Should Unemployment Insurance Vary With the Unemployment Rate? Theory and Evidence

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Abstract

We study theoretically and empirically how optimal unemployment insurance (UI) benefits vary over the business cycle. Theoretically, we characterize how the moral hazard cost and the consumption smoothing benefit of UI vary over the business cycle in a standard job search model. This analysis motivates our empirical strategy which tests whether the effect of UI on unemployment durations and the consumption drop at unemployment varies with the unemployment rate. In our preferred specification, we find that a one standard deviation increase in the state unemployment rate reduces the magnitude of the duration elasticity by 42%. By contrast, using consumption changes upon unemployment, we do not find evidence that the consumption smoothing benefit of UI varies with the unemployment rate. Combining these empirical estimates to calibrate the optimal level of UI benefits implied by our model, we find that a one standard deviation increase in the unemployment rate leads to a 9 to 17 percentage point increase in the optimal replacement rate. (JEL H5, J64, J65)

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1 Introduction

It is commonly accepted that higher unemployment benefits prolong unemployment durations (Hamermesh 1977, Moffitt 1985, Meyer 1990, Chetty 2008). Most of the evidence for this "moral hazard effect" comes from empirical studies that do not distinguish between changes in benefits when labor market conditions are good and changes in benefits when labor market conditions are poor. If the moral hazard cost of unemployment insurance (UI) depends on labor market conditions, this may imply that optimal UI benefits should respond to shifts in labor demand. However, many of the studies that conduct a welfare analysis of UI do not consider whether and to what extent UI benefits should vary with labor market conditions (Baily 1978, Hopenhayn and Nicolini 1997, Chetty 2006, Chetty 2008, Shimer and Werning 2007, Kroft 2008, Lentz 2009).[1] As Alan Krueger and Bruce Meyer (2002, p64-65) remark:

> [F]or some programs, such as UI, it is quite likely that the adverse incentive effects vary over the business cycle. For example, there is probably less of an efficiency loss from reduced search effort by the unemployed during a recession than during a boom. As a consequence, it may be optimal to expand the generosity of UI during economic downturns ... Unfortunately, this is an area in which little empirical research is currently available to guide policymakers.

Similarly, the Congressional Budget Office writes that the availability of long-term unemployment benefits "could dampen people's efforts to look for work, [but that concern] is less of a factor when employment opportunities are expected to be limited for some time."[2]

In this paper, we conduct both positive and normative economic analyses to investigate how the optimal UI benefit level varies over the business cycle. Combining our theoretical model with reduced form empirical evidence, we conclude that a one standard deviation increase in the unemployment rate leads to a 9 to 17 percentage point increase in the optimal

[1] Nicholson and Needels (2006) discuss how worsening labor market conditions in the U.S. in the 1970s and 1980s triggered large, policy-driven, increases in benefit payments.

[2] The CBO quote is available from the following URL: http://www.washingtonpost.com/wp-dyn/content/article/2010/03/08/AR2010030804927_pf.html.

UI benefit level. We briefly summarize how we reach this conclusion in the remainder of this section.

Our main theoretical contribution is to exploit the structure of a standard job search model to derive analytical conditions for how the consumption smoothing benefit of UI (insurance value) and the elasticity of unemployment duration with respect to the UI benefit level (moral hazard cost) vary with the job offer arrival rate. Several studies in the job search literature derive conditions under which the duration of unemployment varies with the job offer arrival rate (Burdett 1981, Flinn and Heckman 1983, Burdett and Ondrich 1985, Jensen and Vishwanath 1985, Vroman 1985, van den Berg 1994); however, this is the first paper to our knowledge that uses a standard job search model to derive conditions for how the *behavioral responses* to UI vary with the job offer arrival rate. These conditions allow us to explain, in a clear and rigorous way, the economic forces that shape the cyclicality of these effects. Moreover, since our model nests other models in the literature that are used to evaluate optimal UI over the cycle, we are able to sharply delineate the key differences in results across models.[3]

Our key theoretical finding is that the cyclicality of the unemployment duration elasticity and the cyclicality of the insurance value of UI are both theoretically ambiguous. Each effect may be either procyclical or countercyclical. In other words, without additional assumptions on the structural parameters, the standard job search model places no restrictions on how the optimal UI level should vary over the cycle. We view the possibility that the moral hazard cost of UI can increase during times of high unemployment – contrary to the speculation of Krueger and Meyer (2002) above – as an interesting prediction of the model. The thereotical ambiguity highlighted by the job search model indicates that how the moral hazard cost and the consumption smoothing benefit of UI each vary with labor market conditions is ultimately an empirical question. This motivates our two-part empirical strategy, which directly estimates each of these terms.

[3]For example, our paper is the only paper in the literature on optimal UI over the cycle that includes reservation wages as a choice variable, in addition to search intensity. Additionally, since we use a dynamic job search model, we can compare and contrast our results to results that are based on a static job search model (Andersen and Svarer 2009).

Our first empirical contribution is to examine how the elasticity of unemployment duration with respect to the UI benefit level varies with labor market conditions. We do this by estimating a hazard model where the effect of the UI benefit level on unemployment durations is allowed to depend on the state unemployment rate. Our identification of this model comes from exploiting variation in UI benefit levels within states over time interacted with within- and between-state variation in the unemployment rate. We pursue this time-series, cross-sectional research design using state unemployment rates rather than a purely time-series design using the national unemployment rate in order to have sufficient variation in UI benefit levels across a wide range of labor market conditions. While this has the benefit of allowing us to more precisely identify how the duration elasticity varies with the unemployment rate, there are several caveats to extrapolating this estimate to national business cycles which we discuss in detail below.

Our second empirical contribution is to estimate how the consumption smoothing benefit of UI varies with the unemployment rate. We replicate and extend previous work on the consumption smoothing benefit of UI (Gruber 1997) by estimating how the effect of UI on the consumption drop upon unemployment varies with the unemployment rate. We also implement an additional test, based on Chetty (2008), which examines whether liquidity effects can account for the significant interaction effect documented above. We view these two tests as complementary, both designed to examine whether the marginal social benefit of UI varies over the cycle.

To preview our findings, we find that the elasticity of unemployment duration with respect to the level of unemployment benefits is 0.61 at the average state unemployment rate. This average duration elasticity estimate is similar to the elasticity estimates reported in the literature. Our new empirical result is that the duration elasticity varies with local labor market conditions; specifically, we find that the duration elasticity is statistically significantly lower when the local unemployment rate is relatively high. Furthermore, the magnitude of this interaction effect is economically large: in our preferred specification, a one standard deviation increase in the unemployment rate (an increase of 1.3 percentage points from a base of 5.4%) reduces the magnitude of the duration elasticity by 0.26 to 0.35 (a decline in magnitude of 42%). By contrast, with available precision, we do not find evidence that the consumption smoothing benefit of UI varies with the unemployment rate. Our estimates are both economically and statistically insignificant, and we can rule out modest magnitudes: the 95% confidence interval allows us to reject that a one standard deviation increase in the unemployment rate increases the effect of UI on the consumption drop at unemployment by more than 16%. Additionally, the duration-based test reveals no evidence that the interaction effect we estimate is driven by liquidity effects, consistent with the consumption-based results. Putting these results together, they imply that the moral hazard cost of UI is procyclical while the consumption smoothing benefit of UI is acyclical. These findings form the basis of our conclusion that optimal benefits should be decreasing in the unemployment rate

An immediate concern with our empirical strategy is that when the state unemployment rate is high, benefits may (endogenously) become more generous and unemployment durations will also become longer, which may bias the estimate of the interaction term in our duration elasticity specifications. We pursue three strategies to address this concern.

First, we always measure the local unemployment rate *relative* to the national unemployment rate, and we control for this relative local unemployment rate directly in all specifications. The use of relative unemployment rates alleviates the concern that UI benefit levels may partially respond to national business cycles. Additionally, if states raise UI benefits in recessions, but do not systematically adjust benefits in good times, then this strategy is preferable to using absolute unemployment rates with year fixed effects, as we discuss below. By controlling for the local unemployment rate in all specifications, we address the concern that benefits may respond endogenously to the local unemployment rate. Under the strong assumption that UI benefit levels are random conditional on the local unemployment rate and the other control variables in our baseline specification, we will consistently estimate our interaction term.

Second, we directly investigate the association between the local unemployment rate and UI benefits. We find weak but suggestive evidence that the local unemployment rate and the UI benefit level are positively correlated. Moreover, our evidence weakly suggests that the positive association is stronger when the unemployment rate is relatively high. This implies that benefits may respond more strongly to local labor market conditions during bad times. We argue that this type of differential correlation between the unemployment rate and UI benefits works against our findings. In particular, any omitted variables bias due this type of policy endogeneity will make the duration elasticity artificially larger during times of high unemployment; however, we find the opposite result: the duration elasticity is *lower* when the local unemployment rate is relatively high.

Third, we investigate several alternative identifying assumptions to gauge the magnitude of omitted variables bias, and we find, if anything, that our results become stronger. First, we include a flexible polynomial in the state unemployment rate, which addresses the concern that benefits may vary non-linearly with the unemployment rate. Second, we include as additional controls the interaction of the state unemployment rate with state fixed effects and year fixed effects. This allows for a more flexible correlation between observable local labor demand shocks and UI benefits. In particular, it captures the possibility that in certain states and/or years, UI benefits may be unusually responsive to changes in labor market conditions. Third, we investigate alternative specifications which allow for unobserved trends across states within a region and within states over time, and we find, if anything, slightly stronger results. Lastly, we find stronger (though somewhat less precise) results when we define local labor markets as metropolitan areas (MSAs) rather than states and exploit purely across-MSA, within-state variation in unemployment rates, holding UI benefit levels constant. We therefore interpret our preferred specification as a *conservative* estimate of the magnitude of the relationship between the duration elasticity and the local unemployment rate.

We also investigate a wide variety of alternative explanations for this finding, and we find no consistent evidence that the interaction effect we estimate is primarily determined by compositional changes, endogenous takeup, or bias from using both between-state and within-state variation in state unemployment rates. Therefore, our interpretation of the empirical results is that they are most consistent with a negative relationship between the moral hazard of cost of UI and the local unemployment rate.

Finally, our third contribution in this paper is to calculate how the optimal UI benefit level varies over the cycle using our reduced form empirical evidence. Specifically, we derive and numerically implement the Baily-Chetty formula for the marginal welfare gain of UI that illustrates the standard trade-off between the consumption smoothing benefit of UI and the moral hazard cost of UI and their dependence on the unemployment rate. We state the formula in terms of our reduced form parameter estimates, thus taking into account how the behavioral response to UI benefits varies over the cycle. Therefore, our welfare analysis is in the spirit of the "sufficient statistics" approach (Chetty 2009).

The primary advantage of this approach is that it does not place any restrictions on the model primitives and is therefore valid for a wide range of underlying mechanisms which cause the duration elasticity and the consumption smoothing benefit each to vary with the unemployment rate.[4] In particular, our welfare analysis does not require assuming a specific functional form for how effort is translated into a job offer arrival rate, which – as we show below – can affect how the duration elasticity varies over the cycle. We also do not need to identify how reservation wages and search effort respond to a change in benefits and how these responses vary over the cycle, nor do we need to make specific assumptions about liquidty effects.

Combining our reduced form empirical estimates to calibrate the optimal UI benefit level implied by our model, we find that a one standard deviation increase in the local unemployment rate leads to a 9 to 17 percentage point increase in the optimal replacement rate, depending on the coefficient of relative risk aversion used in the calibration.[5] To give a sense of the magnitude of this change, it is roughly equivalent to the change in the optimal UI benefit level stemming from a one unit change in the coefficient of relative risk aversion (e.g., from $\gamma = 3$ to $\gamma = 4$), holding constant the duration elasticity and the effect of UI on the consumption drop at unemployment. Thus, our results suggest a countercyclical UI policy, which is broadly consistent with the observed policy in the U.S. Below we discuss how our results shed light on the optimality of current UI policy, which is based on extending the potential duration of unemployment benefits, or the number of weeks for which an unemployed worker can claim benefits – typically 26 weeks in the United States. We also provide an illustration of how one may use our empirical results to shed

[4] Chetty (2009) describes the advantages and disadvantages of the sufficient statistics approach in more detail.

[5] We report results across a range of CRRA values from $\gamma = 2$ to $\gamma = 4$.

light on how extending benefits in a recession affects the aggregate unemployment rate.

Several papers in the literature have explored optimal UI over the business cycle. Kiley (2003) and Sanchez (2008) consider dynamic, discrete-time, search effort models, with a fixed wage and no assets, building on Hopenhayn and Nicolini (1997). These papers impose a functional form on the job finding probability that ensures search effort and a variable affecting the job offer arrival rate are highly complimentary. Under this functional form assumption, UI benefits are more distortionary in good times than bad times; as a consequence, optimal UI benefits are countercyclical. Andersen and Svarer (2009) consider a static model of job search with a fixed wage and no assets and impose a similar functional form assumption on the job finding probability. They incorporate UI financing requirements and show that if the government budget must balance in each state, benefits could be procyclical due to a "budget effect."

Our main contribution relative to these papers is to consider a more general dynamic search model, with stochastic wage offers, as has recently been used in the UI literature (e.g., Shimer and Werning (2007)). This framework allows us to shed light on several new dimensions of the optimal UI problem. First, the model permits us to characterize the cyclical behavior of the behavioral responses of both search effort and reservation wages. This is important if in practice individuals set a reservation wage in addition to choosing search intensity. Second, since our model nests other search models used in the literature, we can use the model to zoom in on the distinctions between them. For instance, our results highlight that the response of search effort to UI benefits over the cycle is pinned down by three factors: (1) a static effect, (2) a dynamic effect and (3) a reservation wage effect. We show that these effects can go in opposite directions. Previous studies have not highlighted this distinction since they considered special cases of our model. Last and most important, these studies are purely theoretical; they do not focus on empirically evaluating how UI benefits should respond to variation in labor market conditions. To our knowledge, this is the first paper to estimate how the optimal UI benefit level varies over the cycle using reduced form empirical estimates of how the consumption smoothing benefit and moral hazard cost of UI varies with the unemployment rate.

While our framework is a partial equilibrium model, another strand of the literature has begun to explore optimal UI over the cycle in a general equilibrium framework. Andersen and Svarer (2010) consider a stylized general equilibrium model and model the business cycle as a markov process, thus allowing for changes in the business cycle situation. They demonstrate that allowing for changes in the business cycle situation changes how the distortion to effort created by UI varies over the cycle, since search effort depends on anticipated changes in the labor market. Another general equilibrium approach is Landais, Michaillat, and Saez (2010), who consider a matching model with search effort and focus on characterizing the optimal benefit level over the cycle. The primary innovation in this paper is the introduction of endogenous job rationing coming through the combination of diminishing marginal returns to production and wage rigitidy. They derive a version of the Baily-Chetty formula for optimal UI in terms of a macro elasticity, which captures the direct effect of a change in UI benefits on search and the indirect effect that arises via changes in the aggregate job finding rate. Though our model is a partial equilibrium model, it can be reinterpreted as a general equilibrium model following Rogerson, Shimer, and Wright (2005). More specifically, one can interpret the model in this paper as the Landais et al. model with the addition of reservation wages and the elimination of job rationing (which would be obtained by assuming constant returns to scale in production, for example).

Finally, while we focus on the optimal *level* of UI benefits over the cycle, contemporaneous research by Schmieder, von Wachter and Bender (2010) explores the optimal *duration* of UI benefits. They consider a fixed wage, search effort model and derive a formula for the marginal welfare gain of extending the maximum length of time an individual is eligible to receive UI benefits. Similar to our work, they pursue a sufficient statistics approach and empirically estimate how the inputs to their formula vary over the cycle. Specifically, they implement a regression discontinuity design using administrative data from Germany to identify the elasticity of non-employment and actual benefit duration with respect to the potential benefit duration. Their research design allows them to estimate an elasticity for each year in their sample (1987-2004). They show that their annual estimate of the non-employment duration elasticity does not correlate significantly with the annual unemployment rate over this time period. On the other hand, the actual benefit duration elasticity is significantly positively correlated with the unemployment rate. While they do not fully evaluate their sufficient statistics formula (because they do not estimate how the insurance value or liquidity effect of UI varies over the cycle), their empirical findings also indicate that the welfare gain of an increase UI benefit generosity (in this case, through UI benefit extensions) is higher during recessions.[6]

Our empirical analysis differs from Schmieder et al. in several ways: first, we consider the US which is a different institutional setting than Germany; second, we consider variation in the benefit level rather than potential benefit duration; third, we focus on monthly variation in the unemployment rate within and between US states, which we believe permits a more powerful test of whether the effect of UI benefits depends on the unemployment rate. We discuss additional explanations for the differences between their findings and the findings in this paper below. Overall, we view our work which focuses on the optimal benefit level as highly complementary to work which focuses on optimal potential duration, and an important task in future work will be to investigate the problem of jointly choosing the optimal benefit level and optimal potential benefit duration over the business cylce.

The remainder of the paper proceeds as follows. The next section develops the search model and describes both the agent and planner problems. Section 3 presents our empirical analysis which estimates how the duration elasticity and consumption smoothing benefit of UI vary with the unemployment rate. Section 4 considers the welfare implications of our empirical findings. Section 5 concludes.

2 Theory

In this section, we describe the setup of a standard continuous-time, infinite-time horizon, job search model. The model closely follows Shimer and Werning (2007).

[6] They also calibrate their search model and consider two comparative static exercises: (1) an increase in the agent's search cost and (2) a decline in re-employment wages. They find these lead to opposite effects on search behavior and the marginal welfare gain of extensions.

2.1 Assumptions

We make several assumptions. First, we focus on benefit level, not potential benefit duration, although the latter is clearly also an important policy parameter.[7] Second, workers consume hand-to-mouth. The only way an unemployed worker can smooth consumption across states is through publicly provided unemployment insurance. We make this assumption since it allows us to characterize analytically how the behavioral responses to UI vary over the cycle. Importantly, our sufficient statistics welfare analysis is valid even when workers have access to liquidity, a point we discuss below. Third, there is no value from leisure time during an unemployment spell.[8] Fourth, workers are homogeneous. Finally, we work in a partial equilibrium setting with no firms.

