by the increase in the unemployment rate for the low-educational group. We add two comments here. First, the reason that the unemployment rate for the high-educational group was unchanged in this experiment (compared to the benchmark case) is that the estimated human capital depreciation rate for the high-educational group is almost zero. Thus, there are actually no differences for the high-educational group in these two transitional paths. Second, though human capital does not depreciate throughout the unemployment period, highly-educated workers still suffer human capital loss at the layoff time.

Overall, this exercise suggests that the common wisdom is still correct in the sense that human capital depreciation has the tendency to increase the unemployment rate.

However, the key message delivered by this section and the previous section is as follows. In an economy with possible human capital loss during unemployment periods, if workers have accounted for and are able to optimally respond to this risk, the unemployment rate may not be higher than in an economy with *no* human capital loss. The reason is that the increase in the unemployment rate led by human capital loss is more than offset by workers' endogenous responses to prevent them from being unemployed.

5.8 The Effects of Human Capital Accumulation

The flip side of human capital loss is human capital accumulation. While much has been said on the role played by human capital loss, this section shows that human capital accumulation seems to be even more important to both the unemployment rate and other macroeconomic variables. This is not difficult to understand as human capital accumulation affects all employed workers which represent 95% of the total labor force. The counterfactual exercise is similar to the one conducted in Section 5.6 and key results are reported in Table 14.

We briefly summarize the key findings here. First, without human capital accumulation on the job, the unemployment rate will increase by an average of 0.7 percentage point per year in the 2008-2012 period.

Second, interestingly and in contrast to the case without human capital loss, the increase in the unemployment rate is mainly driven by the increase in the unemployment rate for the high-educational group. This increase in the unemployment rate was a result of an increase in the separation rate and a decline in the job finding rate. The separation rate increased because there were no opportunities for workers to improve human capital which caused workers and firms to be more willing to separate. The decline in the job finding rate is because workers had less incentive to take a job as they cannot improve their skills on the job. In this case, they have stronger incentives to look for jobs with higher z to compensate for the lost opportunity to improve specific human capital on the job.

Third, quantitatively, the effects on low-educated workers are smaller than those on highly-educated workers . This suggests that human capital accumulation is more important to highly-educated workers. There are two reasons for this to be true. First, the estimated rate of human capital accumulation is higher for highly-educated workers. Second, highly-educated workers on average own more specific human capital.

6 Conclusion

In this paper we argue that workers' human capital dynamics and endogenous responses to economic shocks are important in understanding U.S. labor market dynamics. To do this, we construct and estimate a Mortensen-Pissarides style labor-market matching model with endogenous separation decisions and stochastic changes in workers' human capital. The model parameters are estimated to match the labor market dynamics and wage moments for different educational groups. A series of experiments are conducted to quantify how agents' endogenous choices vary with changes in economic conditions and changes in UI benefits policy in the context of human capital dynamics, including human capital variations in both the unemployment and employment periods.

There are four main results. First, once workers have accounted for and are able to optimally respond to possible human capital loss, the unemployment rate in an economy with human capital loss during unemployment will not be higher than in an economy with *no* human capital loss. The reason is that the increase in the unemployment rate led by human capital loss is more than offset by workers' endogenous responses to prevent them from being unemployed. Second, compared to human capital loss during unemployment, human capital accumulation on the job is quantitatively more important for both the unemployment rate and output. Third, workers' endogenous separation rates will decline when job finding rates fall. Quantitatively, the decline in the job finding rates in the 2008-2012 period caused the endogenous separation rates to decline by almost 1 percentage point in the same period. Fourth, taking into account the endogenous responses, UI extensions in the 2008-2012 period contributed 0.5 percentage point to the increase in the aggregate U.S. unemployment rate, with the impact on highly-educated workers larger than on low-educated workers.

Many extensions can be added to the current framework. For example, it will be interesting to explore how other shocks, such as credit shocks, influence labor market dynamics and interact with human capital dynamics. Such topics will become our future research.

7 Appendix

7.1 Details on Construction of Labor Market Statistics

From the monthly CPS data, we obtain the total number of employed, the total number of unemployed and the number of short-term (less than 5 weeks) unemployed for each education group. The unemployment rate is calculated as unemployed/(employed+unemployed) for each education group.

To calculate the number of short-term unemployed, we follow Shimer (2012) to eliminate the discontinuity associated with the redesign of the CPS in 1994.[12] Specifically, we measure the short-term unemployed from the full sample before 1994. We use only the incoming rotation groups from 1994 onwards. For the later period, we use the CPS data to construct the fraction of short-term unemployed among all unemployed workers for the incoming rotation groups in each month since 1976. We seasonally adjust this series using the Census's X-12-ARIMA algorithm. We use the product of the number of unemployed workers in the full CPS sample and the short-term unemployment share as our measurement for the short-term unemployed from 1994 onwards.

The unemployment inflow and outflow rates are then constructed following section 2 in Shimer (2012) using the total number of employed, the total number of unemployed and the number of short-term unemployed for each education group.

