Assessing the Welfare Effects of Unemployment Benefits Using the Regression Kink Design

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Abstract

I investigate in this paper partial equilibrium labor supply responses to unemployment insurance (UI) in the US. I use administrative data on the universe of unemployment spells in five states from 1976 to 1984, and non-parametrically identify the effect of both benefit level and potential duration in the regression kink (RK) design using kinks in the schedule of UI benefits. I provide many tests for the robustness of the RK design, and demonstrate its validity to overcome the traditional issue of endogeneity in UI benefit variations on US data. I also show how one can use the weighted difference between the behavioral response to an increase in potential duration and to an increase in benefit level to identify the pure moral hazard effect of UI. I then use these estimates to calibrate the welfare effects of an increase in UI benefit level and in UI potential duration.

KEYWORDS: Unemployment insurance, Regression Kink Design.

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Introduction

The motivation of this paper is threefold. First, the socially desirable level of unemployment insurance (UI) depends on labor supply responses to variations in the generosity of unemployment benefits. There is an extensive literature trying to estimate these behavioral responses. Yet, it seems that we still lack credible and consensual estimates of these behavioral responses, especially in the US. During the recent Great Recession, the heated pubic policy debate over the desirability of the federally mandated UI benefit extensions has shown the lack of consensus concerning not only the magnitude of labor supply responses to UI but also how these responses might be affected by changing labor market conditions, thus reaffirming the importance of readily available estimates of these behavioral responses.

Second, UI provides consumption smoothing benefits for unemployed people to the extent that they are (at least partially) credit-constrained. The theoretical literature shows that the optimal provision of UI depends critically on the magnitude of these consumption smoothing benefits, captured in particular by the liquidity effects as opposed to the pure moral hazard effects of UI (Chetty [2008]). Still, we also lack an idea of the size of these consumption smoothing benefits, as well as an idea of how these benefits vary over time and with labor market conditions. More fundamentally, there is to date no clear strategy for estimating the liquidity effects of UI in a timely manner.

Finally, policymakers tend to modify the duration of UI benefits with labor market conditions much more drastically than the benefit level. Yet, we still lack a good intuition for why this should be and thus, we lack a good test for when an increase in the duration of benefits should be preferred to an increase in the level of UI benefits.

This paper contributes to the literature on the optimal design of UI along these three dimensions. I provide new estimates of the partial equilibrium labor supply responses to unemployment insurance (UI) in the US, identifying the effect of both benefit level and potential duration in the regression kink (RK) design, using kinks in the schedule of UI benefits. A large empirical literature is devoted to the estimation of labor supply effects of UI[1]. These studies use very different sources of variation to identify the effect of UI generosity, and so far, the most credible sources of identification have come from sharp discontinuities in the potential duration of benefit entitlements by age that exist in several European countries (see for instance Lalive [2008] in Austria, or Schmieder et al. [2012] in Germany)[2]. Unfortunately, such sharp discontinuities enabling credible non-parametric estimation of the labor supply effects of UI do not exist for the *level* of UI benefit, and do not exist at all in the US. I first contribute to this large body of empirical literature by providing the first credible non-parametric identification of the effect of both UI level and UI potential duration, overcoming the traditional issue of endogeneity in UI benefit variations on US data. While most of the recent development in the empirical literature on unemployment insurance has been achieved using exhaustive administrative data from European countries and sharp discontinuities in eligibility rules, this paper shows that the combination of kinked schedules in state UI rules and access to exhaustive state UI records offers promising avenues for the development of research on UI in the US.

The idea used in this paper of relying on kinky UI schedules to estimate the effect of UI on labor supply originates from Card et al. [2009] who coined the term “regression kink design”. I contribute to the nascent literature on the RK design by providing what is, to the best of my knowledge, the first thorough empirical investigation of its validity. I use administrative data from the Continuous Wage and Benefit History Project (CWBH) on the universe of unemployment spells in five states in the US from 1976 to 1984. Since identification in the regression kink design relies on estimating changes in the slope of the relationship between an assignment variable and some outcomes of interest, the granularity of the CWBH data is a key advantage and smaller samples of UI recipients would in general not exhibit enough statistical power to detect any effect in a RK

[1] A general survey on labor supply responses can be found in Krueger and Meyer [2002] and a survey on the effect of UI potential duration is given in Card et al. [2007b]

[2] Baseline UI durations being significantly longer in most European countries, the validity of these estimates in the US context are questionable.

