Unemployment Insurance, Moral Hazard, and Age Discrimination in the Labor Market

Mingli Zhong*
The Wharton School
University of Pennsylvania

January 2018

Abstract

This paper investigates whether the effect of unemployment insurance benefits on unemployment duration varies by age over the business cycle. When tested individually, the unemployment durations of younger workers are significantly raised by the same level of increase in UI benefits more in a boom than in a recession, while those of older workers are equally affected over the business cycle. This difference between age groups is *not* significant when tested as an interaction effect in a more stringent regression model. Similarly, we also find that the age effect reported in previous study is non-significant when subjected to the same procedure of regression analysis. The current findings suggest that incorporating age into the design of UI benefits should require further study and more credible evidence.

*I thank Olivia S. Mitchell, Hanming Fang, Amanda Chuan, Matt Davis, Andrew Johnston, and Lindsay Relihan, as well as seminar participants in the Wharton Applied Economics Work shop for helpful comments and discussion. I am thankful to Kory Kroft and Matthew Notowidigdo for sharing their data and code with me. I acknowledge research funding from the Pension Research Council/Boettner Center for Pensions and Retirement Research at the Wharton School of the University of Pennsylvania. Opinions and views are solely my responsibility.

1 Introduction

A great deal of research has documented the social welfare gains of extending the duration of unemployment insurance (UI) during recessions (e.g. Krueger and Meyer 2002; Piketty and Saez 2013). An important finding is that unemployment benefits raise unemployment durations to a lesser degree in a recession than in a boom. For example, Rothstein (2011) finds that the impact of UI on raising unemployment durations in the U.S. was smaller during the Great Recession than during booms. Using a more quantitative approach, Kroft and Notowidigdo (2011) show that a one standard deviation increase in the unemployment rate reduces the impact of unemployment benefits on duration by 50 percent.

This paper investigates whether the impact of UI benefits on unemployment duration varies by age over the business cycle. The question is motivated by the finding that UI benefits, on average, raise longer unemployment durations for older workers than for younger workers (Michelacci and Ruffo 2015). One interpretation of this finding is that younger workers want jobs not only to increase their current income but also to acquire labor market skills and so improve career prospects and lifetime income (Michelacci and Ruffo 2015). As a result, the additional income provided by UI does not reduce younger workers' incentive to return to work as much as older workers'. It remains to be explored, however, whether the weaker effect of UI benefits on the unemployment durations of younger workers changes with the overall economy.

Using data from the Survey of Income and Program Participation (SIPP), this paper shows that the impact of UI benefits on unemployment durations is more responsive to economic recessions for younger workers than for older workers. *Responsiveness* is measured by the elasticity of unemployment durations with respect to benefits, following methods used in previous research (Moffitt 1985; Meyer 1990; Chetty 2008; Kroft and Notowidigdo 2011; Michelacci and Ruffo 2015). *Duration elasticity* is defined as the percentage increase in unemployment durations when benefit levels increase by 1%. In particular, we show that duration elasticity for younger workers is significantly larger in a recession than in a boom. By contrast, duration elasticity for older workers remains stable over the business cycle.

We begin by providing graphical evidence comparing the job finding rates of younger and older workers at different phases of the business cycle. Following the work of Kroft and Notowidigdo (2011), the overall economic environment is measured by the state-level unemployment rate of the first month of an individual's unemployment spell. We plot Kaplan-Meier survival curves for younger (20-40 years old) and older (41-60 years old) workers respectively (cf., Michelacci and Ruffo (2015). We show that job finding rates are higher for younger workers than for older workers under weak economic conditions and are similar for the two age groups under strong economic conditions. For example, after being unemployed for 16 weeks in a recession, 60 percent of younger workers are still unemployed, compared to 68 percent of older workers who are still unemployed. After being unemployed for 37 weeks in a recession, 28 percent of younger workers are unemployed, compared to 41 percent of older workers. By contrast, job finding rates are not significantly different between the two age groups during a boom.

Second, we estimate a set of Cox hazard models to evaluate how duration elasticity varies with unemployment rates for each age group. The SIPP dataset includes actual UI benefits to an individual for only a small subset of all subjects. To alleviate the problem of data sparsity, we use two *proxies* for actual UI benefit levels so that each individual's UI benefits can be estimated: the average benefits of all claimants for each state/year pair, and the age-specific state/year average benefits for each age group. The latter can be a more accurate proxy for actual benefits if there exist sizable differences in actual benefits between the two age groups. In three Cox regression models, we find that the effect of unemployment rate on duration elasticity is larger in magnitude for younger workers than for older workers. In the baseline specification, a 10 percent increase in state-level unemployment rate significantly raises the hazard rate with respect to UI benefits by 16.5 percent for younger workers, and by 4 percent for older workers. The estimates imply that a one standard deviation increase in the unemployment rate (1.7 percentage points increase to 8.4%)

significantly reduces the magnitude of duration elasticity for younger workers by 71 percent. By contrast, a one standard deviation increase in the unemployment rate has no significant effect for older workers.

In the following regression analysis, we seek the underlying mechanism to explain the results. We show that increasing unemployment rates reduces the attractiveness of UI benefits to younger workers. As a result, younger workers become more motivated in their job search during economic recessions compared to boom times. By contrast, the attractiveness of UI benefits for older workers does not vary with unemployment rates. Consequently, younger workers increase their job finding rates compared to older workers in economic recessions.

Understanding the variation in behavior between how older and younger workers respond to unemployment benefits over the business cycle has potentially important implications for the aging workplace and for the improvement of public policies concerning workers of different ages. Age-specific social insurance systems can be designed with considerations of different labor supply responses by older and younger workers for social welfare improvement.

The paper proceeds as follows. Section II reviews the relevant literature. Section III describes the data used for analyses. Section IV presents the model for evaluating how duration elasticity varies with unemployment rate by age. Section V presents graphical and statistical results. Section VI concludes.