7.2 Surplus Functions and Wage Functions

As in the standard matching model Nash bargaining implies the net surplus is split by the firm and the worker according to their bargaining weights. Hence wages can be derived from the firms' value functions as follows.

$$\begin{aligned} w_b(z, h_g, h_s, h_s) &= (1-\tau)Azh - (1-\phi)S_b(z, h_g, h_s, h_s) + \Omega \\ &+\beta(1-\alpha)[(1-\lambda_g)\sum_{z', h'_s} \mu^e(h'_s|h_s)Q_g(z'|z)((1-\phi)S_b(z', h_g, h'_s, h'_s) - \Omega) \\ &-\lambda_g\Omega] \end{aligned} \tag{26}$$

[12]Please see the appendix in Shimer (2012) for details.

$$
\begin{aligned}
w_b^0(z,h_g,h_s,b) &= (1-\tau)Azh-(1-\phi)S_b^0(z,h_g,h_s,b) \\
&\quad +\beta(1-\alpha)[(1-\lambda_g)\sum_{z',h_s'}\mu^e(h_s'|h_s)Q_g(z'|z)((1-\phi)S_b(z',h_g,h_s',h_s')-\Omega) \\
&\quad -\lambda_g\Omega] \qquad (27)
\end{aligned}
$$

$$
\begin{aligned}
w(z,h_g,h_s,0) &= (1-\tau)Azh-(1-\phi)S(z,h_g,h_s,0)+\Omega+\beta(1-\alpha)[-\lambda_g\Omega \\
&\quad +(1-\lambda_g)\sum_{z',h_s'}\mu^e(h_s'|h_s)Q_g(z'|z)(\gamma((1-\phi)S_b(z',h_g,h_s',h_s')-\Omega) \\
&\quad +(1-\gamma)((1-\phi)S(z',h_g,h_s',0)-\Omega))] \qquad (28)
\end{aligned}
$$

$$
\begin{aligned}
w^0(z,h_g,h_s,0) &= (1-\tau)Azh-(1-\phi)S^0(z,h_g,h_s,0)+\beta(1-\alpha)[-\lambda_g\Omega \\
&\quad +(1-\lambda_g)\sum_{z',h_s'}\mu^e(h_s'|h_s)Q_g(z'|z)(\gamma((1-\phi)S_b(z',h_g,h_s',h_s')-\Omega) \\
&\quad +(1-\gamma)((1-\phi)S(z',h_g,h_s',0)-\Omega))] \qquad (29)
\end{aligned}
$$

The surplus functions are given by:

$$
\begin{aligned}
S_b(z,h_g,h_s,h_s) &= \max\{0,(1-\tau)Azh-U_b(h_g,h_s,h_s)+\Omega \\
&\quad +\beta(1-\alpha)[-\lambda_g\Omega+\lambda_g\sum_{h_s'}\mu^l(h_s'|h_s)U_b(h_g,h_s',h_s) \\
&\quad +(1-\lambda_g)\sum_{h_s'}\mu^e(h_s'|h_s)U_b(h_g,h_s',h_s') \\
&\quad +(1-\lambda_g)\sum_{z',h_s'}\mu^e(h_s'|h_s)Q_g(z'|z)(S_b(z',h_g,h_s',h_s')-\Omega)]\} \qquad (30)
\end{aligned}
$$

$$
\begin{aligned}
S_b^0(z,h_g,h_s,b) &= \max\{0,(1-\tau)Azh - U_b(h_g,h_s,b) \\
&+\beta(1-\alpha)[-\lambda_g\Omega + \lambda_g \sum_{h_s'} \mu^l(h_s'|h_s)U_b(h_g,h_s',h_s) \\
&+(1-\lambda_g)\sum_{h_s'} \mu^e(h_s'|h_s)U_b(h_g,h_s',h_s') \\
&+(1-\lambda_g)\sum_{z',h_s'} \mu^e(h_s'|h_s)Q_g(z'|z)(S_b(z',h_g,h_s',h_s') - \Omega)]\}
\end{aligned}
\tag{31, 32}
$$

$$
\begin{aligned}
S(z,h_g,h_s,0) &= \max\{0,(1-\tau)Azh - U(h_g,h_s,0) + \Omega + \beta(1-\alpha)[-\lambda_g\Omega \\
&+\lambda_g \sum_{h_s'} \mu^l(h_s'|h_s)(\gamma U_b(h_g,h_s',h_s) + (1-\gamma)U(h_g,h_s',0)) \\
&+(1-\lambda_g)\sum_{h_s'} \mu^e(h_s'|h_s)(\gamma U_b(h_g,h_s',h_s') + (1-\gamma)U(h_g,h_s',0)) \\
&+(1-\lambda_g)\sum_{z',h_s'} \mu^e(h_s'|h_s)Q_g(z'|z)(\gamma S_b(z',h_g,h_s',h_s') \\
&+(1-\gamma)S(z',h_g,h_s',0) - \Omega)]\}
\end{aligned}
\tag{33}
$$

$$
\begin{aligned}
S^0(z,h_g,h_s,0) &= \max\{0,(1-\tau)Azh - U(h_g,h_s,0) + \beta(1-\alpha)[-\lambda_g\Omega \\
&+\lambda_g \sum_{h_s'} \mu^l(h_s'|h_s)(\gamma U_b(h_g,h_s',h_s) + (1-\gamma)U(h_g,h_s',0)) \\
&+(1-\lambda_g)\sum_{h_s'} \mu^e(h_s'|h_s)(\gamma U_b(h_g,h_s',h_s') + (1-\gamma)U(h_g,h_s',0)) \\
&+(1-\lambda_g)\sum_{z',h_s'} \mu^e(h_s'|h_s)Q_g(z'|z)(\gamma S_b(z',h_g,h_s',h_s') \\
&+(1-\gamma)S(z',h_g,h_s',0) - \Omega)]\}
\end{aligned}
\tag{34}
$$