2.2 Agent's Problem

Consider a single worker with flow utility $U(c)$, where $U' > 0$, $U'' < 0$. The worker's subjective discount rate is $\rho \geq 0$. The worker maximizes the expected present value of utility from consumption

$$E_0 \int_0^\infty e^{-\rho t} U(c(t)) dt \tag{1}$$

If the worker is unemployed, she receives unemployment benefit b and samples wage offers from a known distribution function, $F(w)$. Wage offers arrive randomly and individuals affect the offer arrival rate through costly search effort, e. Following Andersen and Svarer (2009), we assume a linear, separable cost of search, denoted by $\psi(e)$. The offer arrival rate $\lambda(e, \alpha)$ has the following properties: $\lambda_1 \geq 0$, $\lambda_{11} \leq 0$, $\lambda_{12} \geq 0$ and $\lambda_2 \geq 0$. We characterize business cycles as shifts in labor demand. Variation in labor demand comes via the parameter α, which proxies for productivity.[9]

Workers who accept a wage offer commence employment immediately. When the worker is employed, she earns a wage w and pays taxes τ which are used to finance unemployment

[7] Shimer and Werning (2008) find that socially optimal UI policy is infinite duration, constant benefits in a model with free access to savings and lending and CARA preferences.

[8] We relax this assumption in Extension 1 in the Appendix.

[9] In Extension 3, we consider business cycles driven by changes in $F(w)$.

benefit payments. Consumption when employed is her net wage, $w - \tau$. Employment is assumed to end exogenously with separation rate s.

Finally, the structural parameters s, $F(w)$, b, τ and ρ are independent of time. All duration dependence in the model comes from shifts in α, which we assume are unanticipated by the individual; that is, she always thinks that it will remain constant at its current value. As Van Den Berg (2001) notes, this is likely to be a reasonable assumption in the case of a random macroeconomic shock.[10] For ease of notation, we suppress the dependence of α on time, t. Empirically, we do not directly observe α. Instead, in our empirical specifications, we allow α to vary across individuals and over time (and not within spells) by using variation in the unemployment rate at the start of an individual's unemployment spell. We describe this in more detail in our empirical section below. It is a well-known result that workers adopt a reservation wage strategy accepting wage offers above the reservation wage, $\overline{w} = \overline{w}(b, \tau)$. We refer the reader to the Appendix for the characterization of the agent's reservation wage and the agent's optimal search intensity.

2.3 Elasticity Concepts

For ease of notation, we define $\theta(\overline{w}) \equiv \frac{f(\overline{w})}{\overline{F}(\overline{w})}$, the hazard rate (or failure rate) of the wage offer distribution, evaluated at the reservation wage. Next, let $\delta(e, \alpha) \equiv \frac{d \log \lambda(e,\alpha)}{de}$ represent the *percentage change* in the job offer arrival rate from an additional unit of search, evaluated at the optimal search effort. In this model, expected duration is the inverse of the job finding probability, $D \equiv 1/[\lambda(e, \alpha)\overline{F}(\overline{w})]$ where $\overline{F}(w) \equiv 1 - F(w)$. Define the total elasticity of expected unemployment duration with respect to the UI benefit level as $\varepsilon \equiv \frac{d \log D}{d \log b}$. We can conveniently express the duration elasticity as:

$$\varepsilon = \varepsilon_{\overline{w}} + \varepsilon_e \tag{2}$$

The first term in (2), $\varepsilon_{\overline{w}} \equiv \theta(\overline{w}) \times \overline{w} \times \frac{d \log \overline{w}}{d \log b}$, is the duration elasticity in a reservation

[10] An alternative formulation is the case where α is permitted to vary in a deterministic way over an individual's unemployment spell. Individuals correctly anticipate a change in α. See Van Den Berg (1990) for an example.

model with exogenous job offer arrivals (Shimer and Werning 2007). The second term in (2), $\varepsilon_e \equiv -\delta(e,\alpha) \times e \times \frac{d\log e}{d\log b}$, is the duration elasticity in a search effort model with a fixed wage (Chetty 2008). This decomposition will prove quite useful in characterizing how the duration elasticity varies over the cycle.

2.4 Planner's Problem

In this section, we consider the optimal unemployment insurance problem. Our approach is to solve for the optimal level of UI in a given labor market state. We then focus on the question of how optimal UI varies over the cycle. A social planner maximizes an unemployed worker's expected lifetime utility, V_u. We restrict the class of feasible policies to those where the unemployment benefit level, b, and the employment tax, τ, are constant. The planner's policy must satisfy a balanced-budget requirement which means that expected benefits paid out equals expected taxes collected. We assume throughout that $r = \rho$, which is a standard assumption in the literature. The social planner's problem is stated formally as:

$$\max_{b,\tau} V_u(b,\tau)$$

$$s.t.\ D(b,\tau(b))b = \frac{\tau}{r+s}$$

The following proposition characterizes the money-metric marginal welfare gain of increasing benefits by \$1.[11]

Proposition 1 *With $r = \rho = 0$, the money-metric welfare gain of raising b is given by*

$$\frac{dW}{db} = \frac{u}{1-u}\left\{\frac{U'(b) - E[U'(w-\tau)|w \geq \overline{w}]}{E[U'(w-\tau)|w \geq \overline{w}]} - \varepsilon\right\} \tag{3}$$

At the optimum,

$$\frac{U'(b) - E[U'(w-\tau)|w \geq \overline{w}]}{E[U'(w-\tau)|w \geq \overline{w}]} = \varepsilon \tag{4}$$

Proof. See Appendix A. ■

[11] We solve the planner's problem by substituting the budget constraint $\tau(b)$ into the objective function and solve the unconstrained problem.

This is the standard "Baily-Chetty condition" of optimal unemployment insurance (Baily 1978, Chetty 2006). If at current levels of UI benefits, $dW/db > 0$, raising the UI benefit level increases welfare. Thus, dW/db should be viewed as a "test" for whether current benefit levels are optimal. The test for the optimality of UI benefits illustrates the standard trade-off between the insurance role of UI benefits against the disincentive effect. Moral hazard arises in the second-best world, since agents do not internalize the planner's balanced-budget constraint. Thus, they impose an externality on the planner's budget, which is captured by the elasticity of expected duration with respect to UI benefits, ε.[12] Importantly, Chetty (2006) shows that equations (3) and (4) are robust to variation in the financial environment. In particular, it does not matter if agents consume hand-to-mouth or have access to liquidity. This result carries over to our setting; as a result, our welfare analysis will be valid, even with savings and borrowing.

2.5 Business Cycle Dependent UI

We now study how the optimal benefit level, characterized in equation (4) varies over the business cycle. First, we consider how the moral hazard cost of UI varies over the cycle.

2.5.1 Duration Elasticity Over the Cycle

Equation (4) demonstrates that the moral hazard cost of UI is determined by the magnitude of the total duration elasticity, ε. To see how ε varies over the cycle, we start by differentiating the agent's reservation wage and optimal search intensity with respect to b, holding taxes constant, to obtain the following lemma[13]:

Lemma 2 *The marginal effects with endogenous search intensity satisfy*

$$\frac{\partial \overline{w}}{\partial b} = \frac{U'(b)}{U'(\overline{w}-\tau)} u > 0 \tag{5}$$

[12] We show in Extension 1 in the Appendix that the basic structure of formula (3) remains intact if unemployment has leisure value and/or there are monetary costs of search that reduce consumption.

[13] We assume that $\frac{\partial \overline{w}}{\partial \tau} = \frac{\partial e}{\partial \tau} = 0$ and focus on the partial derivatives of a benefit change. We do this for analytical tractability and show quantitatively that this has little impact on the results.

where $u \equiv \frac{\rho+s}{\rho+s+\lambda(e,\alpha)\overline{F}(\overline{w})}$.

$$\frac{\partial e}{\partial b} = \left[\frac{d\log\lambda_1(e,\alpha)}{de}\right]^{-1} \frac{U'(b)}{E[U(w-\tau)|w \geq \overline{w}] - U(b) + \psi(e)} < 0 \tag{6}$$

where $\lambda_1(e,\alpha) \equiv \frac{\partial \lambda}{\partial e}$.

Proof. See Appendix A. ■

Corollary 3 *In a fixed wage,* ***dynamic*** *search effort model, the marginal effect for search effort is*

$$\frac{\partial e}{\partial b} = \left[\frac{d\log\lambda_1(e,\alpha)}{de}\right]^{-1} \frac{U'(b)}{U(w-\tau) - U(b) + \psi(e)} < 0 \tag{7}$$

Corollary 4 *In a fixed wage,* ***static*** *search effort model, the marginal effect for search effort is*

$$\frac{\partial e}{\partial b} = \left[\frac{d\log\lambda_1(e,\alpha)}{de}\right]^{-1} \frac{U'(b)}{U(w-\tau) - U(b)} < 0 \tag{8}$$

There are several things worth noting about equations (5) and (6). First, higher UI benefits raise reservation wages. Second, since a higher reservation wage is associated with a lower search intensity, we see that higher benefits reduce search effort. Third, for $\rho \approx 0$, the behavioral responses depend on the *predetermined* unemployment rate, u, that prevails at the time of the benefit increase; consequently, we use the predetermined unemployment rate in our empirical framework below. In addition to the theoretical motivation, this is advantageous from an econometrics standpoint, since it avoids the "reflection problem", a simultaneity bias that is caused by the fact that an increase in UI benefits increases unemployment duration and hence, the unemployment rate. Fourth, equation (5) shows that when $U'' \approx 0$, $\frac{\partial \overline{w}}{\partial b} \approx u$, we can identify the responsiveness of the reservation wage to changes in benefits simply by measuring the unemployment rate that prevails at the time of the benefit increase.[14] Lastly, one can easily see how the search effort response

[14] For the U.S. over the period 1999-2009, $u \in [3.8\%, 10.1\%]$. On the other hand, Feldstein and Poterba (1984) empirically estimate, using variation in UI benefits and reservation wages, $\frac{\partial \overline{w}}{\partial b} \in [13\%, 42\%]$. Therefore, in order to reconcile this range of estimates with the model-based expression for $\frac{\partial \overline{w}}{\partial b}$, it must be the case that risk aversion is relevant at existing UI benefit levels. While others have derived similar expressions for $\frac{\partial \overline{w}}{\partial b}$ (e.g., Chesher and Lancaster 1983) we believe that this is a novel point that has not been highlighted in the literature on job search.

to benefits generalizes from a fixed wage, static search effort model (equation (8)), to a fixed wage, dynamic search effort model (equation (7)) to a dynamic reservation wage model (equation (6)). This will help in characterizing the cyclical behavior of $\partial e/\partial b$ and relating this behavior to earlier results in the literature. In particular, note that equation (8) is exactly the expression in the static search effort model of Andersen and Svarer (2009).

The next proposition characterizes the cyclical behavior of $\frac{\partial \overline{w}}{\partial b}$ and $\frac{\partial e}{\partial b}$.[15] Denote the coefficient of relative risk aversion evaluated at the after-tax reservation wage by $\gamma(\overline{w} - \tau)$. For arbitrary x and y, let $\varepsilon_{x,y} \equiv \frac{d \log x}{d \log y}$.

Proposition 5 *Cyclical Behavior of Marginal Effects.*

(i)

$$\frac{d}{d\alpha}\left[\frac{\partial \overline{w}}{\partial b}\right] > 0 \iff \varepsilon_{u,\alpha} + \gamma(\overline{w} - \tau)\varepsilon_{\overline{w},\alpha} > 0 \tag{9}$$

(ii)

$$\frac{d}{d\alpha}\left[\left|\frac{\partial e}{\partial b}\right|\right] > 0 \iff \varepsilon_{\frac{d \log \lambda_1}{de},\alpha} + \varepsilon_{\rho+s+\lambda\overline{F},e} \times \varepsilon_{e,\alpha} + \frac{u}{1-u} \times \varepsilon_{\rho+s+\lambda\overline{F},\overline{w}} \times \varepsilon_{\overline{w},\alpha} < 0 \tag{10}$$

Proof. See Appendix A. ■

2.5.2 Interpretation and Discussion

Condition (9) illustrates that two effects determine the cyclicality of the responsiveness of reservation wages to UI benefits:

Discount Rate Effect ($\varepsilon_{u,\alpha} < 0$) – The key thing to note is that u effectively represents how the agent weights or discounts an increase in the benefit level b in all periods. An increase in λ (via α) effectively boosts the agent's discount rate, making her less responsive to variation in her future income stream. Intuitively, when u is low, the agent does not expect to be unemployed in the future and thus, attaches little weight to future UI benefits.

[15] For expositional purposes, we focus on exogenous variation in α, but the conditions we provide are essentially identical if we consider exogenous variation in the separation rate, s. Intuitively, this is because increases in α and decreases in s have similar effects on the agent's behavior. In Extension 3 in the Appendix, we derive analogous results for a change in the mean of the wage offer distribution. We show that the conditions are very similar to the conditions we derive in this section.

It is therefore not surprising that if an individual is less likely to be unemployed in the future, an increase in b has a smaller effect on her current reservation wage.

Risk Aversion Effect ($\gamma(\overline{w} - \tau)\varepsilon_{\overline{w},\alpha} > 0$) – An increase in λ raises the option value of search and therefore increases $\overline{w}$, as agents become more choosy about which jobs to accept when times are good. If the agent's utility function is highly curved at the existing reservation wage, an increase in $\overline{w}$ can substantially lower the marginal utility of consumption for the employed relative to the unemployed. This exacerbates the reservation wage response to UI benefits.

Thus, whether reservation wages respond more or less to benefits in a downturn depends on the strength of the "discount rate effect" to the "risk aversion effect". Interestingly, the model predicts a *larger* behavioral response during recessions for conservative levels of risk aversion, in contrast to the hypothesis of Krueger and Meyer discussed in the introduction.

Condition (10) again illustrates a tension between several opposing economic forces in shaping how search effort varies with UI benefits over the cycle:

Static Effect ($\varepsilon_{\frac{d\log\lambda_1}{de},\alpha} < 0$) – This term reflects the degree of complimentarity between e and α. This expression shows that if search effort complimentarities are sufficiently strong ($\lambda_{12} >> 0$), then benefits can be more distortionary in good times, consistent with the Krueger and Meyer intuition. Intuitively, a boost to labor demand raises the marginal efficiency of search and the behavioral response to UI benefits.[16] Andersen and Svarer (2009) consider a static, fixed wage model of search with a linear search cost and show that the cyclicality of $\partial e/\partial b$ depends purely on the sign of this effect; thus, we label it a "static effect".

Dynamic Effect ($\varepsilon_{\rho+s+\lambda,e} \times \varepsilon_{e,\alpha} > 0$) – This term arises in a fixed wage, dynamic search effort model. In a dynamic model, an increase in benefits raises the value of unemployment in all future periods. The agent's behavioral response in a dynamic model is pinned down by the discounted value of this increase. A positive and permanent labor demand shock lowers the probability that the agent is unemployed in all future periods, since it raises

[16] Card & Levine (2000) speculate that in good times, the opportunity cost of cutting back on job search activities may be too great for many and that this would tend to *attenuate* the behavioral response to UI. Our results suggest that although search effort is high in good times, the behavioral response is *exacerbated*.

search effort. This acts to effectively reduce the agent's discount factor and attenuates the behavioral response to UI benefits.

Reservation Wage Effect ($\frac{u}{1-u} \times \varepsilon_{\rho+s+\lambda\overline{F},\overline{w}} \times \varepsilon_{\overline{w},\alpha} > 0$) – Finally, in a model with stochastic wages, one also needs to additionally account for the effect of benefits on reservation wages. When the arrival rate of job offers is high, agents search with a higher reservation wage and this acts to reduce the discount factor and attenuate their behavioral response.

The main result of this section is to show that how the marginal effects vary over the cycle depends on the precise specification and structural parameters of the search model. We now study the consequences for the elasticity of expected duration with respect to the benefit level. Let $\frac{d\varepsilon}{d\alpha} = \frac{d\varepsilon_{\overline{w}}}{d\alpha} + \frac{d\varepsilon_e}{d\alpha}$. We consider each of these in turn.

Proposition 6 *Cyclical Behavior of* $\varepsilon_{\overline{w}}$ *and* ε_e*.*

(i)

$$\frac{d\varepsilon_{\overline{w}}}{d\alpha} > 0 \iff \varepsilon_{u,\alpha} + \left(\gamma(\overline{w} - \tau) + \varepsilon_{\theta,\overline{w}}\right) \varepsilon_{\overline{w},\alpha} > 0 \tag{11}$$

(ii)

$$\frac{d\left|\varepsilon_e\right|}{d\alpha} > 0 \iff \varepsilon_{\frac{d \log \lambda_1}{de},\alpha} + \varepsilon_{\rho+s+\lambda\overline{F},e} \times \varepsilon_{e,\alpha} + \frac{u}{1-u} \times \varepsilon_{\rho+s+\lambda\overline{F},\overline{w}} \times \varepsilon_{\overline{w},\alpha} - \varepsilon_{\delta,e} \times \varepsilon_{e,\alpha} < 0 \tag{12}$$

Proof. *See Appendix A.* ■

Comparing condition (11) to condition (9), we see that there is an additional term $\varepsilon_{\theta,\overline{w}}$ which reflects how the hazard rate of the wage offer distribution varies with the wage, evaluated at the reservation wage. According to Van den Berg (1994), most of the distributions used in structural job search analysis have hazards that are decreasing in the wage, $\varepsilon_{\theta,\overline{w}} < 0$. This would tend to attenuate the "risk aversion effect" and therefore make $\varepsilon_{\overline{w}}$ more likely to be countercyclical.

Next, comparing condition (12) to condition (10), we see that the condition is augmented by the factor $\varepsilon_{\delta,e} \times \varepsilon_{e,\alpha}$. Under the stated assumptions on $\lambda(e,\alpha)$, $\varepsilon_{\delta,e} < 0$. This acts to make ε_e more likely to be countercylical.