2 Literature Review

Previous research on unemployment insurance has proposed a range of formulas for the average level of the optimal unemployment insurance benefits. Baily (1978) and Chetty (2006) derive consumption-based formulas for the average level of optimal UI benefits in terms of three parameters: elasticity of unemployment duration with respect to benefits, the drop in consumption as a function of UI benefits, and the coefficient of relative risk aversion. The UI benefit level is measured by the UI replacement rate, which refers to the ratio of UI benefits to the worker's previous wage. The optimality condition equates the benefit of consumption smoothing to the cost of behavioral distortions. The first parameter, elasticity of unemployment duration with respect to UI benefits, captures the moral hazard cost due to behavioral distortions. The moral hazard cost is defined as a distortionary cost caused by UI recipients to stay away from work longer than those who do not receive unemployment benefits, since UI recipients face lower cost of being unemployed. The second parameter, drop in consumption, measures the gains due to consumption smoothing. The third parameter, risk aversion, reflects the worker's value of having a smoother consumption path.

Several papers have sought to estimate these three parameters, to allow empirical implementation of consumption-based UI formulas. Moffitt (1985), Meyer (1990), and Krueger and Meyer (2002) estimate the elasticity parameter, which quantifies the effect of UI benefits on durations. The consensus estimate is 0.5, meaning that a 10% increase in UI replacement rates leads to 5% longer unemployment duration, where replacement rate is defined as the ratio of UI benefits to pre-unemployment wage. Gruber (1997) evaluates the consumption smoothing benefits of UI. He concludes that a 10% increase in the UI replacement rate causes a 2.8% lower consumption decline. Using Meyer's and his own estimates, Gruber calibrates the optimal replacement rate, which is much lower than the observed benefit level. If the relative risk aversion were 2, for instance, the optimal replacement rate would be 5%, meaning that the optimal UI benefits should be 5% of the previous wage. In fact, however, the observed average UI rate is 50% of the previous wage. One reason why the implied optimal benefit level is far different from the observed could be that it is difficult to measure risk preferences in the context of unemployment insurance. Chetty and Szeidl (2007) suggest that there is also an amplifying impact of consumption commitments on risk aversion. Consumption commitments refer to consumption goods that cannot be adjusted frequently due to fixed adjustment costs, such as housing. This differs from the standard expected utility approach which assumes people can cut back on consumption goods freely. In fact, Chetty and

Szeidl's models of consumption commitments suggest that relative risk aversion might exceed 4 for unemployment shocks. Consequently, the corresponding optimal replacement rate would be much higher, around 45%.

Other studies have devised alternative ways to calculate optimal UI benefits. Shimer and Werning (2007) use the responsiveness of reservation wages to unemployment benefits to test for the optimality of UI. After-tax reservation wages suggest that the take-home pay required to make a worker indifferent between working and remaining unemployed. The optimality condition depends on the gain from benefits and the cost of tax through reservation wage. On the one hand, higher benefits reduce the cost of remaining unemployed and consequently raise the pretax reservation wage. The magnitude of increase in reservation wage is measured by the elasticity of reservation wages to benefits. On the other hand, the increase in benefit must be funded by an increase in the employment tax which therefore reduces the after-tax reservation wage. The primary advantage of the Shimer/Werning approach over the consumption-based formula is that they do not need to independently estimate risk aversion and consumption drop. These two parameters are difficult to identify since risk aversion is context-dependent and measuring consumption declines requires a long and ideally administrative consumption panel dataset. One problem with their reservation wage approach is that it is challenging to find a reliable way to measure the reservation wage.

The third approach to calculating the average level of optimal UI benefits is a revealed preference formula by Chetty (2008). Using Baily (1978)'s formula, Chetty decomposes the effect of UI benefits on duration into two parts: a welfare-enhancing liquidity effect of benefits on duration, and a welfare-reducing moral hazard effect due to distorted incentives. The ratio of the liquidity effect to the moral hazard effect is a sufficient statistic for testing the optimality of UI benefits.

All three approaches to calculating the average optimal UI benefit recognize the disincentive effects of unemployment insurance as evidence of moral hazard. The elasticity of unemployment duration with respect to benefits is commonly used to measure how UI reduces labor supply. Additional evidence of moral hazard is the spike in the exit rate of unemployment at benefit exhaustion.

Moffitt (1985) and Katz and Meyer (1990a, 1990b) interpret the sharp surge in the exit rate as evidence that UI recipients wait until their benefits run out to return to work. Instead of measuring the hazard rate of exiting the UI system, Card, Chetty, and Weber (2007) measure the hazard rate of reemployment. They do not find a sharp spike in job finding at the point of benefit exhaustion, which implies that many individuals leave the unemployment system when their benefits expire without returning to work. Therefore, the spike in the unemployment exit rate overstates the degree of moral hazard induced by UI.

Most existing literature focuses on the average UI benefit rate, though two recent studies have investigated the optimal redistribution pattern of UI benefits over either the life cycle or the business cycle. Michelacci and Ruffo (2015) propose an optimal life cycle unemployment system that increases benefits for younger workers and decreases benefits for older workers. Their argument is that younger workers have little ability to smooth consumption during unemployment and show little evidence of moral hazard. Kroft and Notowidigdo (2011) propose an optimal unemployment system varying over the business cycle. Their finding shows that the moral hazard cost is low during times of high unemployment, and high during times of low unemployment in the United States. Schmieder, Wachter, and Bender (2012) find similar results in Germany. Consequently, optimal UI benefit levels should be positively related to unemployment rate to minimize welfare loss due to moral hazard.

Some UI research presents empirical evidence to corroborate the hypothesis that UI benefits do not raise unemployment durations during times of high unemployment. Rothstein (2011) finds little evidence of moral hazard during the Great Recession, when extended UI payment spells were introduced. UI benefit extensions raised the unemployment rate in early 2011 by only about 0.1-0.5%. The effect of benefit extensions is more significant for staying in labor market and looking for jobs, than for reducing job search incentive. Farber and Valletta (2015) report similar results during the much milder downturn in the early 2000s and the 2009-2012 periods. They find a small reduction in the unemployment exit rate resulted from extended UI benefits in both periods.