The value functions for unemployed workers can be expressed as a function of match surplus as follows.

$$
\begin{aligned}
U_b(h_g,h_s,b) &= \bar{b}(b)+\beta(1-\alpha)[\sum_{h'_s}\mu^u(h'_s|h_s)((1-\delta)U_b(h_g,h'_s,b)+\delta U(h_g,h'_s,0)) \\
&\quad +\sum_{z',h'_s}\mu^u(h'_s|h_s)Q^0_g(z')\phi((1-\delta)\pi^w_g S^0_b(z',h_g,h'_s,b) \\
&\quad +\delta\pi^w_g S^0(z',h_g,h'_s,0))] \qquad (35)
\end{aligned}
$$

$$
\begin{aligned}
U(h,0) &= sa+\beta(1-\alpha)[\sum_{h'_s}\mu^u(h'_s|h_s)U(h_g,h'_s,0) \\
&\quad +\pi^w_g\sum_{z',h'_s}\mu^u(h'_s|h_s)Q^0_g(z')\phi S^0(z',h_g,h'_s,0)] \qquad (36)
\end{aligned}
$$

The free entry condition can also be written as a function of the match surplus:

$$
\begin{aligned}
\chi_g &= \beta[\sum_{h_s,b}\pi^f_g(h_s,b)(\sum_{z',h'_s}\mu^u(h'_s|h_s)Q^0_g(z')(1-\phi)S^0_b(z,h_g,h_s,b)) \\
&\quad +\sum_{h_s}\pi^f_g(h_s,0)(\sum_{z',h'_s}\mu^u(h'_s|h_s)Q^0_g(z')(1-\phi)S^0(z,h_g,h_s,0))] \qquad (37)
\end{aligned}
$$

7.3 UI Benefit Payments

$$
\begin{aligned}
\bar{b}_g(h'_s \neq 0) \;=\; & \frac{\eta}{\sum_z e_g(z,h'_s,h'_s) + e_g(z,h'_s,0)} \\
& \{\sum_{z'} w^0(z',h_g,h'_s,0) \sum_{h_s,b\neq 0} u_{g,t}(h_s,b)\delta\pi^w_g\mu^u(h'_s|h_s)Q^0_g(z')I^0_g(z',h'_s,0) \\
& + \sum_{z',b\neq 0} w^0_b(z',h_g,h'_s,b) \sum_{h_s} u_{g,t}(h_s,b)(1-\delta)\pi^w_g\mu^u(h'_s|h_s)Q^0_g(z')I^0_g(z',h'_s,b) \\
& + \sum_{z'} w^0(z',h_g,h'_s,0) \sum_{h_s} u_{g,t}(h_s,0)\pi^w_g\mu^u(h'_s|h_s)Q^0_g(z')I^0_g(z',h_g,h'_s,0) \\
& + \sum_{z',h_s} w_b(z',h_g,h'_s,h'_s) \sum_{z} e_{g,t}(z,h_s,h_s)(1-\lambda_g)\mu^e(h'_s|h_s)Q_g(z'|z)I_g(z',h'_s,h'_s) \\
& + \sum_{z'} w(z',h_g,h'_s,0) \sum_{z,h_s} e_{g,t}(z,h_s,0)(1-\lambda_g)(1-\gamma)\mu^e(h'_s|h_s)Q_g(z'|z)I_g(z',h'_s,0) \\
& + \sum_{z'} w_b(z',h_g,h'_s,h'_s) \sum_{z,h_s} e_{g,t}(z,h_s,0)(1-\lambda_g)\gamma\mu^e(h'_s|h_s)Q_g(z'|z)I_g(z',h'_s,h'_s)\} \qquad (38)
\end{aligned}
$$

7.4 Details about the GMM LTE in CH (2005)

Let Θ be the set of parameters to be estimated and $\theta \in \Theta$ be a particular parameter vector ($L \times 1$). Let $\{m_1, m_2, ..., m_K\}$ be K selected moments from the data (for example, m_i can be the sizes of certain groups, wages earnings conditional on certain labor-market experience and so on) and $\{\tilde{m}_1(\theta), \tilde{m}_2(\theta), ...\tilde{m}_K(\theta)\}$ be the corresponding moments simulated from the structural model using parameter vector θ. Now define the GMM objective function as follows:

$$L_n(\theta) \;=\; -\frac{1}{2}\sum_{k=1}^{K} w^k(m_k - \tilde{m}_k(\theta))^2$$

A more general matrix form is given by

$$L_n(\theta) \;=\; -\frac{1}{2}(\frac{1}{\sqrt{n}}g_n(\theta))' W_n(\theta)(\frac{1}{\sqrt{n}}g_n(\theta))$$

where $g_n(\theta)$ is a $K \times 1$ vector $(m_1 - \tilde{m}_1(\theta), m_2 - \tilde{m}_2(\theta), .., m_K - \tilde{m}_K(\theta))'$ and n is the sample size.