In summary, we see that taking into account how the technical aspects of $\varepsilon_{\overline{w}}$ and ε_e vary with the cycle (e.g., how $\theta(\overline{w})$ and $\delta(e)$ vary with α) make *both* of them more likely to be countercyclical. It follows that the total duration elasticity, ε, is also likely to be more countercylical. Ultimately, whether ε is procyclical or countercyclical depends on the precise specification of the primatives and functional forms of the model. Figures 1 and 2 illustrate this theoretical ambiguity by calibrating two versions of the job search model in this section. Figure 1 shows that the duration elasticity is increasing in the unemployment rate in a model with an exogenous arrival rate and stochastic wage offers, while figure 2 shows that the duration elasticity is decreasing in the unemployment rate in a model with a fixed wage and an endogenous arrival rate that depends on search effort. The figures suggest that whether the duration elasticity increases or decreases with the unemployment rate ultimately depends on the parameterization of the search model. We next analyze how the insurance effect varies over the cycle.

2.5.3 Consumption Smoothing Over the Cycle

Define $\overline{g} = \frac{U'(b)}{E[U'(w-\tau)|w \geq \overline{w}]}$ as the money-metric amount such that, the government is indifferent between giving \$1 to someone who is unemployed and $\overline{g}$ to someone who is employed.

Proposition 7 *Cyclicality of Insurance Effect.*

$$\frac{d\overline{g}}{d\alpha} = \frac{d\overline{g}}{d\overline{w}}\frac{d\overline{w}}{d\alpha} + \frac{d\overline{g}}{d\tau}\frac{d\tau}{d\alpha} > 0$$

Proof. *See Appendix A.* ■

Reservation Wage Effect ($\frac{d\overline{g}}{d\overline{w}}\frac{d\overline{w}}{d\alpha} > 0$) – The first term comes from the fact that the reservation wage varies over the business cycle. Intuitively, an agent searching for a job with a higher reservation wage expects a higher wage during employment and thus values insurance more. This effect is positive and therefore calls for procyclical UI benefits. Clearly, in a search effort model with a fixed wage, this term will not appear. Thus, relative to Andersen and Svarer (2009), our results suggest a new way that the insurance effect can vary over the cycle.

Budget Effect ($\frac{d\overline{g}}{d\tau}\frac{d\tau}{d\alpha} > 0$) – The second term represents an effect that operates through the balanced-budget constraint. Intuitively, when α is high, fewer taxes need to be raised to finance a given level of benefits. This increases the marginal utility of consumption for the employed relative to marginal utility of consumption for the unemployed since the net wage is $w - \frac{u}{1-u}b$; in order to restore optimality, benefits need to be increased. This effect is positive and ceterus paribus, implies that benefits should be procyclical. In Extension 2 in the Appendix, we relax the budget balance condition and allow the planner to run deficits in bad times and surpluses in good times. We show that the this eliminates the budget effect and the insurance effect only depends on the reservation wage effect. In summary, we see that both the reservation wage effect and the budget effect imply that the insurance effect of UI varies positively with α in this model.

Liquidity Effect – As discussed above and in relation to Chetty (2008), UI can be very valuable if it affects agents' search behavior primarily through a non-distortionary "liquidity effect", rather than through a substitution effect. It is possible that in a bad labor market, workers have fewer means to smooth consumption; for instance, one's spouse may also be out of work, and so a secondary source of income cannot be relied on. In this case, UI would be more valuable in a downturn since it has a larger liquidity effect. We develop this intuition more formally in Extension 4 where we consider a fully credit constrained model where individuals set consumption equal to income in each period.[17] We assume individuals have access to exogenous, non-labor income A each period, in addition to the UI benefit or the net wage. We show that the consumption smoothing benefit of UI – the left-hand side of equation (4) – is identified by the ratio of the liquidity effect in search effort to the substitution effect in search effort. This shows that how the consumption smoothing benefit of UI in our model varies over over the cycle additionally depends on how A varies with α. We explore this question empirically below and consider the implications for our welfare analysis.

In summary, both the reservation wage effect and the budget effect imply that the insurance effect of UI varies positively with α in this model, while the liquidity effect is theoretically ambiguous. This implies that the insurance effect is theoretically ambiguous and will also imply that the optimal UI benefit level over the cycle will be theoretically ambiguous.

[17] Results from Card, Chetty and Weber (2007) suggest this model more accurately describes job search behavior than a perfect consumption smoothing model.

Figures 1 and 2 illustrate this by showing the optimal UI benefit level as a function of the unemployment rate. As above, whether the optimal benefit level increases or decreases with the unemployment rate depends on the precise specification and specific parameters of the model. The figures also show that the magnitude of the relationship between the optimal UI benefit level and the unemployment rate can be quantitatively large.

We conclude that for realistic parameter values, the duration elasticity and the optimal benefit level can vary substantially over the cycle. Our calibration results also suggest that, in contrast with some claims in the literature, the reservation wage model and the fixed-wage, endogenous search effort may have very different normative implications when considering how UI should optimally vary over the cycle.[18] This theoretical ambiguity motivates the empirical analysis in this paper, which estimates directly in the data how the duration elasticity varies with labor market conditions.

3 Empirical Analysis

The theoretical model above predicts that the unemployment duration elasticity (ε) and the insurance effect ($\bar{g}$) vary with labor market conditions (α), but the sign and magnitude of these comparative statics are theoretically ambiguous. To take the model to the data, we make three important assumptions.

First, we assume that the *predetermined* unemployment rate (u) at the start of an unemployment spell is a valid proxy for α. Under this assumption, the relationship between $(\varepsilon, \bar{g})$ and u provides information on the relationship between $(\varepsilon, \bar{g})$ and α. Moreover, using the predetermined unemployment rate, as opposed to the actual unemployment rate at a given time during an unemployment spell, alleviates the concern that the unemployment rate is endogenous to the UI benefit level, as discussed above.

Second, we assume that α is constant within an unemployment spell. This assumption is motivated by the fact that virtually all of the variation in unemployment rates is across-spell

[18] For example, Lentz and Traenes (2005) write that "We do not believe that it is crucial whether the problem is formulated as a choice of reservation wage given a fixed search intensity or (as here) as a choice of search intensity given a fixed wage." While there are many settings where this is true, our calibration results in this section suggest that when studying the *interaction* between optimal UI and the unemployment rate, this modelling choice is not innocuous.

variation, with negligible within-spell variation.[19] Under this assumption, we identify how ε and $\bar{g}$ vary with α by estimating how ε and $\bar{g}$ vary with the unemployment rate. This assumption also implies that individuals do not need to anticipate how α will evolve during the unemployment spell.

Lastly, we rely on variation in unemployment rates between and within states, which implicitly assumes that the relevant local labor market conditions are proxied by the state-level unemployment rate. As discussed above, we pursue this time-series, cross-sectional research design in order to have sufficient variation in UI benefit levels across a wide range of labor market conditions. The primary benefit of this strategy is that we are able to more precisely identify how ε and $\bar{g}$ vary with labor market conditions. We discuss several caveats to extrapolating our estimates over national business cycles in the next section.

3.1 Part 1: Duration Elasticity

The first part of the empirical analysis is to estimate how the duration elasticity varies with the unemployment rate. We present two pieces of evidence: (1) graphical evidence and non-parametric tests of survival curves and (2) semi-parametric estimates of proportional hazard models (Cox models). The empirical strategy closely follows Chetty (2008). Both strategies focus on estimating the effect of UI benefit levels on expected unempoyment duration. All empirical specifications will focus on the benefit level rather than the maximum potential duration that an individual can receive UI benefits, although the latter is clearly also an important policy parameter. Our theory focuses on the optimal benefit level in a model with infinite potential duration, and our results are robust to controlling for variation in maximum potential duration that may be correlated with changes in UI benefit levels.[20]

We use unemployment spell data from the Survey of Income and Program Participation (SIPP) spanning 1985-2000. We impose the same sample restrictions as in Chetty (2008): we focus on prime-age males who (1) report searching for a job, (2) are not on temporary layoff, (3) have at least three months of work history, and (4) took up UI benefits. We also

[19] A variance decomposition of monthly local unemployment rates reveals that 98% of the variance is between-spell and 2% is within-spell.

[20] Specifically, we estimate models where the duration elasticity is only identified off of the weeks before benefits expire, and we find very similar results.

follow Chetty (2008) and censor unemployment spells at 50 weeks. We use two alternative proxies for an individual's actual UI benefits: (1) average benefits for each state-year pair and (2) the maximum weekly benefit amount. Both proxies (and all nominal dollar values in the data) are converted to 2000 CPI-U adjusted dollars.

3.1.1 Graphical evidence and nonparametric tests

We begin by providing graphical evidence on the effect of unemployment benefits on durations. We split the sample into two sub-samples according to whether individuals began their unemployment spell in states with above-median unemployment rates or in states with below-median unemployment rates, where each year we define the median unemployment rate across states that year. We then assign monthly state unemployment rates to unemployment spells based on the unemployment rate in the state that the individual resided in when his spell began. Lastly, we categorize unemployment spells based on whether the prevailing UI benefit level at the start of the spell in a given state and year is above or below the median UI benefit level for that year.

Figures 3 and 4 show the effect of UI benefits on the probability of unemployment for individuals in above-average and below-average unemployment state-years, respectively. In each figure, we plot Kaplan-Meier survival curves for individuals in low-benefit and high-benefit states.[21] The results in figure 3 show that the curves are fairly similar in both low-benefit and high-benefit states when the unemployment rate in a state-year is above the median unemployment rate. The curve in high-benefit states is slightly higher, indicating that UI benefits may marginally increase benefits, but a nonparametric test that the curves are identical does not reject at conventional levels ($p = 0.932$). By contrast, in figure 4 the curves are noticeably different; in particular, durations are significantly longer in high-benefit states, and the difference between the survival curves is strongly statistically significant ($p = 0.007$).[22]

[21] Following Chetty (2008), the plotted curves are adjusted for the "seam effect" in the SIPP panel data, but the test that the survival curves are identical is fully nonparametric and does not make this adjustment.

[22] While the survival curves are statistically significantly different in figure 4 but not in figure 3, one might ask whether the difference in differences (DD) across the two figures is statistically significant. To answer this question, we construct a semiparametric test by estimating a Cox proportional hazard model with separate nonparametric baseline hazard estimates for above-median and below-median unemployment

These figures suggest that the moral hazard cost of UI benefits depends crucially on whether unemployment is high or low. In particular, our findings suggest that the effect of UI benefits on durations is not statistically significant when the unemployment rate is high but is strongly statistically significant when the unemployment rate is low.[23] These effects are based on simple comparisons across spells. It is possible, however, that the characteristics of individuals vary with unemployment rate in a way that would bias these effects. To investigate this issue and other potential biases, as well as to quantify the magnitude of this interaction effect, the next subsection reports results from the estimation of semi-parametric proportional hazard models that include a rich set of individual-level controls. Overall, we find that the results from the hazard models are broadly consistent with the results based on these figures.

3.1.2 Semiparametric Hazard Models

We investigate robustness of the graphical results by estimating a set of Cox proportional hazard models. Each table reports results with alternative sets of control variables in the columns. The baseline estimating equation is the following:[24]

$$\log \lambda_{i,s,t} = \alpha_t + \alpha_s + \beta_1 \log(b_{s,t}) + \beta_2(\log(b_{s,t}) \times u_{s,t}) + \beta_3 u_{s,t} + \mathbf{X}_{i,s,t}\Gamma + e_{i,s,t} \tag{13}$$

where $\lambda_{i,s,t}$ is the hazard rate of exit out of unemployment for individual i in state s at time t, α_t and α_s represent year and state fixed effects, $b_{s,t}$ is the unemployment benefit for individual i at start of spell based on the state the individual resided in at the start of the spell, and $\mathbf{X}_{i,s,t}$ is a set of (possibly time-varying) control variables. Our primary proxy for

state-years. We include two covariates in this Cox model, an indicator for above-median benefits and a DD term which is 1 for above-median benefits in above-median unemployment state-years and 0 otherwise. The p-value on the estimated DD coefficient is 0.050.

[23] We have also looked at the subsample of workers with above-median liquid wealth, and we find broadly similar results (see Appendix Figures A2 and A3). These results suggest that liquidity effects are not primarily accounting for the differential duration elasticity between high and low unemployment, which is broadly consistent with our results in Table 11, described below.

[24] The notation of the estimating equation is a simplified presentation of the true model. The (latent) hazard rate is not actually observed in the data, and there is a flexible (nonparametric) baseline hazard rate which is also estimated when fitting the Cox proportional hazard model. Also, following Chetty (2008), we fit a separate baseline hazard rate for each quartile of net liquid wealth, although our results are very similar when a single nonparametric baseline hazard rate is estimated instead (see Appendix Table A1).

local labor market conditions, $u_{s,t}$, is the log state unemployment rate at the start of the spell relative to the log national unemployment rate. The decision to use log unemployment rates follows Bertrand (2004); we also report similar results with the unemployment rate in levels below. We discuss the decision to use relative rather than absolute unemployment rates below. All variables are de-meaned so that $-\beta_1$ represents the elasticity of unemployment durations with respect to the UI benefit level at the average state unemployment rate.[25] The coefficient on the interaction term ($-\beta_2$) is the incremental change in the duration elasticity for a one log point change in the state unemployment rate.

The identifying assumption that allows us to interpret β_2 as a test of whether the duration elasticity varies with the unemployment rate is the following: conditional on the average UI weekly benefit amount, state unemployment rate, state fixed effects, year fixed effects, and control variables, there are no omitted determinants of the duration of an unemployment spell that vary with the *interaction* of average UI weekly benefit amount and the state unemployment rate. This assumption is considerably more plausible with the inclusion of state and year fixed effects, though there remains the concern that benefits respond endogenously to both observed and unobserved local labor market conditions. In Section 3.2.1, we discuss this (and many other) threats to validity in more detail.

Before turning to our regression results, we present descriptive statistics in Panel A of Table 1. The table presents summary statistics for the overall sample and the two sub-samples used to create figures 3 and 4. The two sub-samples are broadly similar, though unemployed individuals are slightly older in states with high unemployment.[26]

The main results are reported in Table 2. Column (1) of Table 2 reports results of a specification broadly similar to the previous literature (Moffitt (1985), Meyer (1990), Chetty (2008)). This specification controls for age, marital status, years of education, a full set of state, year, industry and occupation fixed effects, and a 10-knot linear spline in log annual wage income. Column (2) reports estimates of equation (13). This column includes the same

[25] We will use this approximation throughout for the unemployment duration $\log(d) \approx \log(1/\lambda) = -\log(\lambda)$, so that the duration elasticity and other marginal effects are given by the negative of the coefficient in the hazard model.

[26] In Table 8 below, we control for the small compositional changes in the sample of unemployed individuals across labor market conditions, and we find extremely similar results.

set of controls in column (1) and estimates the same hazard model; the only difference is the addition of an interaction term between the UI benefit level and the log state unemployment rate. The results indicate that the elasticity of unemployment durations with respect to the UI benefit level is 0.605 (s.e. 0.295) at the average unemployment rate, and this estimate is statistically significant at conventional levels ($p = 0.040$). The coefficient on the interaction term (β_2) represents the change in the duration elasticity for a one log point increase in the log state unemployment rate, holding the national unemployment rate constant. The results in column (2) show an estimate of $-\beta_2$ of -1.256 (s.e. 0.433). The bottom two rows show an alternative way to interpret the interaction term. These rows report the duration elasticity at one standard deviation above and below the mean unemployment rate. At one standard deviation below the mean, the duration elasticity is 0.348 (s.e. 0.294), while at one standard deviation above the mean the duration elasticity is 0.863 (s.e. 0.321). These results imply that the magnitude of the duration elasticity decreases with the unemployment rate and suggest that the moral hazard cost of unemployment insurance is lower when the unemployment rate is relatively high.

3.1.3 What If UI Benefits Respond to Labor Market Conditions?

An immediate concern with our identification strategy is that UI benefits may be correlated with labor market conditions. We pursue several strategies to address this concern.

First, we examine the relationship between UI benefits and the unemployment rate. Table 3 reports OLS estimates from a regression of log UI benefits on the unemployment rate with two sets of controls. In Panel A, the controls are state fixed effects and year fixed effects, while in Panel B the controls include state-specific linear time trends in addition to the fixed effects in Panel A. In both panels, the results in column (1) show a small positive coefficient estimate. In Panel A, the point estimate in column (1) implies that a one standard deviation increase in the relative unemployment rate increases UI benefits by 1.64% (s.e. 1.03%). While these results suggest that benefits appear to be somewhat responsive to local labor market conditions, the association is not statistically significant at conventional levels in either panel.

A concern with this simple test is that it may fail to capture the fact that UI benefits are more responsive to the unemployment rate in bad times than in good times. The pattern of benefit changes that we observe in the data suggest this relationship.[27] This policy endogeneity would bias estimates of β_1 and β_2 in equation (13). We therefore explore alternative assumptions about how the unemployment rate affects benefits. Column (2) in both panels report results which add a quadratic in the state unemployment rate. In both panels, the quadratic term is positive, suggesting that benefits are more responsive to the unemployment rate when the unemployment rate is high. The results in columns (3) and (4) report reuslts which split the sample depending on whether the state unemployment rate is above or below the median, and the results are similar to column (2). While the results are often imprecise, the results in this table provide weak but suggestive evidence that benefits are more responsive to labor market conditions in bad times than in good times.

Motivated by this analysis, we report results in Table 4 which control more flexibly for the local unemployment rate in equation (13). We assess the possible bias from such policy endogeneity through several alternative specifications. Column (1) reports our baseline specification for comparison. Columns (2) through (4) include various polynomial functions of the local unemployment rate and the UI benefit level. These tests address the concern that UI benefits respond non-linearly to the local unemployment rate. Additionally, to the extent that the flexible polynomial in the unemployment rate more thoroughly controls for unobserved local labor market conditions, this specification can be used to gauge the extent of the bias due to policy endogeneity. Though the results are somewhat less precise, the results in these columns suggest that, if anything, the magnitude of our interaction term is larger with these more flexible controls.[28] Columns (5) through (7) include specifications which include some combination of interactions between the state unemployment rate and state fixed effects and interactions between the state unemployment rate and year fixed effects. These specifications capture the possibility that in certain states and/or certain years, UI benefits may be unusually responsive to changes in local labor market conditions.

[27] We find that there are 1374 instances where the change in the maximum weekly benefit amount is weakly positive and only 12 instances where the maximum weekly benefit amount was reduced.

[28] We have also investigated robustness to flexible, non-linear effects of UI benefit level in addition to the local unemployment rate. These results are in Appendix Table A1, where we re-estimate our baseline specification with various non-linear (polynomial) functions of the unemployment rate and the UI benefit level. The results are similar to our baseline specification.