In addition, the reduction is primarily due to a decrease in exits from the labor force rather than a decrease in job finding rate. Both papers suggest that UI does not significantly raise unemployment durations or reduce job search incentive.

Other UI research further investigates whether UI benefits affect labor force attachment or labor search behavior by studying the event of the expiration of UI benefit extension. Farber, Rothstein, and Valletta (2015) show consistent results during the phase-out period of benefit extensions in 2013-2014: this reduced the unemployment rate mainly by moving people out of the labor market instead of increasing the job finding rate. This result is also consistent with what Card, Chetty, and Weber (2007) show, namely that the expiration of unemployment benefits has little effect on reemployment. Hagedorn, Manovskii, and Mitman (2015) investigate the impact of extension expiration on employment from a macroeconomic perspective. They find that 1% drop in benefit duration causes an increase of employment by 0.0161 log points, implying that some 1.8 million additional people took jobs in 2014 due to the UI benefit cut. In addition, the expiration of benefit extensions led to almost 1 million non-participants entering the labor market. A plausible explanation is that non-participants were encouraged by the greater probability of finding jobs, since the expiration of UI extensions sends a positive signal on job creation. The macro evidence contradicts the micro evidence in Farber, Rothstein, and Valletta (2015) that the expiration did not improve job search or job finding rate. The discrepancy between micro and macro evidence of the impact of UI extension expiration on employment needs to be further investigated.

Besides analyzing the transition of labor force status on the extensive margin, several papers document job search behavior of the unemployed on the intensive margin. Krueger and Mueller (2010) find that unemployed workers allocate 41 minutes per day to job search (on weekdays). Job search is inversely related to the generosity of unemployment benefits, with an elasticity between -1.6 and -2.2. Job search intensity for UI benefits recipients increases prior to benefit exhaustion, while remaining constant for non-recipients during unemployment spells. Aguiar, Hurst, and Karabarbounis (2013) document a larger impact on job search time: they report that unemployed workers allocate 2-6 percent of their lost work hours to job search. Given that the average lost work time is about 33 hours per week, the extra time devoted to job search is 40-118 minutes per week. Besides job search, leisure absorbs 50 percent of foregone market work hours, mainly sleeping and television watching. Home production activities absorb 30 percent, including cooking, cleaning, laundry, shopping, home maintenance and repair, and child care. Health care and education investment absorb 12 percent of foregone market work hours. Kutyavina (2015) finds that, during the Great Recession, older unemployed workers spent less time on job search than younger workers.

In summary, previous studies document that elasticity of unemployment duration with respect to UI benefits is smaller in recessions than in booms. The contribution of this paper is to further explore whether the variation in duration elasticities over the business cycle is primarily driven by younger or older workers.

3 Data

In keeping with prior analysis in this field, we use data from the Survey of Income and Program Participation (SIPP) spanning 1985-2000. Each SIPP panel surveys households at 4-month intervals for 2-4 years. Compared to other widely-used data sets such as the Current Population Survey (CPS) and the Panel Study on Income Dynamics (PSID), the main benefits of the SIPP are the availability of weekly data on employment status to compute individual unemployment spells and UI benefit receipt, and its large sample size.

We follow the sample selection criteria adopted by Chetty (2008). Specifically, we focus on males 20-60 years old who (1) report searching for a job, (2) are not on temporary layoff, (3) have at least three months of work history in the survey, and (4) took up UI benefits within one month after job loss. We also censor unemployment spells at 50 weeks to reduce the influence of outliers and to focus on the search behavior for both younger and older workers in the year after job loss. These restrictions leave 4,380 unemployment spells in the core analysis sample, the same sample size as in Michelacci and Ruffo (2015)'s study on optimal age-dependent unemployment insurance. Our sample size (4,380 spells) is slightly smaller than Chetty (2008)'s (4,529 spells) since his age range is from 18-65 years old. The reason for choosing relatively strict age range is to exclude the effect of Social Security on labor supply decisions for older workers. Information on UI benefit levels was obtained from the Employment and Training Administration's Significant Provisions of State Unemployment Insurance Laws (various years). All dollar value in the data are adjusted to real 1990 dollars.

Panel A of Table 1 presents descriptive statistics for the SIPP sample. We divide the SIPP sample into two subsamples according to whether individuals began their unemployment spells in states with above-median unemployment rates or below-median unemployment rates. The median unemployment rate is defined across all unemployment spells in the sample. In keeping with prior studies, we define the unemployment rate assigned to each unemployment spell is the monthly state-level unemployment rate at the starting month of each spell. Panel B of Table 1 shows summary statistics for two age groups with above-median unemployment rates, where two age groups are 20-40 and 41-60 years old following Michelacci and Ruffo (2015). Panel C of Table 1 shows summary statistics for the two age groups with below-median unemployment rates. Individuals with above-median unemployment rate (Panel B) have longer unemployment durations and slightly higher pre-unemployment annual wage on average than those with below-median unemployment rate (Panel C). As expected, the average unemployment rate in Panel B (8%) is much higher than that in Panel C (5%). The weekly unemployment benefits and replacement rate are close between the two subsamples. Other demographic characteristics such as age, years of education, and marital status are also similar between the two subsamples.

Table 1 here

4 Empirical Strategy

The objective of our empirical analysis is to estimate how unemployment duration elasticity with respect to UI benefits varies by age, over the business cycle. Our empirical strategy closely follows Kroft and Notowidigdo (2011), extended to investigate heterogeneity between age groups. We divide the SIPP sample into two age groups, 20-40 years old (the younger workers) and 41-60 years old (the older workers). We use state-level monthly unemployment rates to determine the state of the economy. To address the potential concern that the unemployment rate would be endogenous to UI benefits and durations, we follow Kroft and Notowidigdo (2011) using the unemployment rate in the month at the start of an unemployment spell, instead of the actual unemployment rate at each point during an unemployment spell.