The GMM estimator is therefore the $\theta \in \Theta$ which maximizes the objective function $L_n(\theta)$. In practice, it is difficult to find the maxima when there exist many local maxima

or the objective function is not well behaviored (such as the existence of multiple kinks). Therefore, this paper uses the Laplace type estimator (LTE) which can be easily computed through Markov chain Monte Carlo simulation methods.
The GMM LTE is given by

$$\begin{aligned}\hat{\theta} &= \int_{\Theta} \theta p_n(\theta) d\theta \\ p_n(\theta) &= \frac{e^{L_n(\theta)}\pi(\theta)}{\int_{\Theta} e^{L_n(\theta)}\pi(\theta)d\theta}\end{aligned}$$

where $p_n(\theta)$ is called *quasi-posterior* in CH's paper. More formally, GMM LTE $\hat{\theta}$ minimizes the quasi-posterior risk functions which is defined as

$$\mathcal{Q}_n(\zeta) = \int_{\Theta} \rho_n(\theta - \zeta) p_n(\theta) d\theta$$

with the squared loss function $\rho_n(x) = |\sqrt{n}x|^2$.

Under the assumption 1-4 in the paper, CH (2005) the shows the LTE is asymptotically equivalent to the GMM extremum estimator.

7.4.1 Estimation Procedure

To implement the estimation, we use the Metropolis-Hastings algorithm to simulate the quasi-posterior distribution. Then the parameter estimator θ is given by the sample mean of this simulated distribution. The procedure is as follows.

Step 1. Start with an initial parameter vector $\theta^{(0)}$. Solve the structural model and construct the moments $\{\tilde{m}_1(\theta^{(0)}), \tilde{m}_2(\theta^{(0)}), ...\tilde{m}_K(\theta^{(0)})\}$ based on the generated stationary distribution.
Step 2. Use the simulated moments and data moments to form the GMM objective function $L(\theta^{(0)})$.
Step 3. Apply the Metropolis-Hastings algorithm to generate $120,000$ draws $(\theta^{(1)}, \theta^{(2)}, ..., \theta^{(120,000)})$.

- The probability of the move from current ("old") draw $\theta^{(i)}$ to the next ("new") draw, $\delta(\theta^{(i)}, \theta^{(i+1)})$, is given by

$$\delta(\theta^{(i)}, \theta^{(i+1)}) = \inf\left(\frac{e^{L(\theta^{(i+1)})}\pi(\theta^{(i+1)})}{e^{L(\theta^{(i)})}\pi(\theta^{(i)})}, 1\right)$$

- The transition kernel, $q(\theta^{(i+1)}|\theta^{(i)})$, takes the form of

$$q(\theta^{(i+1)}|\theta^{(i)}) \quad = \quad f(|\theta^{(i+1)} - \theta^{(i)})|)$$

where f is Gaussian density.

Step 4. The parameter estimator $\hat{\theta}$ then is the mean of the last $100,000$ simulated draws.

References

[1] Cairo, Isabel and Tomaz Cajner (2012), Human Capital and Unemployment Dynamics: Why more educated workers enjoy greater employment stability, Working Paper.

[2] Chang, Yongsung, Joao F. Gomes, and Frank Schorfheide (2002), Learning-by-Doing as a Propagation Mechanism, *American Economic Review, vol.92, Dec. 2002.*

[3] Cooper, Daniel (2013), The Effect of Unemployment Duration on Future Earnings and Other Outcomes, *Federal Reserve Bank of Boston Working Paper 13-8*

[4] Couch, Kenneth A and Dana W. Placzek (2010), Earnings Losses of Displaced Workers Revisited, *American Economic Review vol. 100(1), pages 572-89, March.*

[5] Davis, Steve, and Till von Wachter (2011), Recessions and the Costs of Job Loss, Brookings Papers on Economic Activity.

[6] Elsby, Michael W.L., Bart Hobijn, and Aysegul Sahin (2010), The Labor Market in the Great Recession,*Brookings Papers on Economic Activity, Spring 2010.*

[7] Elsby, Michael W. L., Ryan Michaels, and Gary Solon (2009), The Ins and Outs of Cyclical Unemployment, *American Economic Journal: Macroeconomics, 1(1): 84-110.*

[8] Farber, Henry S. (2011), Job Loss in the Great Recession: Historial Perspective from the Displaced Workers Survey, 1984-2010, NBER Working Paper 17040.

[9] Fujita, Shigeru (2010), Economic Effects of the Unemployment Insurance Benefits, Federal Reserve Bank of Philadelphia *Business Review*, 2010 Fourth Quarter, 20-27.

[10] Fujita, Shigeru (2012), An Empirical Analysis of On-the-Job Search and Job-to-Job Transitions, *Federal Reserve Bank of Philadelphia, Working Paper 10-34/R.*

[11] Garin, Julio (2012), Borrowing Constraints, Collateral Fluctuations, and the Labor Market, Working Paper.

[12] Laureys, Lien (2012), The cost of Human Capital Depreciation during Unemployment, Working Paper.