design. I provide compelling graphical evidence and find significant responses of unemployment and non-employment duration with respect to both benefit level and potential duration for all states and periods in the CWBH data. I propose and implement a series of tests for the robustness of the RKD estimates that should constitute the basis for any practical implementation of the RK design. These tests include graphical and regression based tests of the identifying assumptions as well as placebo tests and kink-detection and kink-location tests. I also use variations in the location of the kink over time to implement a difference-in-difference RK strategy to check the robustness of the results. Overall, replicating the RK design for all states and periods, my results suggest that a 10% increase in the benefit level increases the duration of UI claims by about 3%, and that increasing the potential duration of benefit by a week increases the duration of UI claims by about .3 to .5 week. These estimates are higher than estimates found in European countries using sharp RD designs but are still lower than previous estimates on US data. Interestingly, I am able to show that using the same strategy as Meyer [1990], who found slightly higher elasticities on a smaller subset of the same data, one can still find results that converge to my RKD estimates by adding a richer set of controls for previous earnings. I also correlate my results with indicators of labor market conditions and find that the partial equilibrium elasticities of unemployment duration are (slightly) decreasing with the unemployment rate, a result reminiscent of the findings in Schmieder et al. [2012] and Kroft and Notowidigdo [2011].

Another contribution of the paper relates to the identification of liquidity versus moral hazard effects of UI, an issue that has received more attention since the contributions of Chetty [2008] and Shimer and Werning [2008]. Using a simple partial equilibrium dynamic search model where agents are liquidity constrained, I show that one can use the weighted difference between the behavioral response to an increase in potential duration and to an increase in benefit level to identify the pure moral hazard effect of UI. The intuition for this general result is straightforward. Under the assumption that the Euler equation holds until benefit exhaustion, by reweighting the effect of a change in UI benefits at two different times, t (increase in benefit level) and t' (increase in potential duration), by the probability of receiving these benefits, one can make the liquidity effect equivalent (by giving the same liquidity in expectation) and the difference in the two reweighted effect identifies the pure moral hazard effect of UI. In other words, identifying the reaction of search effort to a change in benefit level versus a change in potential duration allows me to look at the reaction to a change in the full *path* of UI benefits. This reveals information about the expected path of marginal utilities over the time of a spell, which is the relevant information for the social planner. I implement empirically this identification strategy, and estimate the ratio of liquidity to moral hazard effects, taking once again advantage of the RKD, which enables me to estimate the effect on search effort of both benefit level and potential duration. My results suggest that the ratio of liquidity to moral hazard effects in the response of labor supply to a variation in unemployment benefits is around .5. This confirms the existence of significant liquidity effects as found in Chetty [2008]. But interestingly, the identification strategy for moral hazard and liquidity effects proposed in this paper only uses administrative UI data and the RK design, and can therefore deliver timely estimates of liquidity effects without the need for data on consumption or on assets.

Finally, I use my RKD estimates of the labor supply responses to UI and of the ratio of liquidity to moral hazard effects to calibrate the welfare implications of an increase in UI benefit level and in UI potential duration. To do so, I first derive simple welfare formulas for the optimal level of both benefit level and potential duration in a simple partial equilibrium model with liquidity constraints. These formulas, in the tradition of the "sufficient statistics" literature are expressed as simple functions of statistics that I can estimate readily in the RK design, namely the elasticities of unemployment and non-employment duration with respect to UI benefits and the ratio of liquidity to moral hazard effects of a change in UI benefits. My calibrations show that the size of the liquidity effect is critical to assess the welfare implications of UI policies and that both an increase in the benefit level and in the potential duration of benefits would have provided positive (yet small) welfare gains. Though these policy recommendations are local, the calibration strategy suggested in this paper can be easily replicated for all US states and at any point in time with simple UI administrative data. By a simple application of this strategy, any UI administration could calibrate in a timely manner the welfare implications of small adjustments to its UI rules (such as a change in the maximum benefit amount or a benefit extension) without the need to estimate separately the consumption smoothing benefits of UI with consumption data.

The remainder of the paper is organised as follows. In section 1, I present briefly the theoretical framework, derive the optimal UI formulas for both the benefit level and potential duration of UI, and show how the moral hazard effect can be identified as a simple linear combination of the effects on search effort of a change in benefit level and in potential duration. In section 2, I present the RKD strategy, the data and provide with institutional background on the functioning of UI rules. In section 3 I present the results of the labor supply effects of benefit level and potential duration, and I present several tests for the robustness of the RKD estimates. Finally, in section 4, I estimate the liquidity to moral hazard ratio of the effect of UI, and calibrate the welfare implications of UI based on my RKD estimates.