Again, the results suggest that, if anything, the magnitude of our interaction term is larger with these more flexible controls.

The previous discussion ignored the possibility of unobserved factors that determine both UI benefits and unemployment durations. Our second strategy now explores this possibility. As our empirical strategy is essentially equivalent to estimating a difference-in-differences regression, we consider the case where the unemployment rate $u_{s,t}$ can only take two values: u_H and u_L, with $u_H > u_L$.[29] Then, estimating equation (13) is equivalent to estimating:

$$\log(d_{i,H,t}) = \beta_H \log(b_{s,t}) + v_H + \alpha_t + \alpha_s + e_{i,H,t} \qquad \text{if } u_{s,t} = u_H \tag{14}$$

and

$$\log(d_{i,L,t}) = \beta_L \log(b_{s,t}) + v_L + \alpha_t + \alpha_s + e_{i,L,t} \qquad \text{if } u_{s,t} = u_L \tag{15}$$

The coefficient β_2 on the interaction term $\log(b_{s,t}) \times u_{s,t}$ in equation (13) is given by the difference between β_H and β_L. Each of these two equations is subject to an identification problem. In particular, each equation is a reduced form equation from a system of two equations: an equation determining durations and an equation determining UI benefits. Thus, the standard endogeneity problem due to simultaneous equations arises. Consider the following simplified two equation system:

$$\begin{aligned} d_q &= \beta_q b + \xi_q \\ b &= \lambda_q \xi_q + \eta_q \end{aligned}$$

where $q = \{H, L\}$. The first equation describes the duration equation and the second equation describes the UI benefit equation. The variable ξ_q represents unobserved labor demand shocks, and η_q represents unobserved factors which shift UI benefits and are orthogonal to local labor market conditions. We can now as what happens if one estimates (14) and (15) ignoring the endogeneity of benefits? It is straightforward to show that $\widehat{\beta}_q$ will be given by:

$$\widehat{\beta}_q = \beta_q + \lambda_q$$

[29] This discussion extends Bertrand (2004).

This illustrates the well-known identification problem that $\widehat{\beta}_q \neq \beta_q$ when $\lambda_q \neq 0$. Under the assumption that $\lambda_q = 0$, it is easy to see that β_H and β_L (and therefore $\beta_H - \beta_L$) can be consistently estimated. This assumption requires that all variation in benefits be driven by shocks that are uncorrelated with unobserved labor demand shocks.

By contrast, if $\lambda_q \neq 0$, we need stronger assumptions for identification. Under the strong assumption that $\lambda_H = \lambda_L$, then $\widehat{\beta}_H - \widehat{\beta}_L = \beta_H - \beta_L$. Thus, while we cannot identify the main effect when $\lambda_H = \lambda_L \neq 0$, we will be able to consistently estimate the interaction term of interest.

A key remaining challenge arises when λ_q depends on q. For ease of exposition, consider the case where benefits are exogenous in good times, but are endogenous to local labor demand conditions in bad times (e.g., $\lambda_L = 0$ and $\lambda_H > 0$). In this case, $\widehat{\beta}_H - \widehat{\beta}_L = \beta_H - \beta_L + \lambda_H$. This illustrates that this particular type of policy endogeneity works against the findings in our baseline specification. Intuitively, if variation in benefits is plausibly exogenous during good times, then we will consistently estimate the duration elasticity in good times; however, if variation in benefits is correlated with unobserved labor market conditions during bad times, then this will cause upward bias in the magnitude of the duration elasticity during bad times (e.g., $\widehat{\beta}_H = \beta_H + \lambda_H > \beta_H$). Since we find that the magnitude of the duration elasticity is significantly *smaller* during bad times, this suggests that this policy endogeneity likely causes us to understate the magnitude of the interaction term.

The last threat to identification we discuss comes from the implicit assumption that UI benefits respond symmetrically to both local and national labor market shocks. If benefits respond to observable and unobservable national labor market conditions, then including year fixed effects, as we do in our baseline specification, addresses the problem. The concern is that when the national labor market is bad, benefits are more correlated with labor market conditions than when national labor market is good. In this case, year fixed effects will not capture the fact that the correlation between benefits and unobservable labor market conditions depends on the year. One strategy for dealing with this is interacting year fixed effects with UI benefits and including this as a control. This means that any variation in benefits that is correlated with the (unobservables in the) year fixed effects is not variation we use to identify the interaction term. Alternatively, one may use relative unemployment rates to address the concern. In regression results not reported, we find that UI benefits are larger when national unemployment rate is high. We also find results that suggest when the national unemployment rate is high, state benefits are more responsive to relative state unemployment rates. Motivated by this concern, we use the state unemployment rate relative to the national unemployment rate in all specifications.[30]

Finally, Table 5 presents results from modifications of our baseline specification which focus on alternative assumptions regarding contemporaneous trends across states within a region and within states over time. To the extent that such smoothly-varying unobserved trends are correlated with the interaction of local labor market conditions and UI benefit levels, this may cause our baseline specification to be biased. The results in columns (2) through (4) suggest that, if anything, the magnitude of the interaction term is slightly larger when we flexibly control for unobserved trends. This is also consistent with the direction of the policy endogeneity bias discussed above.

Overall, given the results in Tables 3 through 5, we interpret our preferred specification as a *conservative* estimate of the magnitude of the relationship between the duration elasticity and the local unemployment rate. We find no evidence that a simple policy endogeneity story is primarily responsible for our findings. The next section explores additional threats to validity and alternative explanations for our findings.

3.1.4 Alternative Explanations and Robustness Tests

Decomposing Variation in State Unemployment Rate

In our baseline specification, identification of the interaction term of interest comes from both across-state and within-state variation in unemployment rates. In figures 5 and 6, we report survival curves analogous to figures 3 and 4 using only within-state variation in unemployment rates. We do this by subtracting the unemployment rate in each state-year by the average unemployment rate in the state over the sample period. Figures 5 and 6 show

[30] We find similar results if we include year fixed effects interacted with UI benefits as a control, and we also find similar results when we include the national unemployment rate interacted with UI benefits as a control.

that the same pattern emerges when using only within-state variation in the unemployment rate. These figures show that there is a statistically significant difference between the high- and low-benefit survival curves when the unemployment rate is relatively low, but not when it is relatively high. Figures 7 and 8 show similar results using only cross-state variation in the state unemployment. To construct these figures, we compute the average state unemployment rate over the sample period and divide states basd on whether they are above or below the median. We quantify these patterns in Table 6, where we report results from a specification where we decompose the variation in the state unemployment rate into across-state variation and within-state variation. The first row reports results from our baseline specification for comparison, and the second row reports results which interact UI benefit level with (1) the average log state unemployment rate (calculated separately for each state over the sample period) and (2) the log state unemployment rate – average log state unemployment rate. This allows us to see separately how across-state and within-state variation in the state unemployment rate affects the duration elasticity. We also find that both interaction terms are the same sign as the interaction term in the baseline specification, with a larger interaction term using solely across-state variation in unemployment rates. Most importantly, the magnitude of the interaction term using purely within-state variation is very similar to the baseline results.

Exploiting Variation Across Metropolitan Areas Within States

Thus far, we have defined local labor markets as states. As an additional robustness test, we instead use metropolitan areas (MSAs) to define local labor markets.[31] In Table 7, we report results from using the MSA unemployment rate rather than the state unemployment rate, which allows us to exploit within-state variation in local labor market conditions. Overall, the results in this table are similar to the baseline specification. In the final column of Table 7, we report results which include a full set of state-by-year fixed effects, so that the only variation used to estimate the interaction term is within-state-year, across-MSA variation in the unemployment rate, holding the state-year UI benefit level constant. The interaction term remains statistically significant ($p = 0.027$), and the magnitude is somewhat

[31] To preserve the sample size, we assign the state unemployment rate to all unemployed individuals who do not have an MSA code, which is roughly 50% of the sample.

larger than in the baseline specification.

Composition Bias, Selection on Observables, and Endogenous Take-up

As the local unemployment rate fluctuates, there may be compositional changes in the pool of unemployed workers receiving UI benefits. If there is heterogeneity in moral hazard across demographic groups and the distribution of demographics of the unemployed varies with the level of unemployment, then this compositional change could mechanically generate an observed change in the average duration elasticity.[32] To test this hypothesis, in Table 8 we report estimates of an augmented version of our baseline specification where we add interactions between UI benefits and the demographic controls in our baseline specification. If the estimates of the baseline interaction term is primarily due to compositional changes among demographic groups with different duration elasticities, then we would expect to see a reduction in the magnitude of the coefficient as we include additional interactions between UI benefits and demographic controls. The results in Table 8 show that our main result is very robust to including such controls – looking across all the columns, we see that adding interactions between demographics and UI benefits has a negligible effect on our main coefficient of interest.[33]

The final column investigates a related source of bias, which is endogenous take-up. As shown in column (8) shows, we find that the effect of UI benefits on take-up varies with the unemployment rate. We also find that the unemployment rate itself is a strong predictor of take-up. These results raise concerns about possible selection bias, though the results in the rest of the columns in Table 8 suggest negligible effects of selection on observables. While the duration elasticity could also vary with unobservable characteristics of individuals, the robustness to selection on observables suggests that it is unlikely that our interaction term is primarily due to selection on unobservables, though of course we cannot test this directly.[34]

[32] Note that even if this were to be the case, how the average duration elasticity varies with the unemployment rate is still the appropriate measure for the welfare calibrations below. Nevertheless, understanding how much of the observed change in the average duration elasticity is due to compositional changes and how much is due to individual-level changes in moral hazard may be important for other economic problems.

[33] The results in this table also reveal suggestive evidence that the duration elasticity varies with years of education. Though accounting for this interaction has no effect on our interaction term of interest, it nevertheless suggests that moral hazard cost may vary with observable level of human capital.

[34] We find that our results are similar if we estimate the following two-step estimator. In the first step, we estimate a probit model of UI receipt on interaction term using the same set of controls used in the

Alternative Measures of the Interaction Term

In our baseline specification, the interaction term of interest is formed by interacting the log of the average weekly UI benefit in the state with the log of the state unemployment rate (relative to the log of the national unemployment rate). Both of these variables are proxies for the underlying variables of interest (an individual's actual UI benefit level and the actual local labor demand conditions). Table 9 explores several alternative measures of the interaction term, and we find that our results are generally robust to these alternatives. Each row of Table 9 reports results from estimating our baseline specification with an alternative measure of our interaction term. The first row reproduces our baseline estimates for comparison. The second row replaces the state unemployment rate with a dummy variable for whether or not the unemployment rate is greater than the median state unemployment rate in that year. This specification corresponds more closely to the nonparametric results presented above. The third row reports results using the state unemployment rate in levels (rather than logs). In both cases, the results are similar to the baseline specification. The fourth row replaces the average weekly UI benefit amount with the maximum weekly benefit amount. The maximum weekly benefit amount corresponds more closely to a specific policy parameter set by states. While this alternative measure may be more plausibly exogenous, the primarily drawback is that it does not exploit all of the variation in UI benefit generosity. The results indicate that the magnitude of our interaction term is very similar with this alterantive measure. The fifth row uses the average replacement rate rather than the average weekly UI benefit amount, and the results are also similar. The last row uses an alternative proxy for local labor demand instead of the local unemployment rate. One concern with the unemployment rate is that it reflects both labor demand and labor supply shocks. We construct variation in state unemployment rates that is driven by plausibly exogenous shifts in local labor demand using a well-established procedure developed in Bartik (1991).[35] Figures 9 and 10 plot survival curves comparing the effect of UI benefits across high and low

baseline proportional hazard model using the expanded sample which includes eligibles who do not receive UI benefits. In the second step, we estimate the baseline hazard specification including as an additional control the inverse Mills ratio evaluated at the fitted values.

[35] We closely following the implementation of the Bartik (1991) procedure in Autor and Duggan (2003). We predict the employment to population ratio by interacting initial cross-sectional distribution of state-level employment shares with national industry employment trends.

predicted employment-to-population ratios. Consistent with figures 3 and 4, this nonparametric evidence indicates that the behavioral effect of UI benefits is largest during periods of high predicted employment. Row 6 of Table 9 reports hazard model estimates, where the magnitude of the interaction term is similar to our baseline specifications, but our estimates are imprecise.[36]

To summarize, across all the specifications in this section, we find no evidence that our baseline results are primarily due to composition bias, liquidity effects, mismeasurement, or nonlinear effects. We therefore conclude that the most likely explanation for our findings is that the disincentive effect of UI benefits decreases with the unemployment rate.

3.1.5 Comparison to Schmieder et al. (2011) and Landais et al. (2011)

While we find consistent evidence that the duration elasticity increases with the unemployment rate, Schmieder et al. (2011) find that the non-employment duration elasticity is not strongly related to the unemployment rate. Besides the differences in institutional setting (United States versus Germany), research design (fixed effects panel versus regression discontinuity), and definition of the labor market (local versus national), we study UI benefit levels while Schmieder et al. study UI benefit extensions. This difference makes the empirical estimates not strictly comparable. In particular, the marginal worker affected by the UI variation in their setting is an experienced worker older than age 40, while the UI variation in our setting affects a majority of the workers eligible for UI.

Additionally, there is another economic explanation for the differences in results. While we study changes in UI benefit levels which affect a majority of unemployment workers, Schmieder et al. study changes in UI benefit generosity across age thresholds, holding program parameters constsant. Therefore, one may interpret the Schmieder et al. estimates as partial equilibrium (PE) estimates and our estimates as general equilibrium (GE) estimates. The logic is that since they analyze the effect of UI by comparising across two groups experiencing the *same* labor market conditions, it is possible that some of the GE effects of UI are "differenced out". By contrast, our estimation strategy primarily relies on comparing

[36]Lastly, Appendix Table A1 reports similar results using alternative sets of control variables, alternative specifications allowing for nonlinear direct effects, and controls for extended benefits.

observably similar individuals receiving the same benefits in *different* labor markets. Under this interpretation, the combined evidence across the two papers suggests that the PE duration elasticity does not vary over the cycle while the GE duration elasticity is strongly decreasing in the unemployment rate. This is precisely the predictions of the job rationing model in Landais et al. (2011), providing a parsimonious explanation for the empirical findings in the two papers. One problem with this interpretation is that the PE estimates in Schmieder et al. are lower than the estimates in this paper, while the Landais et al. paper predicts a larger PE elasticity than GE elasticity. We speculate that this difference may simply be due to different behavioral responses to UI benefit *levels* vs UI benefit *extensions*, although we leave a rigorous investigation of this to future work.

3.2 Part 2: Consumption Smoothing

The second part of the empirical analysis replicates and extends previous work on the consumption smoothing benefit of UI (Gruber 1997). Specifically, we estimate how the effect of UI on the consumption drop upon unemployment varies with the state unemployment rate. The empirical strategy closely follows Gruber (1997), which uses the UI replacement rate rather than the UI benefit level and uses the change in total food consumption as a proxy for the change in total consumption.

We use data from the Panel Study of Income Dynamics (PSID) between 1968 and 1987. We impose the same sample restrictions as in Gruber (1997): we focus on all heads of household who are employed at interview date $t-1$ and unemployed at date t, and we define individuals as unemployed if they are looking for a new job and are not on temporary layoff; furthermore, observations are excluded if any element of food consumption is imputed or there is more than a threefold change in total food consumption.

The baseline specification is the following:

$$\Delta \log C_{i,t} = \alpha_t + \alpha_s + \delta_1 b_{i,s,t} + \delta_2 (b_{i,s,t} \times u_{s,t}) + \delta_3 u_{s,t} + \mathbf{X}_{i,s,t}\Gamma + e_{i,s,t} \tag{16}$$

where $\Delta \log C_{i,t}$ is the difference in log total food consumption for individual i between date $t-1$ and date t, $b_{i,s,t}$ is the UI replacement rate, $u_{s,t}$ is the state unemployment rate, α_t

and α_s are year and state fixed effects, and $\mathbf{X}_{i,s,t}$ is the same set of control variables used in Gruber (1997).[37]

Table 10 reports results of estimating equation (16). Column (1) presents our results which closely replicate column (4) in Table 2 of Gruber (1997).[38] These results show the consumption smothing benefit of UI on average. Replicating the key finding in that paper, we find that a ten percentage point increase in the replacement rate reduces the consumption drop upon unemployment by 2.8%.[39] Column (2) reports our preferred specification which includes the interaction between the replacement rate and the unemployment. The interaction term is not statistically significant at conventional levels ($p = 0.230$), and the magnitude is about 23% of the magnitude of the interaction term in the duration elasticity results above. Morever, there is enough precision to rule out modest magnitudes. The 95% confidence interval allows us to reject that a one standard deviation increase in the unemployment rate increases the consumption smoothing benefit of UI by more than 16%. The remaining columns of Table 10 report a variety of alternative of specifications of equation (16), and none of the results provide significant evidence that the consumption smoothing benefit of UI varies with the state unemployment rate.

In addition to the results based on consumption data, we can also modify the duration elasticity specifications from above to study the insurance value of UI. Recent work by Chetty (2008) raises a concern with interpreting the duration elasticity as a pure moral hazard effect; he presents evidence that a component of the observed duration elasticity represents an income effect (or "liquidity effect"). This suggests that the interaction term which we estimate in our baseline specification in the first part of our empirical analysis could plausibly represent a liquidity effect which varies systematically with local labor market conditions. In principle, the consumption smoothing results rule out this possibility since

[37] As in the first part of the empirical analysis, in our preferred specification we use the log difference between the state unemployment rate and the national unemployment rate. Also, we use the previous year's unemployment rate because we do not observe individuals at the start of their spell, and we want to ensure that the unemployment rate is predetermined, for reasons discussed above.

[38] In ongoing work, we are incoporating taxes to try to more closely match the results in Gruber (1997).

[39] This coefficient estimate matches Gruber (1997) to at least three decimal places, but the standard errors are higher. We have been unable to account for the difference. Though we report standard errors which allow for arbitrary variance-covariance matrix within states over time, our standard errors are similar using OLS standard errors assuming homoskedasticity.

they incorporate liquidity effects. Nevertheless, we present additional results which test whether our interaction term in the duration results above is driven by liquidity effects.