[13] Ljungqvist, Lars and Thomas J. Sargent (1998), The European Unemployment Dilemma. *Journal of Political Economy 106.*

[14] Ljungqvist, Lars and Thomas J. Sargent (2007), Understanding European Unemployment with Matching and Search-Island Models. *Journal of Monetary Economics, vol.54, 2007, pp. 2139-2179.*

[15] Ljungqvist, Lars and Thomas J. Sargent (2008), Two Questions about European Unemployment. *Econometrica, vol. 76, 2008, pp. 1-29.*

[16] Nakajima, Makoto (2012), A Quantitative Analysis of Unemployment Benefit Extensions, Journal of Monetary Economics, Volume 59, Issue 7, November 2012, Pages 686702.

[17] Nie, Jun (2010), Training or search? Evidence and an Equilibrium Model, Research Working Paper RWP 10-03, Federal Reserve Bank of Kansas City.

[18] Shimer, Robert, Reassessing the Ins and Outs of Unemployment, *Review of Economic Dynamics, 15(2): 127-148.*

[19] Valletta, Rob and Katherine Kuang (2010), Extended Unemployment and UI Benefits, Federal Reserve Bank of San Francisco *Economic Letter*, 2010-12.

[20] von Wachter, Till, Jae Song and Joyce Manchester. 2011. Long-Term Earnings Losses due to Mass-Layoffs During the 1982 Recession: An Analysis Using Longitudinal Administrative Data from 1974 to 2008. Mimeo, Columbia University.