We estimate unemployment duration elasticities for each age group using cross-state and time variation in unemployment benefit levels. The unemployment duration data are collected in the SIPP, which reports the weekly employment status of every individual in the sample. We compute each individual's duration of unemployment by summing the number of consecutive weeks without a job, starting from the date of job separation and ending when the individual finds a job that lasts for at least one month. It is not possible to estimate each individual's UI benefit amount precisely, so we use two proxies for the actual UI benefit level: the average benefit of all claimants for each state/year pair obtained from the Department of Labor, and the age-specific state-year average benefits for each age group. The latter can be a more accurate proxy for the actual benefits if there are sizable differences in actual benefits between two age groups.

We estimate a set of Cox hazard models to evaluate how duration elasticity varies by age, with the unemployment rate. Let $h_{i,s,t}$ denote the unemployment exit hazard rate for individual i in state s at time t of an unemployment spell, $\alpha_{s,t}$ the baseline hazard rate in state s at time t, $b_{i,s,t}$ the state-level unemployment benefits for individual i at the start of the spell, $u_{s,t}$ the state-level monthly unemployment rate for individual i at the start of the spell, and $X_{i,s,t}$ a set of control variables. We estimate the following hazard baseline model:

$$\log h_{i,s,t} = \alpha_{s,t} + \beta_1 \log(b_{s,t}) + \beta_2 \log(u_{s,t}) + \beta_3 \Big(\log(b_{s,t}) * \log(u_{s,t})\Big) + \beta_4 \mathrm{X}_{i,s,t}. \qquad (1)$$

All results report standard errors clustered by state. Like Kroft and Notowidigdo (2011), all independent variables are de-meaned so that the coefficient β_1 corresponds to the elasticity of unemployment durations with respect to the UI benefits at the average state unemployment rate. The coefficient β_2 represents the elasticity of unemployment durations with respect to the unemployment rate for an average individual receiving the average UI benefits. The key coefficient of interest, β_3, is the additional change in duration elasticity for a one log point change in the state unemployment rate, holding other independent variables constant.

The baseline model (1) includes the same controls as Kroft and Notowidigdo (2011): state, year, industry and occupation fixed effects; a 10-piece log-linear spline for the claimant's pre-unemployment wage; age, education; dummies for marital status and being on the seam between interviews to adjust for the seam effect; and the interaction between log of UI benefits and year fixed effect to control for any time-varying effect of the benefits on durations. All control variables are also de-meaned.

Besides the baseline model, we estimate the following extended regression model including a three-way interaction term between unemployment rate, UI benefits, and age dummy:

$$\log h_{i,s,t} = \alpha_{s,t} + \beta_1 \log(b_{s,t}) + \beta_2 \log(u_{s,t}) + \beta_3 \mathbf{1}\{\text{41-60}\} + \beta_4 \Big(\log(b_{s,t}) * \log(u_{s,t})\Big)$$
$$+\beta_5 \Big(\mathbf{1}\{\text{41-60}\} * \log(b_{s,t})\Big) + \beta_6 \Big(\mathbf{1}\{\text{41-60}\} * \log(u_{s,t})\Big) + \beta_7 \Big(\mathbf{1}\{\text{41-60}\} * \log(b_{s,t}) * \log(u_{s,t})\Big) + \beta_8 \mathrm{X}_{i,s,t}, \qquad (2)$$

where the indicator variable, $\mathbf{1}\{\text{41-60}\}$, equals one for older workers 41-60 years old. The key coefficient of interest, β_7, represents the difference in the effect of unemployment rate on duration elasticity between younger and older workers. The reason to propose the extended model is that it tests a more stringent hypothesis and reaches a more direct conclusion on differential age effect on duration elasticity compared to the baseline model: the baseline model tests whether unemployment rate significantly affects duration elasticity for younger and older workers respectively. The extended model tests whether the effect of unemployment rate on duration elasticity is significantly different between younger and older workers.

In addition, we also estimate the following extended regression model including a two-way interaction between unemployment rate and UI benefits:

$$\log h_{i,s,t} \;=\; \alpha_{s,t} \,+\, \beta_1 \log(b_{s,t}) \,+\, \beta_2 \mathbf{1}\{41\text{-}60\} \,+\, \beta_3\Big(\mathbf{1}\{41\text{-}60\} * \log(b_{s,t})\Big) \,+\, \beta_4 \mathrm{X}_{i,s,t}. \quad (3)$$

Equation (3) is an extended regression equation of Michelacci and Ruffo (2015)'s baseline model. The conclusion from their baseline model is that duration elasticity with respect to UI benefits on average is significantly different from zero for younger workers, not for older workers. The purpose of estimating equation (3) is to further evaluate whether duration elasticity on average is significantly different between older and younger workers. The key coefficient of interest, β_3, represents the difference in the average duration elasticity between older and younger workers. Combining the results from equation (2) and (3) can identify the robustness of age-specific responses to UI benefits.

5 Results

5.1 Graphical Evidence and Nonparametric Tests

To compare job finding rates between the two defined age groups (young versus old) under high and low unemployment rates. Kaplan-Meier survival curves are plotted to illustrate the relation between the fraction of workers who remain unemployed with respect to the total number of unemployed workers at week zero (the y-axis in Figures 1a and 1b) and the number of weeks of unemployment spell (the x-axis in Figures 1a and 1b)[1].

Figure 1 here

By definition, the fraction of unemployed workers at week zero is one, both the younger and the older groups have the same starting point in Figures 1a and 1b. Figure 1a shows that when the unemployment rate is above the median, suggesting a recession is in effect, the fraction of unemployed workers in the younger group decreased faster than that in the older group (nonparametric Wilcoxon test $p < 0.05$)[2]. For example, in a recession, 16 weeks after job loss 60 percent of younger workers are unemployed, while 68 percent of older workers are still unemployed; In a recession, 37 weeks after job loss, 28 percent of younger workers are unemployed, versus 41 percent of older workers. This results suggest that younger workers can find jobs much more quickly than older workers in a recession given the same level of UI benefits. By contrast, when the unemployment rate is below the median, the two age groups behave similarly in their tendencies to find new jobs once unemployed (see Figure 1b; Wilcoxon test $p > 0.5$).

The results presented in Figure 1a and 1b suggest that the job finding rates for younger workers are higher than those for older workers under weak economic conditions, while they are similar under strong economic conditions. It is not yet clear whether the difference is caused by younger or older workers responding to UI benefits differently over the business cycle. The next section investigates the question.