Table 11 reports these alternative specifications which investigate whether liquidity effects affect the interaction term. Column (1) reports our baseline specification for comparison. Column (2) reports results for the subsample of workers in the 3rd and 4th quartiles of net liquid wealth, where liquidity effects are likely to be less important. The coefficient on the interaction is slightly larger than in the baseline specification.[40] Columns (3) and (4) report results which include a full set of liquid wealth quartile dummy variables interacted with a combination of occupation fixed effects, industry fixed effects, unemployment duration, and the UI benefit level, and the results are, if anything, slightly stronger. Lastly, column (5) verifies that the interaction term does not vary with liquid wealth. The results consistently support the interpretation that the moral hazard cost of UI decreases with the unemployment rate, and that our results are not primarily due to liquidity effects varying with local labor market conditions. More broadly, the results in this table do not provide clear evidence that the consumption smoothing benefit (or insurance value) of UI varies with the unemployment rate, which is consistent with the consumption-based tests above. We therefore conclude that how the optimal UI benefit level varies with the unemployment rate will be driven largely by how the duration elasticity varies with the unemployment rate, as the results in this section suggest that the consumption smoothing benefit is approximately constant across labor market states.

We next discuss the implications of our empirical results for national business cycles, conduct a welfare analysis using our baseline empirical results, compare optimal UI policy to current policy in the U.S., and discuss aggregate implications of extending benefits in recessions.

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[40] The interaction term when using the subsample of unemployed workers without a mortgage (another proxy for individuals that are not liquidity constrained used in Chetty (2008)) is even larger in magnitude than columns (1) and (2), again providing no evidence that liquidity effects are primarily responsible for the interaction term in our baseline specification.

4 Interpretation and Implications

4.1 Extrapolating Estimates to National Business Cycles

Our estimate of how the duration elasticity varies with labor market conditions is identified off of variation in local unemployment rates. To study the impact of national business cycles on the duration elasticity, ideally one would want to conduct a full general equilibrium analysis that explicitly accounts for all margins that could potentially be distorted. While such an analysis is outside the scope of this paper, the aim of this subsection is to shed light on this question by drawing inferences from our empirical estimates.

First, the nature of a national shock compared to a local shock may differ. In particular, one may argue that the persistence of national shocks and local shocks differs, and that the behavioral response to UI, conditional on a given level of persistence, may differ. One piece of evidence against differential responses by persistence comes from the results in Table 6. If we associate the between-state variation in unemployment rates with a measure of permanent shocks and the within-state variation with a measure of temporary shocks, we find that with available statistical precision, we cannot reject the hypothesis that the correlation between the duration elasticity and the unemployment rate is the same across both sources of variation.

Second, a local unemployment shock may differ from a national unemployment shock since it changes mobility incentives. If only New York gets hit with a labor market shock, out-migration may increase as individuals move to neighboring states to search for a job. However, the relevant question is whether mobility patterns induced by such a shock vary across states with different levels of UI benefits. Current U.S. law mandates that individuals collect UI benefits in the state of their previous employer. Given this restriction, we believe the mobility response to UI benefits is likely to be low.

Finally, a national shock may have different budgetary implications than a local shock, though it is not clear which direction this will cause our estimates to be biased. In the case of a local shock that persists for some time, states could use the federal government as a buffer to finance UI expenditures; however, a particularly acute local shock may force states to raise taxes to finance the additional UI expenditures. Since the federal government has the ability to run budget deficits over a longer time horizon, this budget effect may have additional welfare implications.

4.2 Calibrating the Welfare Implications

Our empirical results suggest that moral hazard decreases with the unemployment rate. To see what this finding implies for optimal policy, we now calibrate the optimal UI level implied by our model, following the spirit of the "sufficient statistic" approach to welfare analysis. To review, this method requires using the reduced form empirical estimates as inputs into the optimal UI formula.

One can think of $\varepsilon_{D,b} = h(\log(u))$, where $h()$ is a non-linear function. In order to exploit our empirical estimates, we assume that $h()$ can be locally approximated by a linear function of $\log(u)$. A first-order approximation of $h(\log(u))$ around $\log(u) = \log(\overline{u})$ yields:

$$\varepsilon_{D,b}(\log(u)) = \varepsilon_{D,b}(\log(\overline{u})) + \frac{d\varepsilon_{D,b}(\log(\overline{u}))}{du} \times (u - \log(\overline{u}))$$

This can also be derived directly from our reduced form estimating equation (13):

$$-\log(d) \approx \log(\lambda) = \alpha + \beta_1 \log(b) + \beta_2 \log(b) \times (\log(u) - \log(\overline{u})) + e \tag{17}$$

With this specification,

$$\varepsilon_{D,b}(\log(u)) = \frac{d(\log(d))}{d\log(b)} = -\beta_1 - \beta_2 \times (\log(u) - \log(\overline{u}))$$

Thus, $-\beta_1 = \varepsilon_{D,b}(\log(\overline{u}))$ and $-\beta_2 = \frac{d\varepsilon_{D,b}(\log(\overline{u}))}{d\log(u)}$. Our empirical results imply that $-\widehat{\beta}_1 = 0.605$ and $-\widehat{\beta}_2 = -1.256$. To analyze the welfare implications, we will assume that the budget effect can be ignored. This is motivated by current US policy where states' UI trust funds run deficits in recessions and surpluses in booms.

Recall, the consumption smoothing benefit of UI is the following:

$$\frac{U'(b) - E[U'(w-\tau)|w \geq \overline{w}]}{E[U'(w-\tau)|w \geq \overline{w}]}$$

Following Chetty (2006), we can show that the consumption smoothing benefit can be approximated as

$$\left[\gamma\frac{\Delta c}{c}(b)\left(1+\frac{1}{2}\delta\frac{\Delta c}{c}(b)\right)+1\right]F-1$$

where δ is the coefficient of relative prudence and $F=\frac{1}{1+\frac{1}{2}\gamma\delta s_e^2}$ is a correction factor that accounts for the volatility in consumption when employed. It is defined in terms of s_e, the coefficient of variation of consumption when employed. For ease of computation, we assume a fixed wage, search effort model, so that $F=1$ and the consumption smoothing benefit of UI becomes

$$\gamma\frac{\Delta c}{c}(b)\left(1+\frac{1}{2}\delta\frac{\Delta c}{c}(b)\right)$$

We calibrate the consumption smoothing benefit using the estimate for the consumption drop ($\frac{\Delta c}{c}=0.23-0.28\times b$) based on Gruber (1997).[41] Given the considerable uncertainty over the value of risk aversion, we present calibration results for a range of values $\gamma=2,3,4$ ($\delta=3,4,5$). Table 12 presents results from the numerical implementation of expression (4). At $\bar{u}=5.4\%$ and $\gamma=4$, the optimal replacement rate is 40.4%. At an unemployment rate of 7.1% (roughly one standard deviation above the mean unemployment rate), the formula implies an optimal replacement rate of 49.1%. Thus, we see that variation in the unemployment rate can substantially affect replacement rates. The basic lesson to emerge from the table is that plausible variation in the unemployment rate generates wide variation in the optimal level of UI. To give a sense of the quantitative importance of this variation, the magnitude is roughly equivalent to a one unit change in the coefficient of relative risk aversion in the model (e.g., from $\gamma=3$ to $\gamma=4$), holding the unemployment rate constant.[42] While the previous literature has emphasized the sensitivity of the optimal UI benefit level to risk aversion, our results suggest that the optimal UI benefit level is equally sensitive to labor market conditions.

[41] The results are very similar if we allow $\Delta c/c$ to vary with u based on the small, insignificant results in Table 10 above.

[42] The results in the second column of Table 10 show that at one standard deviation below the mean unemployment rate ($u=3.7\%$), the optimal replacement rate is 32.8%. Changing the coefficient of relative risk aversion from 4 to 3 and holding rest of parameters constant results in optimal replacement rate of 30.7% (at $u=5.4\%$).

4.3 Comparing Optimal UI Policy to Extended Benefits Policy in the U.S.

In terms of existing UI policy in the U.S., the potential duration of UI benefits has typically been adjusted in response to slackness in the labor market, rather than the level of UI benefits. Historically, benefits have been extended by 13 weeks when a state's insured unemployment rate exceeded some threshold (Card and Levine, 2001). To shed light on the optimality of such a policy, we consider the case where the unemployment rate increases from 3.7% to 5.4%.[43] The question we seek to address is whether the expected payout from an increase in the optimal benefit level comes close to the expected payout from an extension of benefits in line with what we observe with existing UI policy. We emphasize that these stylized calculations are primarily meant to be illustrative and that considerable caution should be exercised in interpreting the quantitative results.

Table 10 shows that the weekly optimal benefit level increases from \$102 to \$141. Given a mean unemployment duration of roughly 18 weeks based on Table 1, this implies total expected benefits paid out to a given individual increase by \$702 ($= 18 \times (\$141 - \$102)$), assuming no behavioral response. A duration elasticity with respect to the benefit level of 0.605 increases the total expected payout to \$846 ($= (\$141 - \$102) \times (18 + 0.605 \times 18 \times \frac{\$141-\$102}{\$102})$).

Next, consider instead a benefit extension of 13 weeks. The expected increase in payments to an individual, assuming a potential duration of 26 weeks for the regular UI program, is given by

$$\$102 \sum_{t=1}^{13} t \times \Pr\{duration = 26 + t\} + \$102 \times 13 \times \Pr\{duration > 39\}$$

For simplicity, let's assume that $\Pr\{duration = 26 + t\} = \Pr\{duration = 26\}$ for all t. In our SIPP sample, we calculated that the average frequency that a spell lasts exactly t weeks where $t \in [27, 39]$ is roughly 0.009 and $\Pr\{duration > 39\} = .12$. Roughly 76% of the

[43] Schwartz (2010) notes that extensions are triggered if the insured unemployment rate exceeds 5% and has increased by 20% over the two prior years.

unemployment spells in our data end at 26 weeks or less. Therefore, the expected increase in total payments paid to an individual are \$243 ($= 0.009 \times 91 \times \$102 + 0.12 \times 13 \times \$102$), assuming no behavioral response. The results from Card and Levine (2000) suggest that an extra 13 weeks of benefits raise durations by 1 week. If we assume that this one week increase would result in receipt of a full week's worth of benefits, the total expected payout incorporating behavioral responses is \$345. Thus, based on this simple illustration, the actual UI policy appears to be slightly less generous in terms of expected payouts as the optimal policy from adjusting the replacement rate would imply.

4.4 Implications of Extending Benefits During Recessions

An important policy question is how extended benefits affect the unemployment rate in a recession. Ideally, credible empirical evidence on how durations respond to benefit extensions and how this effect varies with labor market conditions would shed light on this question. Unfortunately, such evidence does not exist for the U.S.. The key challenge is that benefits are typically extended during recessions, making them endogenous and unreliable for empirical analysis. For illustrative purposes, we show how one can use our reduced form empirical results to shed light on how extended benefits affect the unemployment rate in a recession.

To fix ideas, we focus on the recent extension in potential duration from 26 weeks to 104 weeks in the U.S. Card and Levine (2000) estimate during normal economic times that a 13-week extension increases unemployment duration by 1 week. Extrapolating from their estimate, a 78 week increase in potential duration is expected to prolong durations on average by 6 weeks in normal times. We now compute how much the UI benefit *level* has to increase to raise durations by 1 week, based on our estimates. We know that unemployment duration is 18 weeks at the mean unemployment rate in our sample of 5.4%. Further, the duration elasticity is 0.605. Thus, 1 extra week of unemployment duration would require a percent increase in benefits equal to $.092 = (1/18)/.605$.

Now suppose that the unemployment rate has increased to 8.8%.[44] Our estimates imply

[44] The estimates of the unemployment rate at the start and end of the U.S. recession are very similar to the estimates reported in Schmieder et al (2010).

that a 9.2% increase in benefits would increase durations by roughly 3.1% or .031*18 = 0.6 weeks. Using our estimates, and assuming that the potential duration elasticity is also lower in bad times, a 13-week extension would raise durations by 0.6 weeks in bad times, compared to the 1 week from Card and Levine. Thus, a 78 week increase in potential duration leads to a 3.6 week increase in durations, rather than the 6 week increase one would obtain based on Card and Levine's estimate.

To see what this implies for the aggregate unemployment rate, we make use of the steady-state relationship, $u = s/(p + s)$, where s is the separation rate and p is the job finding rate. For the monthly job separation rate, we set $s = .0125$, which is similar to the estimate in Shimer (2007). At this separation rate, $p = 0.22$ gives you an unemployment duration of roughly 18 weeks and an unemployment rate of 5.4%. After the benefit extension, durations rise to $21.6 = 18 + 3.6$ weeks or 5.4 months, giving a new unemployment rate of $u = .0125/(.0125 + 1/5.4) = 6.3\%$. Thus, our calculations imply that extended benefits can account for roughly 25% of the observed increase in the aggregate unemployment rate during the recession in the U.S..

5 Conclusions

In this paper, we have considered a standard job search model and have shown that the relationship between both the moral hazard cost and the consumption smoothing benefit of UI and the unemployment is theoretically ambiguous. This motivated our two-part empirical strategy which (1) estimated how the elasticity of unemployment duration with respect to the UI benefit level varies with the unemployment rate and (2) estimated how the effect of UI on the consumption drop upon unemployment varies with the unemployment.

Our empirical findings indicate that moral hazard is lower when unemployment is high, consistent with the speculation of Krueger and Meyer (2002) who claimed that there is likely less of an efficiency loss from reduced search effort by the unemployed when local labor market conditions are poor. On the other hand, we do not find evidence that the consumption smoothing benefit of UI varies with the unemployment rate. We have also shown how one can use the empirical relationship between the duration elasticity and the unemployment rate to calibrate a simple optimal UI formula.

We view the concept that the moral hazard cost of social policies may vary with local labor market conditions as quite general, extending beyond the application of unemployment insurance considered in this paper. It is plausible that the disincentive effects of other government policies may also be lower in times of high unemployment. For example, if the labor supply response to tax changes is lower during recessions, it may be more efficient to redistribute during recessions. In the case of disability insurance and workers compensation, the adverse incentive effect of such programs may be influenced by the severity of the health or income shock. It would be interesting to study whether moral hazard varies with the size of the shock that triggers these programs, particulary since, as we showed here, benefits can be conditioned on the size of the shock. To the extent that the moral hazard cost of social insurance programs varies with labor market conditions, one should draw caution in comparing elasticitity estimates across studies to the extent that there are different labor market conditions that underlie these estimates.

Lastly, while we focused on the UI benefit level as the policy parameter, in practice, the potential benefit duration is typically extended during times of high unemployment. In ongoing work, we are studying theoretically how governments should optimally set the time path of UI benefits and how this varies with labor market conditions. We hope that this analysis will shed light on the federal supplemental benefits programs in the U.S. and other developed countries.

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Table 1
Descriptive Statistics

Panel A: Duration elasticity sample (SIPP)

	Full Sample		State Unemp. Rate ≥ Median		State Unemp. Rate < Median		p-value of difference in means
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
Annual Income ($000's)	20.925	13.570	20.932	13.554	20.921	13.581	0.979
Age	37.165	11.066	36.590	11.112	37.483	11.030	0.011
Years of Education	12.171	2.877	12.119	2.869	12.200	2.882	0.372
Marital Dummy	0.616	0.486	0.609	0.488	0.620	0.486	0.501
Average UI Weekly Benefit Amount ($'s)	163.33	26.80	163.08	26.07	163.46	27.21	0.660
1{Net liquid wealth in 1st quartile}	0.259	0.438	0.260	0.439	0.258	0.438	0.914
2{Net liquid wealth in 1st quartile}	0.238	0.426	0.232	0.422	0.240	0.427	0.544
3{Net liquid wealth in 1st quartile}	0.271	0.444	0.273	0.446	0.269	0.444	0.775
4{Net liquid wealth in 1st quartile}	0.233	0.423	0.235	0.424	0.232	0.422	0.842
Unemployment duration (weeks)	18.510	14.351	16.950	13.605	19.373	14.678	0.000
Number of Spells	4307		2774		1533		

Panel B: Consumption change sample (PSID)

	Full Sample		State Unemp. Rate ≥ Median		State Unemp. Rate < Median		p-value of difference in means
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
UI Replacement Rate	0.511	0.138	0.503	0.122	0.518	0.151	0.032
Real wage	2.278	1.761	2.198	1.658	2.350	1.847	0.074
Age	34.765	11.448	34.918	11.806	34.627	11.119	0.599
Female Dummy	0.232	0.422	0.248	0.432	0.218	0.413	0.142
Marital Dummy	0.565	0.496	0.544	0.498	0.585	0.493	0.082
White Dummy	0.509	0.500	0.485	0.500	0.531	0.499	0.055
Black Dummy	0.449	0.498	0.485	0.500	0.417	0.493	0.005
Education	4.110	1.573	4.072	1.623	4.144	1.525	0.347
Change in log food needs	0.007	0.257	0.000	0.256	0.012	0.257	0.321
Kids	1.218	1.403	1.187	1.423	1.246	1.386	0.384
Change in log consumption upon unemployment	-0.062	0.426	-0.063	0.419	-0.061	0.433	0.911
Number of Observations	1719		815		904		

Notes: In Panel A, data are individual-level unemployment spells from 1985-2000 SIPP. In Panel B, data are individual-level observations from 1968-1987 PSID. See text for details.

Table 2
How does Duration Elasticity vary with the Unemployment Rate?

		(1)	(2)
log(Average UI WBA)	**(A)**	-0.503	-0.605
		(0.291)	(0.295)
		[0.083]	[0.040]
log(Average UI WBA) ×	**(B)**		**1.256**
log(State Unemp. Rate / National Unemp. Rate)			**(0.433)**
			[0.004]
log(State Unemp. Rate / National Unemp. Rate)		-0.002	-0.014
		(0.128)	(0.119)
		[0.989]	[0.904]
log(Average UI WBA) ×		0.003	0.003
Unemployment Duration		(0.009)	(0.009)
		[0.704]	[0.746]
Age		-0.017	-0.017
		(0.002)	(0.002)
		[0.000]	[0.000]
Marital Dummy		0.207	0.207
		(0.040)	(0.040)
		[0.000]	[0.000]
Years of Education		0.004	0.004
		(0.006)	(0.006)
		[0.500]	[0.500]
Number of Spells		4307	4307
Post-estimation: **(A)** + σ × **(B)**			-0.348
			(0.294)
			[0.236]
Post-estimation: **(A) -** σ × **(B)**			-0.863
			(0.321)
			[0.007]

Notes: All columns report semiparametric (Cox proportional) hazard model results from estimating equation (13). Data are individual-level unemployment spells from 1985-2000 SIPP. All specifications include state, year, industry and occupation fixed effects, 10-knot linear spline in log annual wage income and a control for being on the seam between interviews to adjust for the "seam effect." The Average UI WBA is the average weekly benefit amount paid to individuals claiming unemployment insurance in a given state. All columns estimate nonparametric baseline hazards stratified by quartile of net liquid wealth. The final two rows report linear combinations of parameter estimates to produce the duration elasticity when the state unemployment rate is one standard deviation above/below the mean. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state over time, are in parentheses and p-values are in brackets.