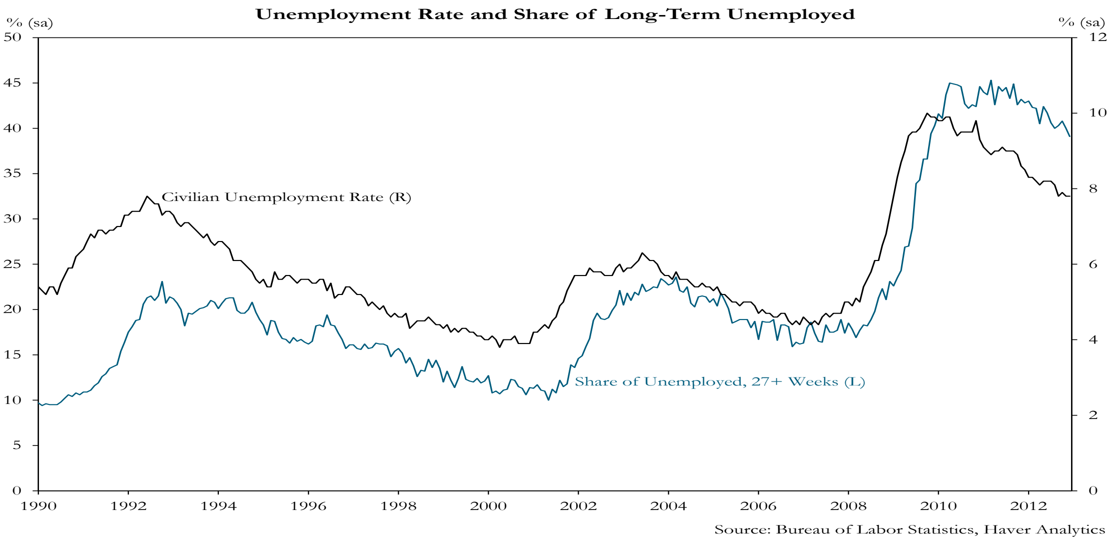

Figure 1: The U.S. Unemployment Rate

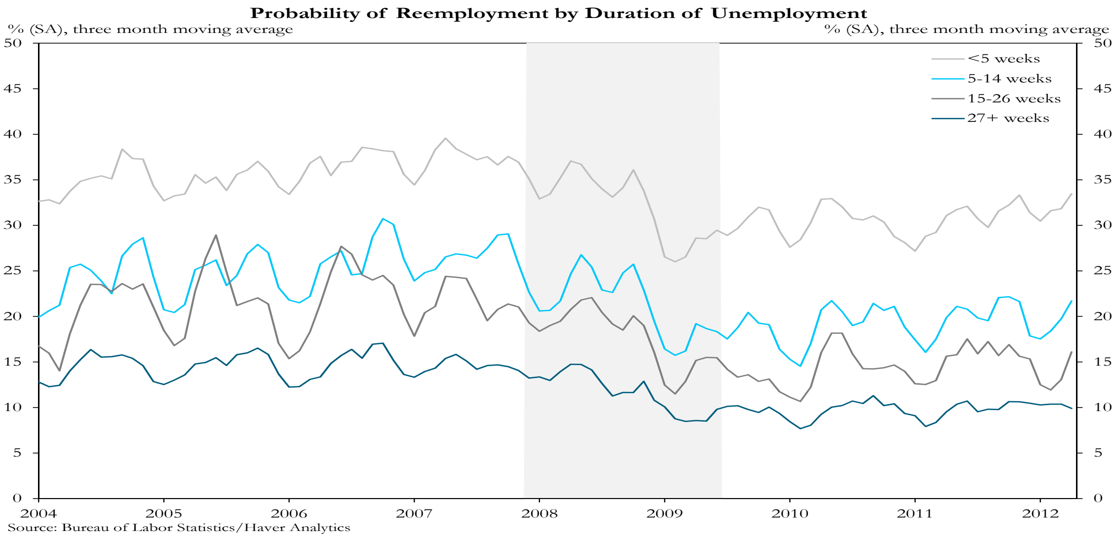

Figure 2: Reemployment Probability by Unemployment Duration

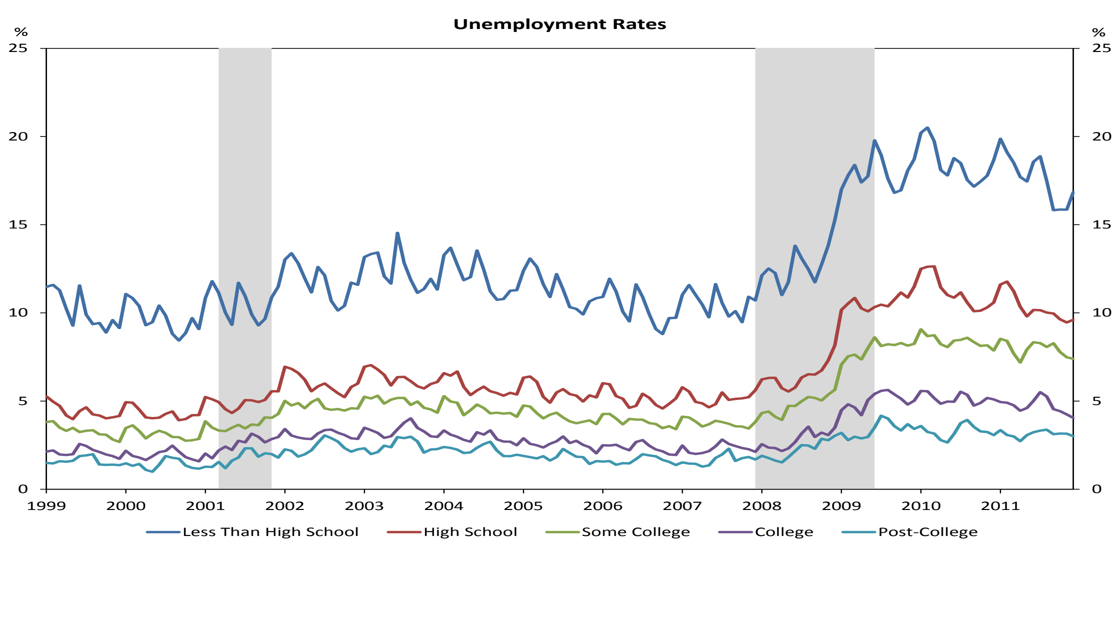

Figure 3: Unemployment Rates by Educational Attainment

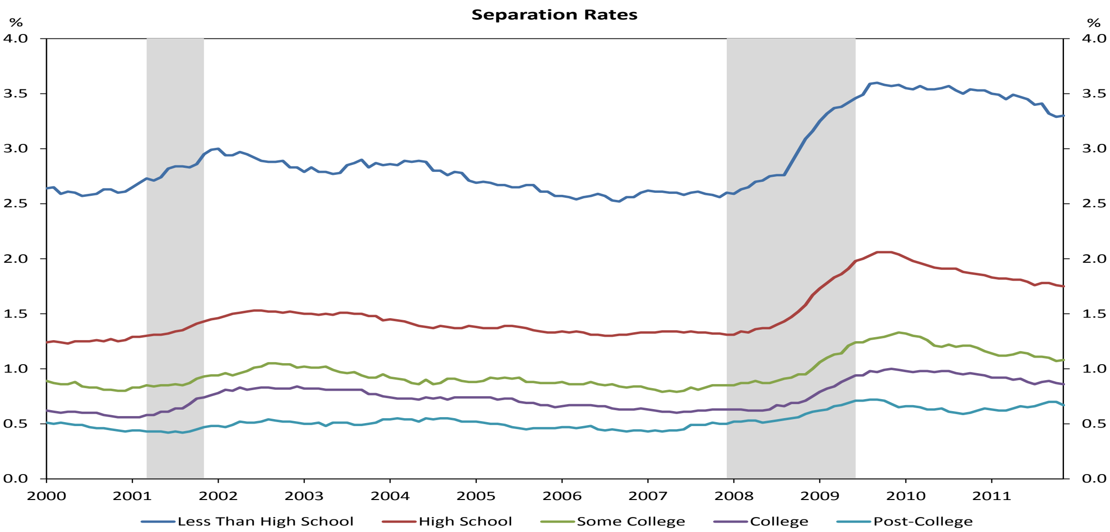

Figure 4: E-U Transitional Rates by Educational Attainment

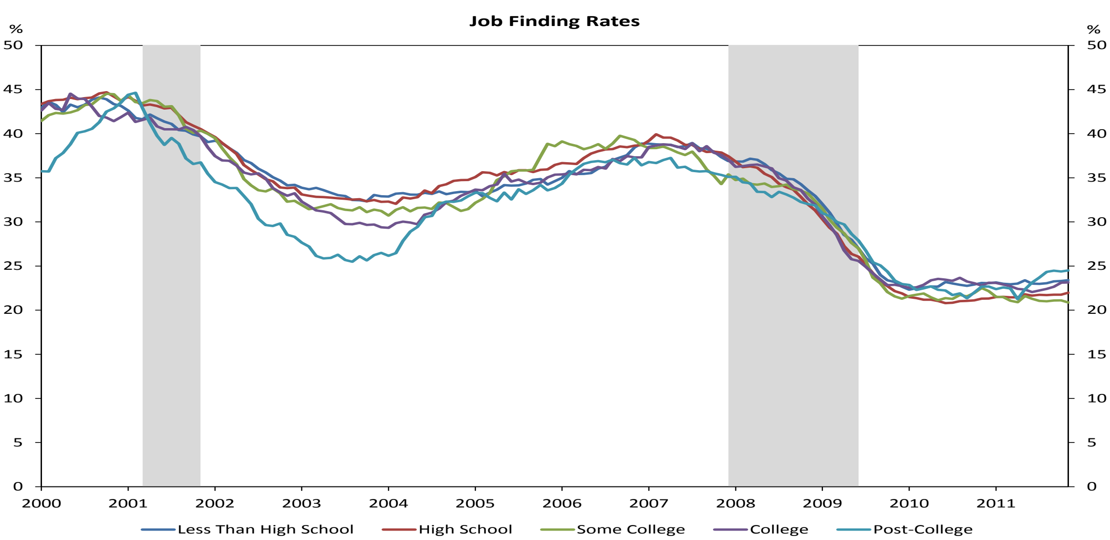

Figure 5: U-E Transitional Rates by Educational Attainment

Table 7: Transitional Dynamics (The Benchmark Economy)

	2007	2008	2009	2010	2011	2012
(1) aggregate u	4.91	5.03	7.65	9.17	8.64	7.96
(2) gdp	100.00	95.34	88.96	88.64	91.08	93.65
(3) lp	100.00	95.45	91.59	92.78	94.80	96.77
(4) total borrowing	100.00	94.36	85.70	84.38	87.40	90.65
(5) TFP	100.00	98.51	96.47	98.23	100.52	102.77
(6) credit shock	20.00	20.00	20.00	20.00	20.00	20.00
(7) high-edu u	2.51	2.41	3.81	4.49	4.23	3.94
(8) low-edu u	5.90	6.12	9.24	11.11	10.47	9.63
(9) high sepa. rate	1.15	1.06	1.38	1.16	1.11	1.14
(10) low sepa. rate	3.44	3.53	3.87	3.34	3.19	3.14
(11) high endog. sepa.rate	0.28	0.29	0.22	0.17	0.18	0.17
(12) low endog. sepa.rate	1.02	0.00	0.00	0.00	0.00	0.00
(13) high exog. sepa.rate	0.88	0.77	1.15	0.98	0.94	0.96
(14) low exog. sepa.rate	2.42	3.53	3.87	3.34	3.19	3.14
(15) high job finding rate	44.66	42.22	32.74	24.84	25.47	28.13
(16) low job finding rate	54.75	53.56	36.58	26.52	27.77	29.94
(17) high wage	100.00	98.47	93.30	93.39	95.95	98.71
(18) low wage	100.00	92.21	85.16	85.13	87.85	90.55