1 These survival curves plotted using the SIPP data are adjusted for the seam effect in panel surveys following Chetty (2008). The seam effect arises because individuals are interviewed at 4-month intervals in the SIPP and tend to repeat answers about weekly job status in the past 4 months. Consequently, we observe a disproportionately large number of transitions in labor force status on the "seam" between interviews, which leads to artificial spikes in the hazard rate at 4 and 8 months. To smooth out these spikes, we add a time-varying indicator for being on a seam between interviews as a control variable in a Cox model. The resulting seam-adjusted survival curves represents the probability of remaining unemployed after t weeks of a spell for an individual who never crosses an interview seam.

2 Since the job finding rates are not normally distributed over time, a nonparametric test is appropriate when the parametric assumption of normally distribution is unlikely to satisfy.

5.2 Hazard Model Estimation

To evaluate the robustness of the graphical results presented above, we estimate the hazard model (1) to identify how duration elasticity with respect to UI benefits varies with unemployment rate by age. We report three coefficients in all specifications: β_1 is the elasticity of unemployment durations with respect to the UI benefits at the average state unemployment rate; β_2 is the elasticity of unemployment durations with respect to the unemployment rate for an average individual receiving the average UI benefits; and β_3, the key coefficient of interest, is the additional change in duration elasticity for a one log point change in the state unemployment rate, holding other independent variables constant.

We first estimate the hazard model (1) on the full sample from 20-60 years old to replicate the results from Kroft and Notowidigdo (2011). Column 1 of Table 2 reports Kroft and Notowidigo's baseline model estimates. Column 2 reports my own estimates of equation (1). My findings indicate that a 10 percent increase in UI benefit rate reduces hazard rate by 15.2 percent, at average unemployment rate. In addition, a 10 percent increase in state-level unemployment rate significantly boosts the hazard rate with respect to UI benefits by 13.8 percent. Results for the key coefficient of interest, β_3, are similar with the same significance level ($p<0.01$) between the two specifications. My own estimates of β_1 and β_2 are close to but slightly larger than Kroft and Notowidigdo's, due to the fact that they had a slightly different sample size from mine (their model dropped some observations for an unknown reason). The bottom two rows of Table 2 report duration elasticity when state unemployment rate is one standard deviation (1.7%) above and below the mean unemployment rate (6.7%) for the pooled sample. A one standard deviation increase in the unemployment rate (8.4%) reduces the magnitude of duration elasticity by 48 percent (from 1.518 to 0.796). A one standard deviation decrease in the unemployment rate (5%) raises the magnitude of duration elasticity by 48 percent (from 1.518 to 2.239). The magnitudes are similar to the results in Kroft and Notowidigdo (2011). Their estimates indicate that one standard deviation change in the unemployment rate is correlated with the change in the magnitude of duration elasticity by roughly 50 percent.

Table 2 here

The main results are reported in Table 3. Columns 1-2 report results for the pooled sample, Columns 3-4 for the 20-40 age group, and Columns 5-6 for the 41-60 age group. Columns 1, 3, and 5 report the baseline results of the regression equation excluding unemployment rate and the interaction term between unemployment rate and UI benefits as independent variables. The only key variable in Column 1, 3, and 5 is UI benefits. Columns 2, 4, and 6 report results of equation (1). Panel A of Table 3 uses average UI benefits as a measure of individual UI benefit levels, and Panel B uses age-specific average UI benefits.

Table 3 here

The main results from Table 3 can be summarized as follows: although duration elasticity is larger for older than for younger workers on average, duration elasticity for younger workers is more responsive to the overall economic conditions. In other words, duration elasticity for younger workers in a recession is significantly larger than that in a boom. By contrast, duration elasticity for older workers remains stable over time. In both panels, the estimate of β_1, the effect of UI benefits on hazard rate, is smaller in magnitude for younger than for older workers. This result is consistent even when the interaction term is not included. By contrast, the estimates of the key coefficient β_3, the effect of unemployment rate on duration elasticity, is larger in magnitude for younger workers than for older workers. In Panel A, for example, the estimate of β_3 in Column 4 indicates that a 10 percent increase in state-level unemployment rate raises the hazard rate with respect to UI benefits for younger workers by 16.5 percent. The elasticities derived from the estimates in Column 4 suggest that a one standard deviation increase in the unemployment rate (8.4%) reduces the magnitude of duration elasticity for younger workers by 71 percent (from 1.225 to 0.361). A one standard deviation decrease in the unemployment rate (5%) raises the magnitude of duration elasticity for younger workers by 71 percent (from 1.225 to 2.088). The elasticities in Column 6 suggest that a one standard deviation increase in the unemployment rate (8.4%) reduces the magnitude of duration elasticity for older workers by 7 percent (from 2.923 to 2.716). Overall, the main results suggest that the negative relationship between unemployment rate and duration elasticity documented in Kroft and Notowidigdo (2011) is primarily driven by younger workers. Older workers have a persistently high unemployment duration elasticity that is insensitive to aggregate economic conditions. By contrast, younger workers have a lower duration elasticity during a weak labor market.

The results of the extended regression model in Table 4 show that the differential impacts of unemployment rate on duration elasticity between older and younger workers are not robust. Column 1 in Table 4 displays the results of the regression equation (2) with a three-way interaction between unemployment rate, UI benefits, and age dummy, in which the estimate of the coefficient of the three-way interaction is not significant. The insignificance of the three-way interaction coefficient suggests that although the effect of unemployment rate on duration elasticity is significantly different from zero for younger workers, the effect is not significantly different between older and younger workers. In addition, Column 2 in Table 4 displays the results of estimating equation (3), which is an extended regression equation of Michelacci and Ruffo (2015)'s baseline model. The estimate of the coefficient of the two-way interaction between age dummy and UI benefits suggests that their baseline results also fail the robustness test: although the average duration elasticity is significantly different from zero for younger workers, the average duration elasticity is not significantly different between older and younger workers. Overall, the differential age effect on duration elasticity is not statistically significant.