Table 3
How do UI Benefits vary with the Unemployment Rate?

Dependent variable: Log of Maximum UI Weekly Benefit Amount				
		Sample Restrictions:		
	Full Sample	Full Sample	Unemp. Rate ≥ Median	Unemp. Rate < Median
	(1)	(2)	(3)	(4)
Panel A: State FEs + Year FEs				
log(State Unemp. Rate / National Unemp. Rate)	0.080	0.103	0.117	0.008
	(0.050)	(0.062)	(0.137)	(0.088)
	[0.122]	[0.104]	[0.399]	[0.924]
$(\log(\text{State Unemp. Rate / National Unemp. Rate}))^2$		0.100		
		(0.107)		
		[0.355]		
N	672	672	336	336
Panel B: State FEs + Year FEs + State-specific linear trends				
log(State Unemp. Rate / National Unemp. Rate)	0.015	0.044	0.109	-0.010
	(0.032)	(0.025)	(0.058)	(0.046)
	[0.641]	[0.078]	[0.068]	[0.822]
$(\log(\text{State Unemp. Rate / National Unemp. Rate}))^2$		0.091		
		(0.049)		
		[0.071]		
N	672	672	336	336

Notes: All columns report OLS regressions with the log of the statutory maximum weekly UI benefit in the state as the dependent variable. Data set is state-level panel of the 42 states used in the baseline SIPP sample between 1985 and 2000. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state over time, are in parentheses and p-values are in brackets.

Table 4
Robustness to Allowing UI Benefits to Respond Flexibly to the Unemployment Rate

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(Average UI WBA)	**(A)**	-0.605	-0.615	-0.741	-0.693	-0.781	-0.631	-0.575
		(0.295)	(0.331)	(0.373)	(0.351)	(0.331)	(0.341)	(0.369)
		[0.040]	[0.063]	[0.047]	[0.048]	[0.018]	[0.064]	[0.119]
log(Average UI WBA) ×	**(B)**	**1.256**	**1.264**	**1.599**	**1.737**	**2.576**	**1.320**	**2.529**
log(State Unemp. Rate / National Unemp. Rate)		**(0.433)**	**(0.463)**	**(0.442)**	**(0.472)**	**(1.205)**	**(0.388)**	**(0.901)**
		[0.004]	**[0.006]**	**[0.000]**	**[0.000]**	**[0.033]**	**[0.001]**	**[0.005]**
Quadratic in State Unemployment Rate		N	Y	N	N	N	N	N
Cubic in State Unemployment Rate		N	N	Y	N	N	N	N
Quadratic in State Unemployment Rate		N	N	N	Y	N	N	N
State FEs x State Unemployment Rate		N	N	N	N	Y	N	Y
Year FEs x State Unemployment Rate		N	N	N	N	N	Y	Y
Post-estimation: **(A)** + σ × **(B)**		-0.348	-0.348	-0.356	-0.414	-0.253	-0.361	-0.056
		(0.294)	(0.294)	(0.316)	(0.348)	(0.329)	(0.326)	(0.362)
		[0.236]	[0.236]	[0.259]	[0.234]	[0.442]	[0.269]	[0.876]
Post-estimation: **(A) -** σ × **(B)**		-0.863	-0.863	-0.874	-1.069	-1.309	-0.902	-1.093
		(0.321)	(0.321)	(0.371)	(0.417)	(0.483)	(0.372)	(0.458)
		[0.007]	[0.007]	[0.018]	[0.010]	[0.007]	[0.015]	[0.017]

Notes: All columns report semiparametric (Cox proportional) hazard model results from estimating equation (13). Data are individual-level unemployment spells from 1985-2000 SIPP. Number of spells = 4307. See Table 2 for more details on the baseline specification. The final two rows reports linear combinations of parameter estimates to produce the duration elasticity when the state unemployment rate is one standard deviation above/below the mean. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state over time, are in parentheses and p-values are in brackets.

Table 5

Robustness to Flexibly Controlling for Unobserved Trends

		(1)	(2)	(3)	(4)
log(Average UI WBA)	**(A)**	-0.605	-0.765	-0.625	-0.809
		(0.295)	(0.379)	(0.456)	(0.467)
		[0.040]	[0.044]	[0.171]	[0.083]
log(Average UI WBA) ×	**(B)**	**1.256**	**1.430**	**1.737**	**1.236**
log(State Unemp. Rate / National Unemp. Rate)		**(0.433)**	**(0.514)**	**(0.841)**	**(0.547)**
		[0.004]	**[0.005]**	**[0.039]**	**[0.024]**
Number of Spells		4307	4307	4307	4307
State FEs + Year FEs		Y	Y	Y	Y
Region-specific linear time trends		N	Y	N	N
Region × Year FEs		N	N	Y	N
State-specific linear time trends		N	N	N	Y
Post-estimation: **(A)** + σ × **(B)**		-0.348	-0.472	-0.269	-0.556
		(0.294)	(0.388)	(0.460)	(0.493)
		[0.236]	[0.224]	[0.559]	[0.259]
Post-estimation: **(A) -** σ × **(B)**		-0.863	-1.058	-0.981	-1.063
		(0.321)	(0.399)	(0.514)	(0.467)
		[0.007]	[0.008]	[0.057]	[0.023]

Notes: All columns report semiparametric (Cox proportional) hazard model results from estimating equation (13). Data are individual-level unemployment spells from 1985-2000 SIPP. See Table 2 for more details on the baseline specification. The final two rows reports linear combinations of parameter estimates to produce the duration elasticity when the state unemployment rate is one standard deviation above/below average. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state over time, are in parentheses and p-values are in brackets.

Table 6
Decomposing Variation in State Unemployment Rate

	Hazard Model Results			Post-estimation	
	(A)	**(A) × (B)**	**(B)**	**(A)** + σ ×**(B)**	**(A)** - σ ×**(B)**
(1) **(A)** log(Average UI WBA) ×	-0.605	**1.256**	-0.014	-0.348	-0.863
(B) log(State Unemp. Rate / National Unemp. Rate)	(0.295)	**(0.433)**	(0.119)	(0.294)	(0.321)
	[0.040]	**[0.004]**	[0.904]	[0.236]	[0.007]
(2) **(A)** log(Average UI WBA) ×		**2.830**	-1.467	-0.220	-1.100
(B) Average of log(State Unemp. Rate / National Unemp. Rate), 1985-2000		**(2.122)**	(0.518)	(0.363)	(0.580)
	-0.660	**[0.182]**	[0.005]	[0.545]	[0.058]
(A') log(Average UI WBA) ×	(0.354)	**1.059**	-0.026	-0.511	-0.808
(B') (log(State Unemp. Rate / National Unemp. Rate) - **(B)**)	[0.062]	**(0.465)**	(0.121)	(0.368)	(0.352)
		[0.023]	[0.826]	[0.165]	[0.022]
p-value of test **(B)** = **(B')**: 0.440					
Number of Spells	4307				

Notes: All rows report semiparametric (Cox proportional) hazard model results from estimating equation (13); each column reports separate parameter estimate. Data are individual-level unemployment spells from 1985-2000 SIPP. See Table 2 for more details on the baseline specification. The final two columns report linear combinations of parameter estimates to produce the duration elasticity when the state unemployment rate is one standard deviation above/below the mean. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state over time, are in parentheses and p-values are in brackets.

Table 7
Exploiting Variation Across Metropolitan Areas Within States

	(1)	(2)	(3)	(4)
log(Average UI WBA) **(A)**	-0.430	-0.397	-0.894	
	(0.277)	(0.393)	(0.490)	
	[0.121]	[0.312]	[0.068]	
log(Average UI WBA) × (B)	**0.986**	**1.145**	**1.284**	**2.013**
log(Metropolitan Unemp. Rate / National Unemp. Rate)	**(0.396)**	**(0.636)**	**(0.483)**	**(0.970)**
	[0.013]	**[0.072]**	**[0.008]**	**[0.038]**
log(Metropolitan Unemp. Rate / National Unemp. Rate)	-0.065	0.066	0.009	0.078
	(0.094)	(0.157)	(0.096)	(0.157)
	[0.494]	[0.675]	[0.922]	[0.620]
Number of Spells	4307	4307	4307	4307
MSA FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Region × Year FEs	N	Y	N	N
State-specific linear time trends	N	N	Y	N
State × Year FEs	N	N	N	Y
Post-estimation: **(A)** + σ × **(B)**	-0.149	-0.071	-0.528	
	(0.294)	(0.428)	(0.523)	
	[0.613]	[0.868]	[0.312]	
Post-estimation: **(A) -** σ × **(B)**	-0.710	-0.723	-1.259	
	(0.304)	(0.437)	(0.494)	
	[0.020]	[0.098]	[0.011]	

Notes: All columns report semiparametric (Cox proportional) hazard model results from estimating equation (13). Data are individual-level unemployment spells from 1985-2000 SIPP. See Table 2 for more details on the baseline specification. To preserve sample size, observations without MSA codes are grouped together within a state and assigned the state unemployment rate. The final two rows reports linear combinations of parameter estimates to produce the duration elasticity when the state unemployment rate is one standard deviation above/below average. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state over time, are in parentheses and p-values are in brackets.

Table 8
How Much Do Demographics Explain Why Moral Hazard Varies with the State Unemployment Rate?

Dependent variable:		Unemployment Duration							Take-up dummy
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Average UI WBA)	**(A)**	-0.605	-0.583	-0.606	-0.584	-0.504	-0.488	-0.447	0.105
		(0.295)	(0.291)	(0.295)	(0.290)	(0.302)	(0.322)	(0.309)	(0.079)
		[0.040]	[0.045]	[0.040]	[0.044]	[0.094]	[0.130]	[0.147]	[0.192]
log(Average UI WBA) ×	**(B)**	**1.256**	**1.244**	**1.255**	**1.249**	**1.268**	**1.211**	**1.240**	**-0.313**
log(State Unemp. Rate / National Unemp. Rate)		**(0.433)**	**(0.434)**	**(0.427)**	**(0.437)**	**(0.442)**	**(0.413)**	**(0.413)**	**(0.134)**
		[0.004]	**[0.004]**	**[0.003]**	**[0.004]**	**[0.004]**	**[0.003]**	**[0.003]**	**[0.024]**
log(State Unemp. Rate / National Unemp. Rate)		-0.014	-0.015	-0.014	-0.014	-0.022	-0.021	-0.018	0.117
		(0.119)	(0.119)	(0.119)	(0.118)	(0.117)	(0.116)	(0.115)	(0.023)
		[0.904]	[0.900]	[0.904]	[0.906]	[0.854]	[0.859]	[0.878]	[0.000]
log(Average UI WBA) × Age			0.009					0.010	
			(0.008)					(0.010)	
			[0.284]					[0.281]	
log(Average UI WBA) × Marital Dummy				0.005				-0.078	
				(0.175)				(0.202)	
				[0.979]				[0.701]	
log(Average UI WBA) × Years of Education					0.050			0.051	
					(0.026)			(0.031)	
					[0.053]			[0.101]	
Number of Spells		4307	4307	4307	4307	4307	4307	4307	16322
log(Average UI WBA) × Occupation FEs		N	N	N	N	Y	N	Y	Y
log(Average UI WBA) × Industry FEs		N	N	N	N	N	Y	Y	Y
Post-estimation: **(A)** + σ × **(B)**		-0.348	-0.328	-0.348	-0.328	-0.245	-0.240	-0.193	0.036
		(0.294)	(0.292)	(0.293)	(0.289)	(0.297)	(0.313)	(0.299)	(0.064)
		[0.236]	[0.262]	[0.235]	[0.255]	[0.410]	[0.444]	[0.519]	[0.579]
Post-estimation: **(A) -** σ × **(B)**		-0.863	-0.838	-0.863	-0.840	-0.764	-0.736	-0.701	0.174
		(0.321)	(0.316)	(0.321)	(0.317)	(0.332)	(0.352)	(0.339)	(0.100)
		[0.007]	[0.008]	[0.007]	[0.008]	[0.021]	[0.036]	[0.039]	[0.083]

Notes: Columns (1) through (7) report semiparametric (Cox proportional) hazard model results from estimating equation (13) using individual-level unemployment spells from 1985-2000 SIPP. See Table 2 for more details on the baseline specification. Column (8) reports OLS estimates using individual-level data from 1968-1987 PSID. The final two rows reports linear combinations of parameter estimates to produce the marginal effects when the state unemployment rate is one standard deviation above/below average. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state over time, are in parentheses and p-values are in brackets.

Table 9
Alternative Measures of the Interaction Term

	Hazard Model Results			Post-estimation	
	(A)	**(A) × (B)**	**(B)**	**(A) +** σ **×(B)**	**(A) -** σ **×(B)**
(1) **(A)** log(Average UI WBA) ×	-0.605	**1.256**	-0.014	-0.348	-0.863
(B) log(State Unemp. Rate / National Unemp. Rate)	(0.295)	**(0.433)**	(0.119)	(0.294)	(0.321)
	[0.040]	**[0.004]**	[0.904]	[0.236]	[0.007]
(2) **(A)** log(Average UI WBA) ×	-1.236	**0.966**	-0.016	-0.270	
(B) **1**{State Unemp. Rate $\geq$ Median}	(0.355)	**(0.199)**	(0.044)	(0.314)	
	[0.001]	**[0.000]**	[0.718]	[0.390]	
(3) **(A)** log(Average UI WBA) ×	-0.564	**0.136**	-0.001	-0.383	-0.745
(B) (State Unemp. Rate - National Unemp. Rate)	(0.318)	**(0.069)**	(0.018)	(0.304)	(0.356)
	[0.076]	**[0.048]**	[0.965]	[0.207]	[0.036]
(4) **(A)** log(Statutory Maximum UI WBA) ×	-0.228	**1.219**	0.010	0.021	-0.478
(B) log(State Unemp. Rate / National Unemp. Rate)	(0.282)	**(0.470)**	(0.130)	(0.264)	(0.328)
	[0.417]	**[0.009]**	[0.940]	[0.936]	[0.145]
(5) **(A)** log(Average UI Replacement Rate) ×	-0.425	**1.425**	-0.010	-0.133	-0.717
(B) log(State Unemp. Rate / National Unemp. Rate)	(0.252)	**(0.502)**	(0.111)	(0.274)	(0.270)
	[0.092]	**[0.005]**	[0.926]	[0.628]	[0.008]
(6) **(A)** log(Average UI WBA) ×	-0.736	**0.867**	0.687	-0.559	-0.914
(B) -1 * log(Predicted Employment-to-Pop Ratio)	(0.427)	**(1.043)**	(1.992)	(0.326)	(0.591)
	[0.084]	**[0.406]**	[0.730]	[0.087]	[0.122]

Notes: All rows report semiparametric (Cox proportional) hazard model results from estimating equation (13); each column reports separate parameter estimate. Data are individual-level unemployment spells from 1985-2000 SIPP. See Table 2 for more details on the baseline specification. The median unemployment rate across all states in sample is calculated separately each year. The Average UI WBA is the average weekly benefit amount paid to individuals claiming unemployment insurance. The Statuatory Max UI WBA is the maximum weekly benefit amount an individual can receive in a state-year. The Average UI Replacement Rate is the Average UI WBA divided by the average weekly wages in a given state-year for prime-age males (computed using the CPS). In row (2) we set σ = 1.0 becasue the interaction term includes a dummy variable rather than a continuous measure. The Predicted Employment to Population Ratio is computed following the "shift share" procedure of Bartik (1991); see text for details. The final two columns report linear combinations of parameter estimates to produce the duration elasticity when the state

Table 10

How Does Effect of UI on Consumption Drop Upon Unemployment Vary with the Unemployment Rate?

	Gruber (1997)	Replication Sample			
	(1)	(2)	(3)	(4)	(5)
UI replacement rate	0.280	0.280	0.273	0.263	0.246
	(0.105)	(0.125)	(0.125)	(0.103)	(0.136)
		[0.030]	[0.033]	[0.014]	[0.077]
Implied consumption drop at replacement rate of 0	-0.231	-0.231	-0.227	-0.225	-0.208
UI replacement rate ×		-0.288	-0.281	-0.300	-0.212
log(State Unemp. Rate / National Unemp. Rate)		(0.236)	(0.242)	(0.257)	(0.237)
		[0.230]	[0.250]	[0.248]	[0.374]
log(State Unemp. Rate / National Unemp. Rate)		0.161	0.140	0.261	0.097
		(0.129)	(0.145)	(0.181)	(0.150)
		[0.218]	[0.340]	[0.155]	[0.521]
N	1604	1719	1719	1719	1719
R^2		0.079	0.084	0.147	0.098
MSA and Year FEs	Y	Y	Y	Y	Y
Region-specific linear time trends	N	N	Y	N	N
Region × Year FEs	N	N	N	Y	N
State-specific linear time trends	N	N	N	N	Y

Notes: Column (1) reproduces the results from column (4) in Gruber (1997), Table 2. Remainder of columns report OLS results on a replication sample. Data are individual-level observations from 1968-1987 PSID. See text for more details on the baseline specification. The implied consumption drop is computed as the average fitted value across the sample when the replacement rate is set to 0 for all observations. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state over time, are in parentheses and p-values are in brackets.