(19) high π^f	62.80	56.95	50.65	39.98	38.61	41.86
(20) low π^f	15.40	10.36	8.33	6.33	6.23	6.36
(21) high π^w	84.30	75.43	53.32	40.32	41.27	46.71
(22) low π^w	94.00	53.85	36.70	26.57	27.81	29.99
(23) employed high-skilled	75.10	75.69	75.46	74.88	74.38	73.98
(24) unemp. high-skilled	77.80	66.92	67.16	66.42	65.53	65.26
(25) high-skilled share (high-edu u)	45.40	42.14	51.00	57.67	58.23	57.85
(26) high-skilled share (low-edu u)	83.60	71.03	69.92	67.88	66.77	66.53
(27) high v	100.00	93.36	115.81	132.54	132.31	128.91
(28) low v	100.00	87.84	111.32	129.07	128.92	125.27
(29) high $\frac{v}{u}$	1.36	1.32	1.05	1.01	1.07	1.12
(30) low $\frac{v}{u}$	6.13	5.21	4.39	4.20	4.46	4.71
(31) average Az	100.00	95.24	91.29	92.61	94.81	96.94
(32) average z	100.00	96.67	94.63	94.28	94.32	94.33
(33) high ave. z	100.00	100.12	99.36	98.58	98.40	98.37
(34) low ave. z	100.00	95.18	92.53	92.33	92.50	92.52

Table 8: No UI Extensions (Difference from the Benchmark)

	2007	2008	2009	2010	2011	2012
aggregate u (%)	0.00	−0.01	−0.20	−0.51	−0.49	−0.41
high-edu u (%)	0.00	0.00	−0.29	−0.71	−0.64	−0.53
low-edu u (%)	0.00	−0.01	−0.17	−0.43	−0.42	−0.36
high sepa. rate(%)	0.00	0.00	0.02	0.06	0.07	0.06
low sepa. rate (%)	0.00	0.00	0.00	0.00	0.00	0.00
high job finding rate(%)	0.00	0.24	3.79	6.79	6.27	6.12
low job finding rate (%)	0.00	0.10	0.88	1.28	1.25	1.25
gdp	0.00	0.01	0.13	0.35	0.35	0.33
labor productivity	0.00	0.00	−0.07	−0.15	−0.15	−0.10

Table 9: No TFP shocks (Difference from the Benchmark)