Table 4 here

6 Conclusion

This paper has investigated how unemployment duration elasticity with respect to UI benefits varies with unemployment rates by age. When tested in each age group individually, a one standard deviation increase in unemployment rate reduces the magnitude of duration elasticity for younger workers by 71 percent. By contrast, a one standard deviation increase in unemployment rate reduces the magnitude of duration elasticity for older workers by 7 percent.

The difference in the responsiveness of duration elasticity to unemployment rates between younger and older workers is not statistically significant when tested as an interaction effect in a more stringent regression model. In addition, the difference in the average duration elasticity reported in Michelacci and Ruffo (2015) is not significant either when subjected to the same procedure of regression analysis. Since the current results do not support the hypothesis that additional UI benefits will raise unemployment durations to a less degree for younger workers than for older workers over the business cycle, we cannot conclude that redistributing UI benefits from older workers to younger workers, as which is proposed by Michelacci and Ruffo (2015), can improve social welfare. Incorporating age into the design of UI benefits should require further study and more credible evidence.

References

Aguiar, Mark, Erik Hurst, and Loukas Karabarbounis. 2013. "Time Use during the Great Recession." *American Economic Review* 103 (5): 1664–1696.

Baily, Martin Neil. 1978. "Some Aspects of Optimal Unemployment Insurance." *Journal of Public Economics* 10 (3): 379–402.

Card, David, Raj Chetty, and Andrea Weber. 2007. "The Spike at Benefit Exhaustion: Leaving the Unemployment System or Starting a New Job?" *American Economic Review*: 113–118.

Chetty, Raj. 2006. "A General Formula for the Optimal Level of Social Insurance." *Journal of Public Economics* 90 (10): 1879–1901.

Chetty, Raj. 2008. "Moral Hazard versus Liquidity and Optimal Unemployment Insurance." *Journal of Political Economy* 116 (2): 173–234.

Chetty, Raj, and Adam Szeidl. 2007. "Consumption Commitments and Risk Preferences." *Quarterly Journal of Economics* 122 (2): 831–877.

Farber, Henry S., Jesse Rothstein, and Robert G. Valletta. 2015. "The Effect of Extended Unemployment Insurance Benefits: Evidence from the 2012-2013 Phase-Out." *American Economic Review Papers and Proceedings* 105 (5): 171–176.

Farber, Henry S., and Robert G. Valletta. 2015. "Do Extended Unemployment Benefits Lengthen Unemployment Spells? Evidence from Recent Cycles in the US Labor Market." *Journal of Human Resources (forthcoming)*.

Gruber, Jonathan. 1997. "The Consumption Smoothing Benefits of Unemployment Insurance." *American Economic Review*: 192–205.

Hagedorn, Marcus, Iourii Manovskii, and Kurt Mitman. 2015. "The Impact of Unemployment Benefit Extensions on Employment: The 2014 Employment Miracle?" NBER Working Paper No. 20884.

Katz, Lawrence F., and Bruce D. Meyer. 1990. "The Impact of the Potential Duration of Unemployment Benefits on the Duration of Unemployment." *Journal of Public Economics* 41 (1): 45–72.

Katz, Lawrence F., and Bruce D. Meyer. 1990. "Unemployment Insurance, Recall Expectations, and Unemployment Outcomes." *Quarterly Journal of Economics* 105 (4): 973–1002.

Kroft, Kory, and Matthew J. Notowidigdo. 2011. "Should Unemployment Insurance Vary with the Local Unemployment Rate? Theory and Evidence." NBER Working Paper No. 17173.

Krueger, Alan B., and Bruce D. Meyer. 2002. "Labor Supply Effects of Social Insurance." In *Handbook of Public Economics*, ed. by Alan Auerbach and Martin Feldstein, 4:2327–2392. Amsterdam: North-Holland.

Krueger, Alan B., and Andreas Mueller. 2010. "Job Search and Unemployment Insurance: New Evidence from Time Use Data." *Journal of Public Economics* 94 (3): 298–307.

Kutyavina, Marina. 2015. "Variation in Job Search Intensity across Age Groups: Evidence from the Great Recession." Unpublished Working Paper, University of San Diego.

Meyer, Bruce D. 1990. "Unemployment Insurance and Unemployment Spells." *Econometrica* 58 (4): 757–782.

Michelacci, Claudio, and Hernán Ruffo. 2015. "Optimal Life Cycle Unemployment Insurance." *American Economic Review* 105 (2): 816–859.

Moffitt, Robert. 1985. "Unemployment Insurance and the Distribution of Unemployment Spells." *Journal of Econometrics* 28 (1): 85–101.

Piketty, Thomas, and Emmanuel Saez. 2013. "Optimal Labor Income Taxation." In *Handbook of Public Economics*, 5:391–474.

Rothstein, Jesse. 2011. "Unemployment Insurance and Job Search in the Great Recession." *Brookings Papers on Economic Activity*: 143–210.

Schmieder, Johannes F., Till von Wachter, and Stefan Bender. 2012. "The Effects of Extended Unemployment Insurance Over the Business Cycle: Evidence from Regression Discontinuity Estimates Over 20 Years." *Quarterly Journal of Economics* 127 (2): 701–752.

Shimer, Robert, and Iván Werning. 2007. "Reservation Wages and Unemployment Insurance." *Quarterly Journal of Economics*: 1145–1185.