Table 11
Moral Hazard and Net Liquid Wealth

		(1)	(2)	(3)	(4)	(5)
log(Average UI WBA)	**(A)**	-0.605	-0.467	-0.563		
		(0.295)	(0.451)	(0.289)		
		[0.040]	[0.300]	[0.052]		
log(Average UI WBA) ×	**(B)**	**1.256**	**1.553**	**1.427**	**1.463**	**1.619**
log(State Unemp. Rate / National Unemp. Rate)		**(0.433)**	**(0.734)**	**(0.466)**	**(0.481)**	**(0.594)**
		[0.004]	**[0.034]**	**[0.002]**	**[0.002]**	**[0.006]**
log(Average UI WBA) ×						-0.390
log(State Unemp. Rate / National Unemp. Rate) ×						(0.698)
1{3rd and 4th liquid wealth quartiles}						[0.576]
Number of Spells		4307	2170	4307	4307	4307
3rd and 4th liquid wealth quartiles only		N	Y	N	N	N
Occupation FEs × Liquid wealth quartile		N	N	Y	Y	Y
Industry FEs × Liquid wealth quartile		N	N	Y	Y	Y
Unemployment duration × Liquid wealth quartile		N	N	N	Y	Y
log(Average UI WBA) × Liquid wealth quartile		N	N	N	Y	Y
Post-estimation: **(A)** + σ × **(B)**		-0.348	-0.149	-0.270		
		(0.294)	(0.469)	(0.295)		
		[0.236]	[0.750]	[0.359]		
Post-estimation: **(A) -** σ × **(B)**		-0.863	-0.786	-0.855		
		(0.321)	(0.482)	(0.315)		
		[0.007]	[0.103]	[0.007]		

Notes: All columns report semiparametric (Cox proportional) hazard model results from estimating equation (13). Data are individual-level unemployment spells from 1985-2000 SIPP. See Table 2 for more details on the baseline specification. The final two rows reports linear combinations of parameter estimates to produce the duration elasticity when the state unemployment rate is one standard deviation above/below average. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state over time, are in parentheses and p-values are in brackets.

Table 12
Sufficient Statistics Calibrations:
Optimal UI and the Unemployment Rate

u	2.0%	3.7%	5.4%	7.1%	8.8%
$\varepsilon_{D,b}$	1.147	0.811	0.605	0.456	0.339
Panel A: Coefficient of Relative Risk Aversion, $\gamma = 2$					
$r*$	0.0%	0.0%	1.5%	18.0%	32.2%
$b*$	\$0	\$0	\$5	\$63	\$113
Panel B: Coefficient of Relative Risk Aversion, $\gamma = 3$					
$r*$	0.0%	12.6%	27.1%	38.5%	48.3%
$b*$	\$0	\$44	\$95	\$135	\$169
Panel C: Coefficient of Relative Risk Aversion, $\gamma = 4$					
$r*$	13.1%	29.3%	40.4%	49.1%	56.5%
$b*$	\$46	\$102	\$141	\$172	\$198

Notes: All columns report optimal UI benefit levels at various levels of the unemployment rate. Subsequent rows report the elasticity of unemployment duration with respect to UI benefit level, the optimal UI benefit level ($b*$) and the optimal UI replacement rate ($r*$). Both $b*$ and $r*$ are censored at 0. The optimal replacement rate is computed by dividing UI benefit level by the average wage. See Section 4.2 for more details on the computations. The optimal benefit level is computed assuming a weekly wage of $350.

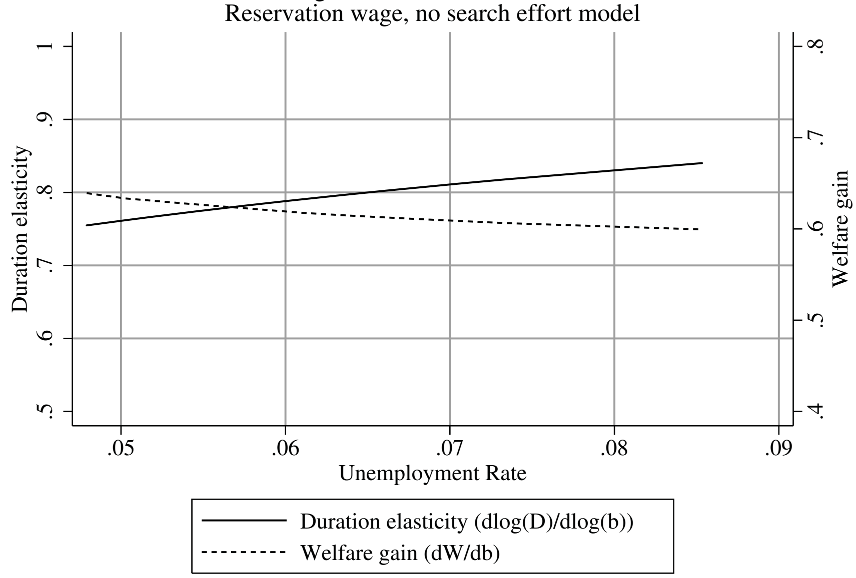
Appendix Table A1

Other Robustness Tests: Alternative Controls, Nonlinear Direct Effects, Extended Benefits

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(Average UI WBA)	**(A)**	-0.605	-0.584	-0.438	-0.408	-0.534	-0.262	-0.551
		(0.295)	(0.297)	(0.193)	(0.190)	(0.426)	(0.516)	(0.244)
		[0.040]	[0.049]	[0.023]	[0.032]	[0.210]	[0.611]	[0.024]
log(Average UI WBA) ×	**(B)**	**1.256**	**1.243**	**0.896**	**0.759**	**1.267**	**1.707**	**1.419**
log(State Unemp. Rate / National Unemp. Rate)		**(0.433)**	**(0.446)**	**(0.537)**	**(0.529)**	**(0.463)**	**(0.437)**	**(0.413)**
		[0.004]	**[0.005]**	**[0.095]**	**[0.151]**	**[0.006]**	**[0.000]**	**[0.001]**
Stratified baseline hazard		Y	N	N	N	N	Y	Y
State, Occupation, Industry FEs		Y	Y	N	N	Y	Y	Y
Age, Marital Dummy, Education, Wage Spline		Y	Y	Y	N	Y	Y	Y
Quadratic in State Unemp. Rate, Average UI WBA		N	N	N	N	Y	Y	N
Cubic in State Unemp. Rate, Average UI WBA		N	N	N	N	N	Y	N
Controls for potential duration and extended benefits		N	N	N	N	N	N	Y
Post-estimation: **(A)** + σ × **(B)**		-0.348	-0.329	-0.254	-0.253	-0.274	0.088	-0.261
		(0.294)	(0.296)	(0.191)	(0.198)	(0.409)	(0.520)	(0.261)
		[0.236]	[0.266]	[0.184]	[0.203]	[0.503]	[0.866]	[0.317]
Post-estimation: **(A)** - σ × **(B)**		-0.863	-0.839	-0.621	-0.564	-0.793	-0.612	-0.842
		(0.321)	(0.324)	(0.249)	(0.237)	(0.462)	(0.526)	(0.256)
		[0.007]	[0.010]	[0.013]	[0.017]	[0.086]	[0.245]	[0.001]

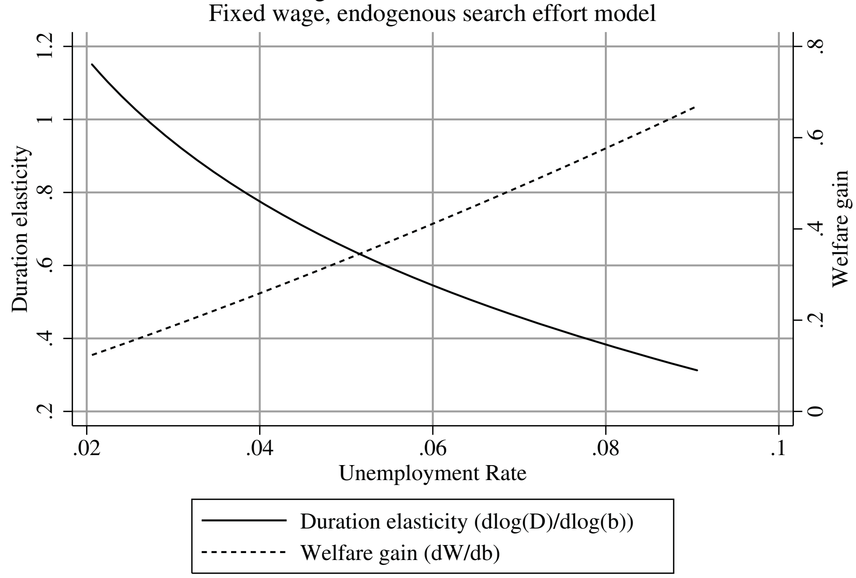
Notes: All columns report semiparametric (Cox proportional) hazard model results from estimating equation (13). Data are individual-level unemployment spells from 1985-2000 SIPP. Number of spells = 4307. See Table 2 for more details on the baseline specification. The final column controls for maximum potential duration of benefits by setting log(Average UI WBA) to 0 for all weeks beyond this maximum number of weeks (where the maximum accounts for extended benefits programs). The final two rows report linear combinations of parameter estimates to produce the duration elasticity when the state unemployment rate is one standard deviation above/below the mean. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state over time, are in parentheses and p-values are in brackets.

Figure 1: Model Simulation
Reservation wage, no search effort model



Notes: This figure is generated by calibrating the job search model in the main text with the following parameters. The wage distribution is assumed to be log-normal with mean 0.1 and standard deviation of 0.3. The benefit level is set to 0.067. There is no discounting and interest rate is set to 0 (i.e., $r = \rho = 0$). The job offer arrival rate is $\lambda(e, \alpha) = \alpha$; i.e., there is no search effort decision. The job separation rate is $s = 0.002$.

Figure 2: Model Simulation
Fixed wage, endogenous search effort model



<u>Notes:</u> This figure is generated by calibrating the job search model in the main text with the following parameters. The wage distribution is degenerate with mean 0.25. The benefit level is set to 0.125. There is no discounting and interest rate is set to 0 (i.e., $r = \rho = 0$). The job offer arrival rate is $\lambda(e, \alpha) = \Lambda e^{\alpha}$, with $\Lambda = 0.0667$. The cost of search is ϕe^{κ}, with $\phi = 0.3$ and $\kappa = 1.1$. The job separation rate is $s = 0.0089$.

Figure 3
Survival Curves Under High Unemployment Rate

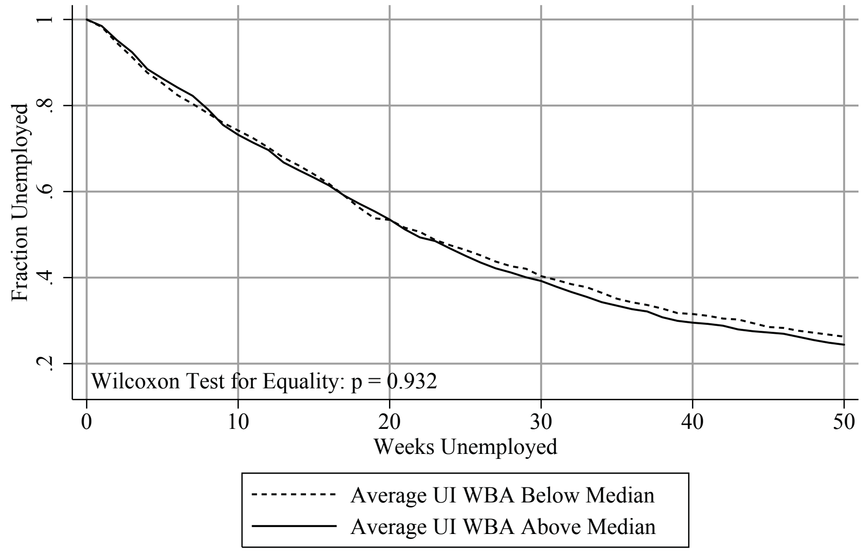
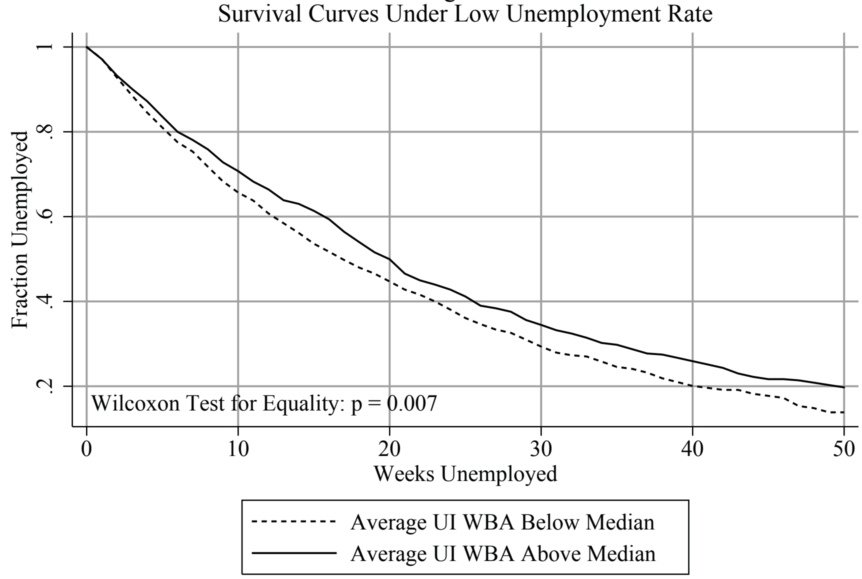


Figure 4
Survival Curves Under Low Unemployment Rate



Notes: Data are individual-level unemployment spells from 1985-2000 SIPP. Each figure plots (Kaplan-Meier) survival curves for two groups of individuals based on whether or not Average UI Weekly Benefit Amount (WBA) in individual's state is above or below the median. The survival curves are adjusted following Chetty (2008), which parametrically adjusts for "seam effect" by fitting a Cox proportional hazard model with a seam dummy and then recovering the baseline hazard.

Figure 5
Survival Curves Under High Unemployment Rate
(Within−state variation)

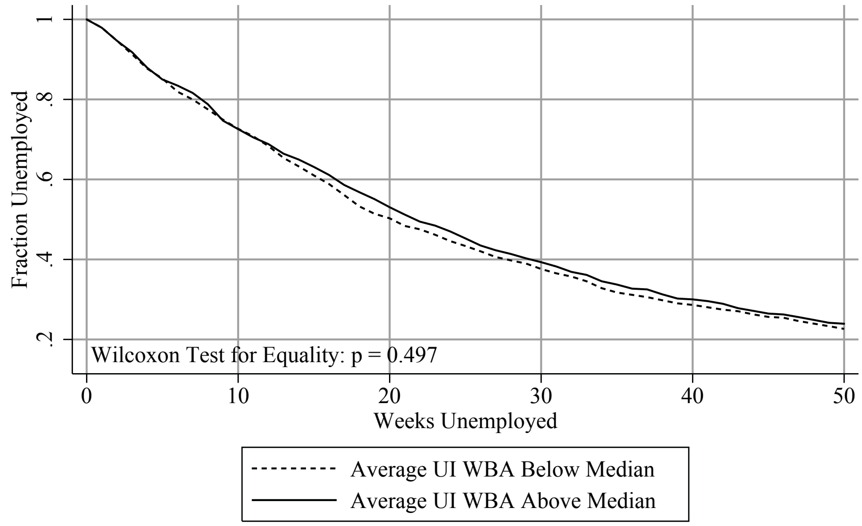
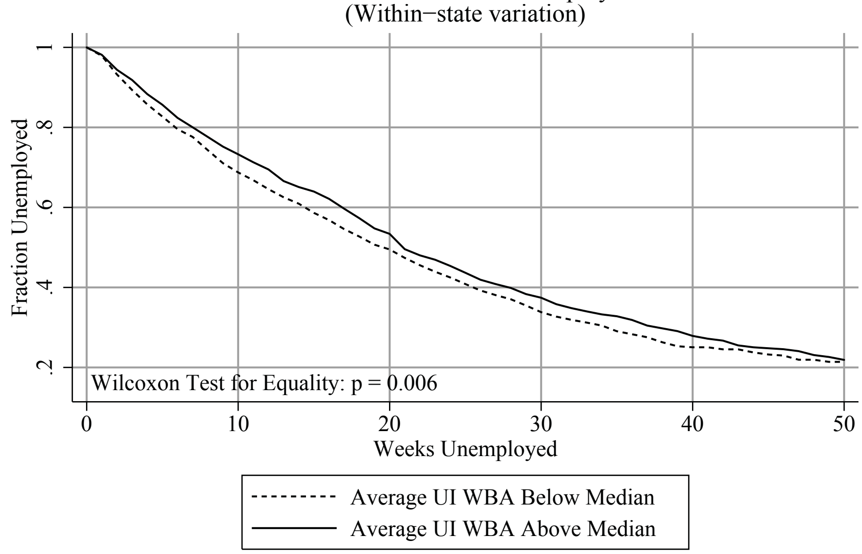


Figure 6
Survival Curves Under Low Unemployment Rate
(Within−state variation)



Notes: Data are individual-level unemployment spells from 1985-2000 SIPP. Each figure plots (Kaplan-Meier) survival curves for two groups of individuals based on whether or not Average UI Weekly Benefit Amount (WBA) in individual's state is above or below the median. The survival curves are adjusted following Chetty (2008), which parametrically adjusts for "seam effect" by fitting a Cox proportional hazard model with a seam dummy and then recovering the baseline hazard. The figures report results for sub-samples defined depending on whether the unemployment rate is above or below the median unemployment rate in the state during the sample period.