	2007	2008	2009	2010	2011	2012
aggregate u (%)	0.00	−0.03	−0.13	−0.12	0.00	0.11
high-edu u (%)	0.00	−0.01	−0.08	−0.08	−0.01	0.07
low-edu u (%)	0.00	−0.03	−0.15	−0.13	0.00	0.12
high sepa. rate(%)	0.00	0.00	−0.00	−0.00	−0.00	−0.00
low sepa. rate (%)	0.00	0.00	0.00	0.00	0.00	0.00
high job finding rate(%)	0.00	0.34	0.81	0.38	−0.10	−0.60
low job finding rate (%)	0.00	0.34	0.75	0.31	−0.09	−0.48
gdp	0.00	1.46	3.36	1.72	−0.44	−2.62
labor productivity	0.00	1.44	3.33	1.69	−0.45	−2.60

Table 10: No Changes in Matching Efficiency (Difference from the Benchmark)

	2007	2008	2009	2010	2011	2012
aggregate u (%)	0.00	1.04	−0.53	−2.54	−2.39	−1.77
high-edu u (%)	0.00	−0.10	−0.50	−1.30	−1.36	−1.04
low-edu u (%)	0.00	1.51	−0.54	−3.06	−2.82	−2.07
high sepa. rate(%)	0.00	0.01	0.05	0.10	0.08	0.08
low sepa. rate (%)	0.00	1.04	1.00	0.91	0.88	0.88
high job finding rate(%)	0.00	2.60	7.52	14.37	14.87	12.64
low job finding rate (%)	0.00	0.63	14.25	22.43	21.34	19.34
gdp	0.00	1.86	5.00	7.56	7.77	7.43
labor productivity	0.00	2.95	4.60	5.18	5.46	5.71

Table 11: No Changes in Exogenous Separations (Difference from the Benchmark)

	2007	2008	2009	2010	2011	2012
aggregate u (%)	0.00	−1.20	−2.71	−2.59	−1.91	−1.74
high-edu u (%)	0.00	0.27	−0.79	−0.76	−0.32	−0.37
low-edu u (%)	0.00	−1.81	−3.51	−3.35	−2.57	−2.31
high sepa. rate(%)	0.00	0.11	−0.28	−0.12	−0.07	−0.09
low sepa. rate (%)	0.00	−1.11	−1.46	−0.92	−0.78	−0.72
high job finding rate(%)	0.00	−0.44	1.49	0.87	0.41	0.44
low job finding rate (%)	0.00	1.17	1.74	1.13	0.95	0.92
gdp	0.00	1.63	3.76	3.95	3.19	3.11
labor productivity	0.00	0.43	1.15	1.46	1.31	1.36

Table 12: No Human Capital Loss (Difference from the Benchmark)

	2007	2008	2009	2010	2011	2012
aggregate u (%)	0.00	0.55	0.54	0.60	0.59	0.55
high-edu u (%)	0.00	−0.03	−0.11	−0.10	−0.05	−0.03
low-edu u (%)	0.00	0.79	0.82	0.90	0.85	0.79
high sepa. rate(%)	0.00	−0.00	0.01	0.02	0.02	0.02
low sepa. rate (%)	0.00	0.00	0.00	0.00	0.00	0.00
high job finding rate(%)	0.00	0.72	1.45	0.91	0.68	0.68
low job finding rate (%)	0.00	−7.20	−3.48	−2.26	−2.28	−2.45
gdp	0.00	−0.02	0.37	0.79	1.31	1.83
labor productivity	0.00	0.54	0.92	1.46	1.98	2.47

Table 13: Effects of Human Capital Depreciation (Difference from the Benchmark)

	2007	2008	2009	2010	2011	2012
aggregate u (%)	0.00	−0.02	−0.04	−0.08	−0.08	−0.08
high-edu u (%)	0.00	0.00	−0.00	−0.00	−0.00	−0.00
low-edu u (%)	0.00	−0.03	−0.06	−0.11	−0.12	−0.11
high sepa. rate(%)	0.00	0.00	0.00	0.00	0.00	0.00
low sepa. rate (%)	0.00	0.00	0.00	0.00	0.00	0.00
high job finding rate(%)	0.00	0.00	0.00	0.01	0.01	0.01
low job finding rate (%)	0.00	0.29	0.29	0.31	0.35	0.37
gdp	0.00	0.09	0.28	0.53	0.79	1.01
labor productivity	0.00	0.08	0.24	0.49	0.74	0.95

Table 14: No Human Capital Accumulation (Difference from the Benchmark)

	2007	2008	2009	2010	2011	2012
aggregate u (%)	0.00	1.11	0.29	0.58	0.68	0.66
high-edu u (%)	0.00	0.44	1.01	2.00	2.01	1.84
low-edu u (%)	0.00	1.39	−0.01	−0.01	0.13	0.17
high sepa. rate(%)	0.00	−0.05	0.08	0.15	0.15	0.15
low sepa. rate (%)	0.00	0.45	0.00	0.00	0.00	0.00
high job finding rate(%)	0.00	−9.43	−6.80	−6.12	−6.14	−6.55
low job finding rate (%)	0.00	−5.16	0.12	−0.06	−0.43	−0.59
gdp	0.00	−0.76	−1.79	−3.12	−4.38	−5.62
labor productivity	0.00	0.38	−1.57	−2.68	−3.88	−5.16