Table 1: Summary Statistics by Age for SIPP Sample

	20-40 Years Old		41-60 Years Old		Full Sample	
	mean	sd	mean	sd	mean	sd
Panel A: Pooled						
Unemployment duration (weeks)	17.3	13.7	19.7	14.8	18.1	14.2
Weekly unemployment benefits ($)	153.2	47.1	187.8	47.0	165.2	49.9
Individual replacement rate	50%	0.07	50%	0.09	50%	0.08
Age	30.3	5.7	48.7	5.6	36.7	10.4
Years of education	12.1	2.9	12.1	3.3	12.1	3.0
Percent married	50%	0.5	80%	0.4	60%	0.5
Pre-unemployment annual wage ($)	18797.4	11874.9	24892.5	15480.5	20915.4	13552.3
State unemployment rate	7%	0.02	7%	0.02	7%	0.02
Number of unemployment spells	2858		1522		4380	
	20-40 Years Old		41-60 Years Old		Full Sample	
	mean	sd	mean	sd	mean	sd
Panel B: State Unemployment Rate above Median						
Unemployment duration (weeks)	18.3	14.2	21.0	15.2	19.2	14.6
Weekly unemployment benefits ($)	153.6	49.1	188.2	49.1	165.3	51.8
Individual replacement rate	50%	0.08	50%	0.09	50%	0.09
Age	30.4	5.6	48.8	5.6	36.6	10.3
Years of education	12.1	2.9	12.1	3.6	12.1	3.2
Percent married	50%	0.5	70%	0.4	60%	0.5
Pre-unemployment annual wage ($)	19003.9	12480.5	25556.7	15694.2	21220.7	13996.5
State unemployment rate	8%	0.01	8%	0.01	8%	0.01
Number of unemployment spells	1344		682		2016	
	20-40 Years Old		41-60 Years Old		Full Sample	
	mean	sd	mean	sd	mean	sd
Panel C: State Unemployment Rate below Median						
Unemployment duration (weeks)	16.4	13.3	18.6	14.4	17.2	13.7
Weekly unemployment benefits ($)	152.9	45.3	187.5	45.3	165.1	48.2
Individual replacement rate	50%	0.07	50%	0.09	50%	0.08
Age	30.2	5.8	48.6	5.5	36.8	10.5
Years of education	12.0	2.8	12.2	3.0	12.1	2.9
Percent married	50%	0.5	80%	0.4	60%	0.5
Pre-unemployment annual wage ($)	18616.6	11319.4	24353.2	15292.9	20655.0	13159.1
State unemployment rate	5%	0.009	5%	0.010	5%	0.010
Number of unemployment spells	1524		840		2364	

Notes: The data are individual-level unemployment spells from the 1985-2000 SIPP data set. All dollar values are in real 1990 dollars. See the main text for more details.

Table 2: Replication of Kroft and Notowidigdo's Baseline Results

	Dependent variable: log(hazard rate) = $-$log(duration)	
	20-60 years old	
	KN's baseline results	My replication
	(1)	(2)
Demeaned log(average UI benefit)	-0.632*	-1.518**
	(0.332)	(0.652)
Demeaned log(state unemployment rate)	0.035	0.053
	(0.124)	(0.122)
Demeaned log(average UI benefit) x	1.346***	1.381***
Demeaned log(state unemployment rate)	(0.457)	(0.480)
Number of spells	4307	4380
Implied elasticities:		
High unemployment elasticity (u=8.4%)	-0.277	-0.796
	(0.364)	(0.586)
Low unemployment elasticity (u=5%)	-0.987***	-2.239***
	(0.343)	(0.795)

Notes 1: Data are individual-level unemployment spells from 1985-2000 SIPP. All columns report semiparametric Cox hazard model from estimating equation (1). Column 1 of Table 2 reports Kroft and Notowidigo's baseline model estimates (see Column 1 of table 2 in Kroft and Notowidigdo (2011)). Column 2 reports my own estimates of equation (1). The average UI benefit amount is the average weekly benefit paid to claimants in a given state-year. Both specifications include state, year, industry, and occupation fixed effects, a 10-piece log-linear spline for the claimant's pre-unemployment wage, age, education, dummies for marital status and being on the seam between interviews, and interaction between year fixed effects and log of the UI benefit amount. The final two rows report linear combination of parameter estimates to produce the duration elasticity when the state unemployment rate is one standard deviation above or below the median. Standard error are reported in parentheses and are clustered by states.

Note 2: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effect of UI Benefits on Unemployment Duration by Age

	Dependent variable: log(hazard rate) = $-$log(duration)					
	All		20-40 years old		41-60 years old	
	Baseline	Interaction	Baseline	Interaction	Baseline	Interaction
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average UI Benefits						
Demeaned log(average UI benefit)	-0.603**	-1.518**	-0.375	-1.225**	-1.340***	-2.923**
	(0.277)	(0.652)	(0.334)	(0.614)	(0.495)	(1.386)
Demeaned log(state unemployment rate)		0.053		0.140		-0.085
		(0.122)		(0.164)		(0.315)
Demeaned log(average UI benefit) x		1.381***		1.653**		0.397
Demeaned log(state unemployment rate)		(0.480)		(0.764)		(1.561)
Number of spells	4380	4380	2858	2858	1522	1522
Implied elasticities:						
High unemployment elasticity (u=8.4%)		-0.796		-0.361		-2.716*
		(0.586)		(0.558)		(1.501)
Low unemployment elasticity (u=5%)		-2.239***		-2.088**		-3.130*
		(0.795)		(0.872)		(1.709)
Panel B: Age Specific UI Benefits						
Demeaned log(age-specific average UI	-0.336*	-0.735	-0.191	-0.513	-1.363***	-2.220**
benefit)	(0.204)	(0.509)	(0.248)	(0.488)	(0.456)	(1.046)
Demeaned log(state unemployment rate)		-0.064		0.161		-0.507
		(0.113)		(0.172)		(0.354)
Demeaned log(age-specific average UI		0.646*		1.729**		1.022
benefit) x Demeaned log(state unemployment rate)		(0.365)		(0.799)		(1.201)
Number of spells	4380	4380	2858	2858	1522	1522
Implied elasticities:						
High unemployment elasticity (u=8.4%)		-0.398		0.390		-1.686
		(0.467)		(0.452)		(1.159)
Low unemployment elasticity (u=5%)		-1.073*		-1.417*		-2.753**
		(0.611)		(0.788)		(1.278)

Notes 1: Data are individual-level unemployment spells from 1985-2000 SIPP. All columns report semiparametric Cox hazard model from estimating equation (1). The average UI benefit amount in Panel A is the average weekly benefit paid to claimants in a given state-year. The age specific UI benefit amount in Panel B is the average weekly benefit of each age group in a given state-year. Column 1, 3, and 5 report elasticities of hazard rate with respect to UI benefits for the full sample and for each age group. The estimates of the interaction term in column 2, 4, and 6 report the effect of unemployment rate on duration elasticity with respect to benefits for the full sample and for each age group. All columns include state, year, industry, and occupation fixed effects, a 10-piece log-linear spline for the claimant's pre-unemployment wage, age, education, dummies for marital status and being on the seam between interviews, and interaction between year fixed effects and log of the UI benefit amount. The final two rows of each panel report linear combination of parameter estimates to produce the duration elasticity when the state unemployment rate is one standard deviation above or below the median. Standard error are reported in parentheses and are clustered by states.