Figure 7
Survival Curves Under High Unemployment Rate
(Cross−state variation)

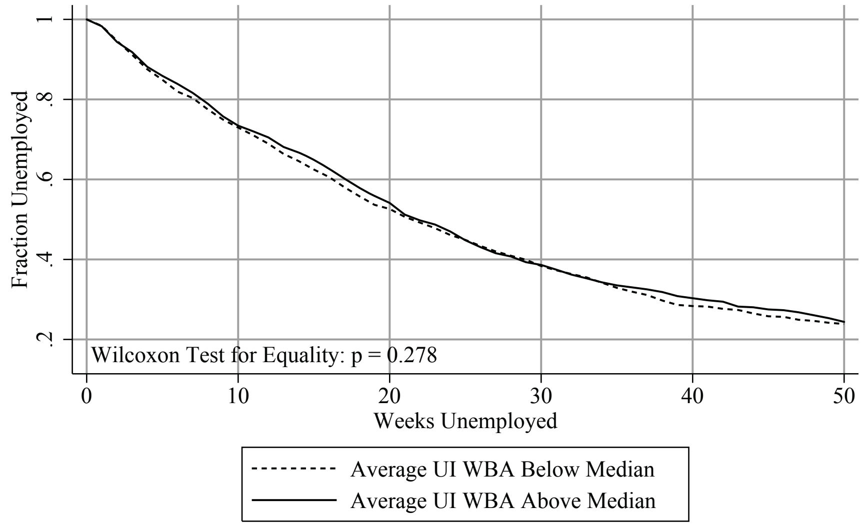
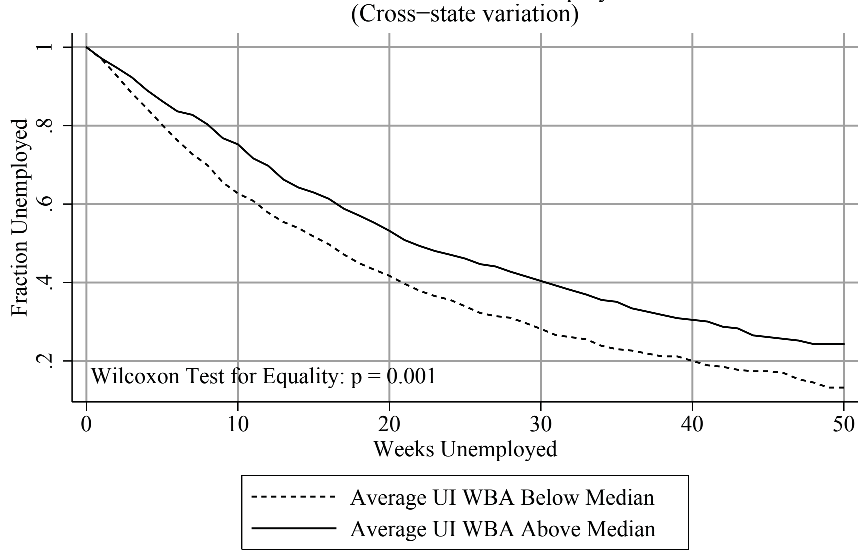


Figure 8
Survival Curves Under Low Unemployment Rate
(Cross−state variation)



Notes: Data are individual-level unemployment spells from 1985-2000 SIPP. Each figure plots (Kaplan-Meier) survival curves for two groups of individuals based on whether or not Average UI Weekly Benefit Amount (WBA) in individual's state is above or below the median. The survival curves are adjusted following Chetty (2008), which parametrically adjusts for "seam effect" by fitting a Cox proportional hazard model with a seam dummy and then recovering the baseline hazard. The figures report results for sub-samples defined depending on whether the average unemployment rate in the state during the sample period is above or below the median across all states in the sample.

Figure 9
Survival Curves Under Low Predicted Emp−to−Pop

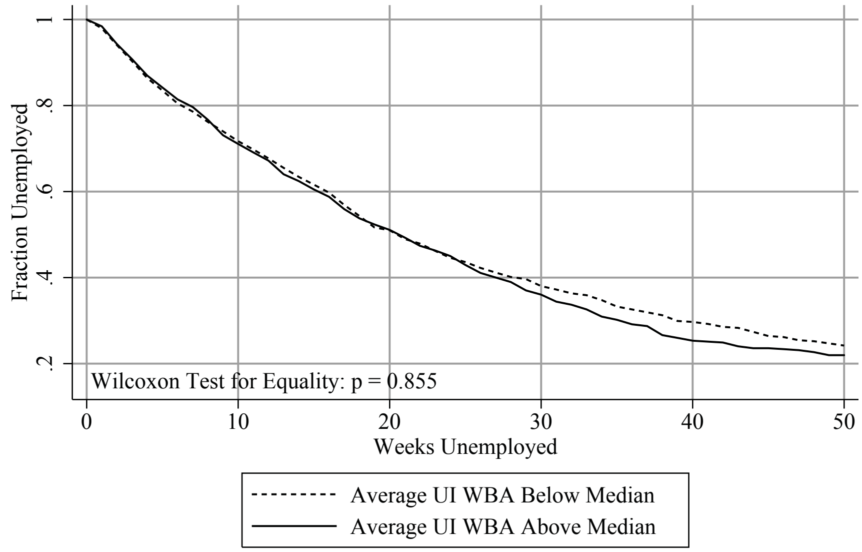
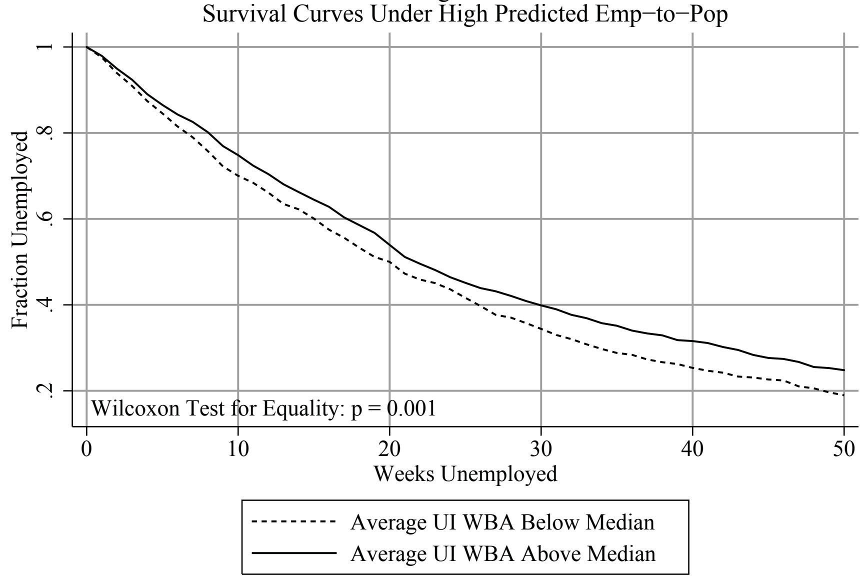
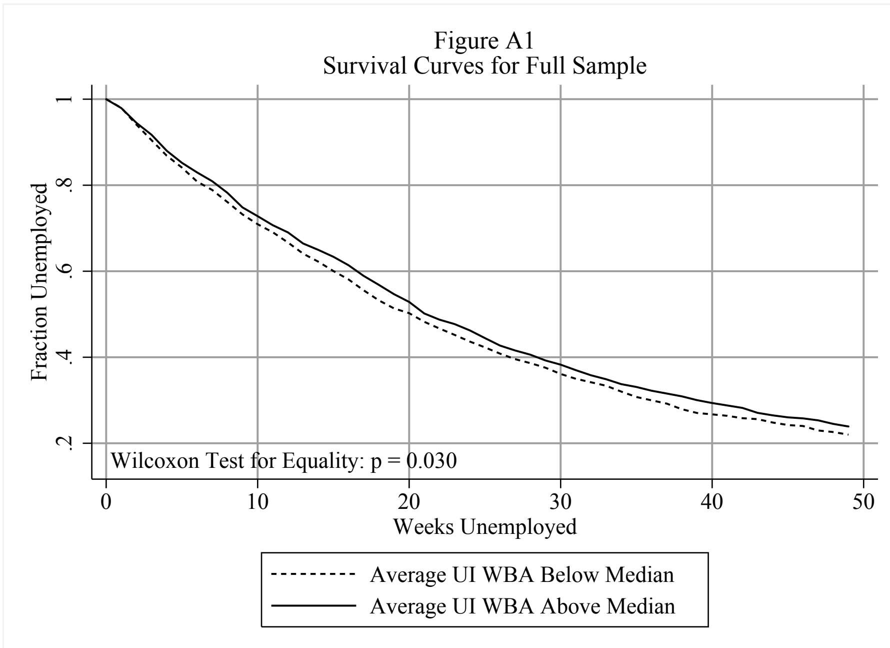


Figure 10
Survival Curves Under High Predicted Emp−to−Pop



Notes: Data are individual-level unemployment spells from 1985-2000 SIPP. Each figure plots (Kaplan-Meier) survival curves for two groups of individuals based on whether or not Average UI Weekly Benefit Amount (WBA) in individual's state is above or below the median. The survival curves are adjusted following Chetty (2008), which parametrically adjusts for "seam effect" by fitting a Cox proportional hazard model with a seam dummy and then recovering the baseline hazard. The employment-to-population ratio is predicted following Bartik (1991); see text for details.



Notes: Data are individual-level unemployment spells from 1985-2000 SIPP. The figure plots (Kaplan-Meier) survival curves for two groups of individuals based on whether or not Average UI Weekly Benefit Amount (WBA) in individual's state is above or below the median. The survival curves are adjusted following Chetty (2008), which parametrically adjusts for "seam effect" by fitting a Cox proportional hazard model with a seam dummy and then recovering the baseline hazard.

Figure A2
Survival Curves Under High Unemployment Rate

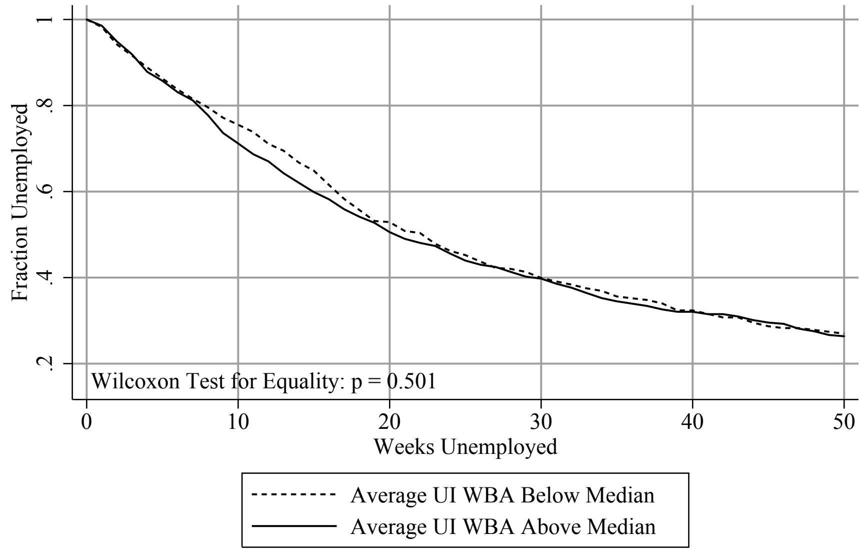
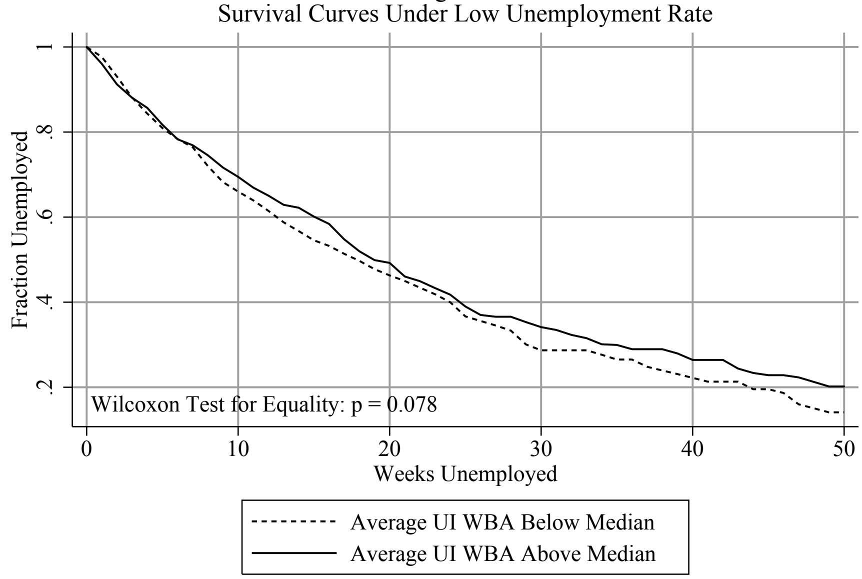
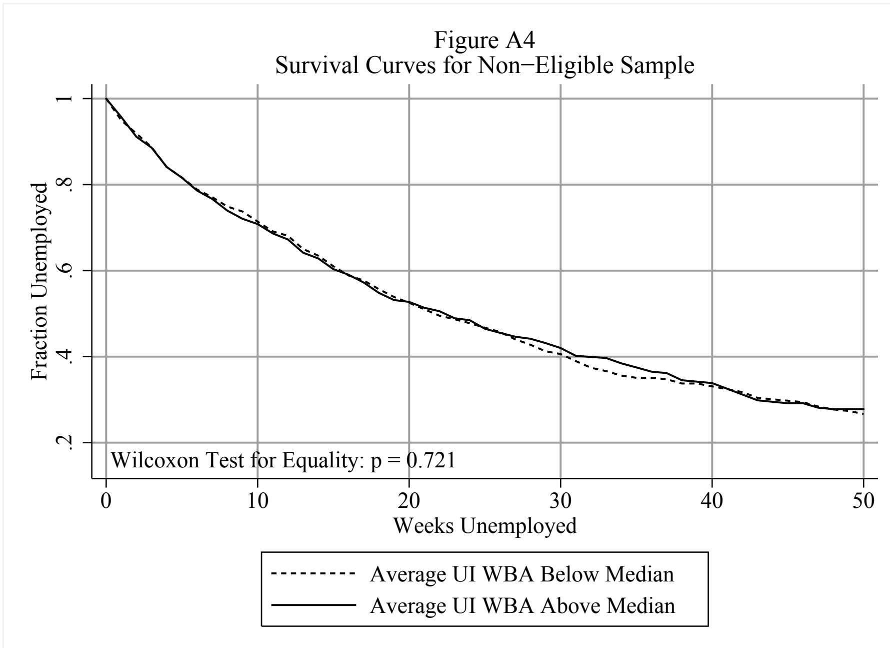


Figure A3
Survival Curves Under Low Unemployment Rate



Notes: Data are individual-level unemployment spells from 1985-2000 SIPP. In order to minimize liquidity effects, the sample is limited to individuals with net liquid wealth above the median. Each figure plots (Kaplan-Meier) survival curves for two groups of individuals based on whether or not Average UI Weekly Benefit Amount (WBA) in individual's state is above or below the median. The survival curves are adjusted following Chetty (2008), which parametrically adjusts for "seam effect" by fitting a Cox proportional hazard model with a seam dummy and then recovering the baseline hazard.



Notes: Data are individual-level unemployment spells from 1985-2000 SIPP with the sample restricted to unemployed individuals who are ineligible for UI. The figure plots (Kaplan-Meier) survival curves for two groups of individuals based on whether or not Average UI Weekly Benefit Amount (WBA) in individual's state is above or below the median. The survival curves are adjusted following Chetty (2008), which parametrically adjusts for "seam effect" by fitting a Cox proportional hazard model with a seam dummy and then recovering the baseline hazard.

Figure A5
Survival Curves Under High Unemployment Rate
(Non−eligible sample)

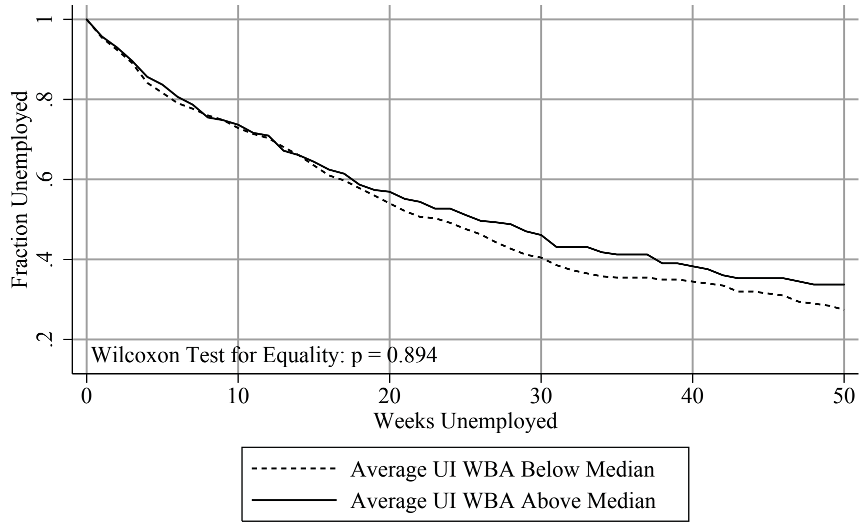
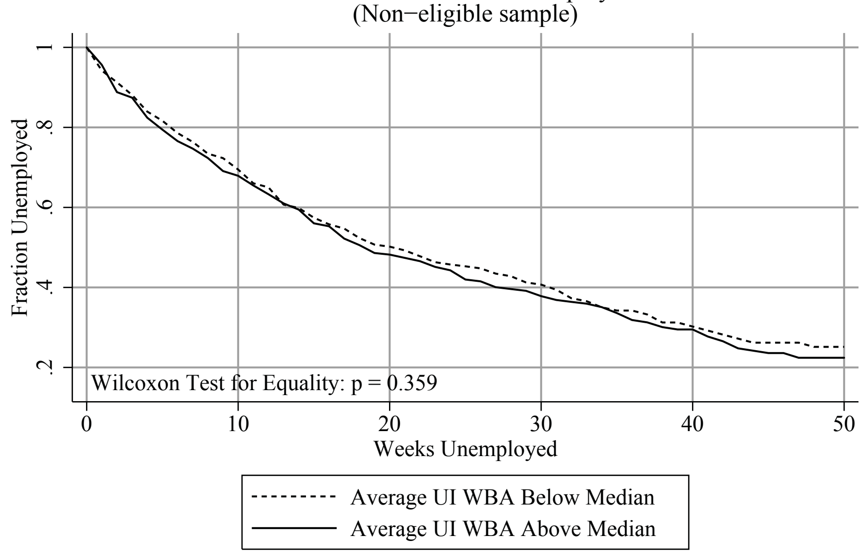


Figure A6
Survival Curves Under Low Unemployment Rate
(Non−eligible sample)



Notes: Data are individual-level unemployment spells from 1985-2000 SIPP with the sample restricted to unemployed individuals who are ineligible for UI. The figure plots (Kaplan-Meier) survival curves for two groups of individuals based on whether or not Average UI Weekly Benefit Amount (WBA) in individual's state is above or below the median. The survival curves are adjusted following Chetty (2008), which parametrically adjusts for "seam effect" by fitting a Cox proportional hazard model with a seam dummy and then recovering the baseline hazard.