Note 2: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

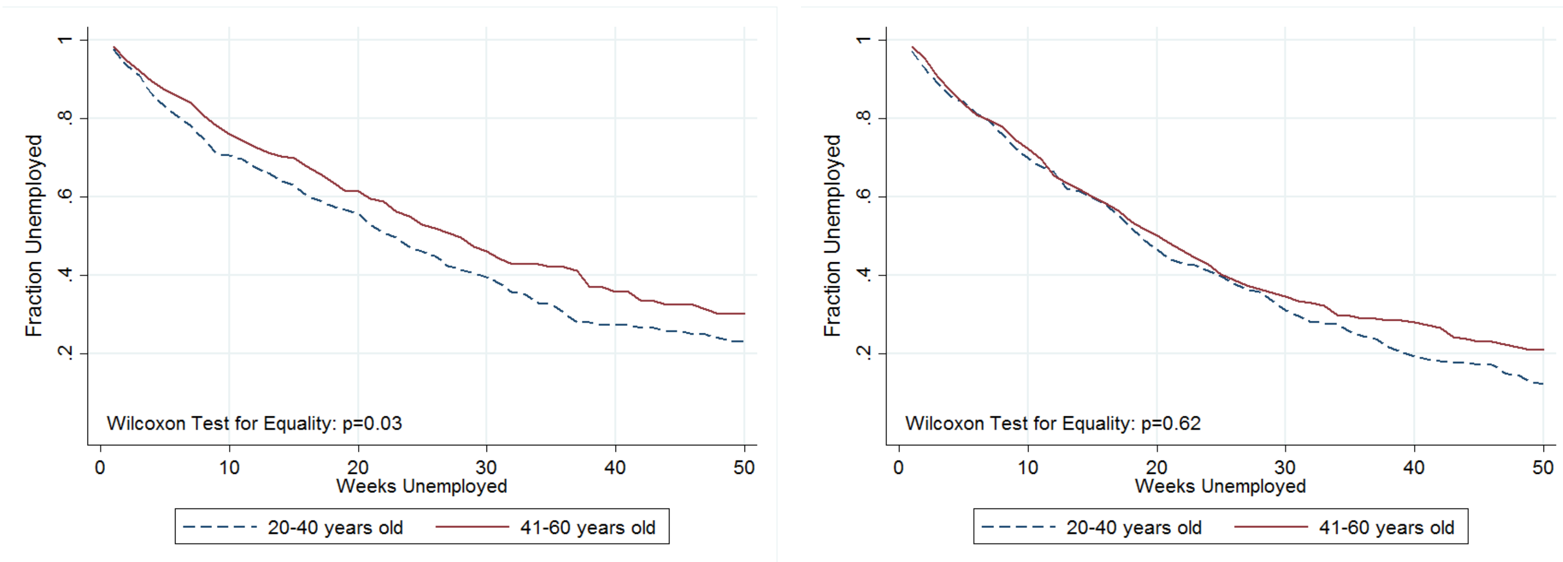
Table 4: Extended Model

	Dependent variable: log(hazard rate) = $-$log(duration)	
	20-60 years old	
	Three-way interaction	Two-way interaction
Demeaned log(average UI benefit)	-1.563**	-1.193**
	(0.639)	(0.578)
Demeaned log(state unemployment rate)	0.060	
	(0.119)	
Demeaned log(average UI benefit) x Demeaned log(state unemployment rate)	1.421***	
	(0.538)	
1{41-60 years old}	-0.258***	-0.255***
	(0.034)	(0.033)
1{41-60 years old} x Demeaned log(average UI benefit)	0.113	0.135
	(0.191)	(0.188)
1{41-60 years old} x Demeaned log(state unemployment rate)	-0.048	
	(0.137)	
1{41-60 years old} x Demeaned log(average UI benefit) x Demeaned log(state unemployment rate)	-0.602	
	(0.957)	

Notes 1: Data are individual-level unemployment spells from 1985-2000 SIPP. Column 1 reports estimates from equation (2). The last coefficient of column 1 is the estimate of the coefficient of a three-way interaction between unemployment rate, UI benefits, and age dummy. The three-way interaction coefficient is not significant, which suggests that the effect of unemployment rates on duration elasticity is not significantly different between older and younger workers. Column 2 report estimates from equation (3). The last coefficient of column 2 is the estimate of a 2-way interaction between UI benefits and age dummy. The two-way interaction coefficient is not significant, which suggests that the average duration elasticity is not significantly different between older and younger workers. Both columns include state, year, industry, and occupation fixed effects, a 10-piece log-linear spline for the claimant's pre-unemployment wage, education, dummies for marital status and being on the seam between interviews, and interaction between year fixed effects and log of the UI benefit amount. Standard error are reported in parentheses and are clustered by states.

Note 2: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Survival curves under high/low unemployment rate by age



(a) High unemployment

(b) Low unemployment

Note: Data are taken from individual-level unemployment spells from 1985-2000 SIPP. In Figure 1a, the sample includes spells in states with unemployment rates above the median across states. See Panel B of Table 1 for the descriptive statistics of the above-median sample. In Figure 1b, the sample includes spells in states with unemployment rates below the median across states. See Panel C of Table 1 for the descriptive statistics of the below-median sample. Each figure plots Kaplan-Meier survival curves for two age groups. The survival curves are adjusted for a seam effect by fitting a Cox model with a seam dummy and recovering baseline hazards as in Chetty (2008).