1 Theoretical Framework

To analyze the welfare effects of increasing UI level or UI duration, I build on a simple partial equilibrium dynamic search model where agents are liquidity constrained and cannot smooth perfectly consumption between the state of unemployment and that of employment. This class of models has been used extensively to analyze the welfare implications of UI benefits (Chetty [2008], Schmieder et al. [2012]). As shown in Chetty [2006], the optimality condition for the level of UI benefits in these models, which trades off the consumption smoothing benefits of unemployment insurance versus the moral hazard cost, is extremely general and can be shown to hold in many different settings and classes of moral hazard models. Importantly, this trade-off can be written as a function of estimable statistics in the spirit of the Baily-Chetty formula to assess the welfare implications of different UI policies. The moral hazard is then captured by the elasticity of unemployment duration with respect to benefits. Estimating the consumption smoothing benefits of UI is much more difficult and relies on the estimation of the consumption drop at unemployment and on the curvature of the utility function (Gruber [1997], Kroft and Notowidigdo [2011]). Chetty [2008] shows that the consumption smoothing benefits of UI are related to the liquidity to moral hazard ratio of the effect of UI benefits on search effort. The contribution of this section is to show that under reasonable and testable assumptions, the consumption smoothing benefits of UI are recoverable from the behavioral responses of search effort to variations in benefit level and in UI potential duration. And the relative welfare gains of increasing the benefit level or the potential duration of UI can be assessed directly by estimating from administrative UI data the responses of labor supply to variations in unemployment benefits, without the need for data on consumption as in Gruber [1997] or on severance payments as in Chetty [2008].

The model: Here, I only briefly present the model and the main results. Most of the proofs and discussion are in appendix C. The model describes the behavior of a worker living T discrete periods (e.g., weeks) who is laid-off and therefore becomes unemployed in period zero. When unemployed, the worker exerts search effort in each period s_t that translates into a probability to find a job[3]. This probability is normalized to s_t to simplify presentation. Search effort is not observable (hence the presence of moral hazard) and has a utility cost $\psi(s_t)$ increasing and convex. Wages w_t are exogenous[4], and when an unemployed finds a job, it lasts forever. When unemployed, an agent starts her unemployment spell with asset level A_0[5] and receives unemployment insurance benefits b_t each period. The presence of liquidity constraints is captured by the fact that workers cannot deplete their asset A_t below a certain value L. To finance the unemployment benefits, the government levies a lump sum tax τ on each employed worker.

[3] This captures the presence of search frictions in the labor market.

[4] Empirical evidence seems to support this assumption that wages in fact do not respond much to UI. There is a vast empirical micro literature in labor trying to estimate how re-employment wages are affected by the generosity of UI benefits. The striking finding is that it has proven impossible to find such an effect. Card et al. [2007a] use full population administrative payroll data from Austria in a compelling regression discontinuity design and find no effects (very precisely estimated) on subsequent re-employment wages. Wages of workers who are already on the job are even less likely to respond to a change in benefits than wages of workers who are coming from unemployment and negotiating with employers. So wages of existing workers are likely to respond less than wages of new hires to UI generosity.

[5] As a baseline, I consider that the initial asset level A_0 is exogenous. I also do not allow for heterogeneity in the baseline. But, as in Chetty [2008], both assumptions can easily be relaxed to allow for partial self insurance and heterogeneity, without affecting the results.

The value function of finding a job at time t is:

$$V(A_t) = \max_{A_{t+1} \geq L} u(A_t - A_{t+1} + w_t - \tau) + \beta V(A_{t+1})$$

where β is the agent's discount factor. The value function of being unemployed at time t is:

$$U(A_t) = \max_{A_{t+1} \geq L} u(A_t - A_{t+1} + b_t) + \beta J(A_{t+1})$$

$$J(A_t) = \max_{s_t} \; s_t \cdot V(A_t) + (1 - s_t) \cdot U(A_t) - \psi(s_t)$$

In this set up[6], the optimal search effort in period t is implicitly defined by the first-order condition $\psi'(s_t) = V_t(A_t) - U_t(A_t)$. The effect of a change in benefit b_t on optimal search effort at time t can be expressed as the sum of two effects: $\frac{\partial s_t}{\partial b_t} = \frac{\partial s_t}{\partial A_t} - \frac{\partial s_t}{\partial w_t}$. The first term is a liquidity effect that is proportional to the difference in marginal utility of consumption while employed and unemployed. Intuitively, the larger the liquidity constraints, the more an agent needs to reduce consumption while unemployed. An increase in UI benefits, by providing cash-on-hand to the unemployed reduces the wedge in marginal utilities, and the unemployed face less pressure to find a job quickly. The second term is the standard moral hazard effect that arises because b_t works as an unemployment subsidy, and distorts the relative price of employment. Since the government cannot observe effort and cannot contract directly on s_t, any increase in b_t leads to a decline in search effort.

Planner's problem: The planner sets taxes τ and benefits b_t to maximize welfare W_0 (defined as the expected life-time utility of an unemployed worker), under a balanced-budget constraint: $D_B \cdot b = (T - D)\tau$ where D_B is the duration of paid unemployment and D is the total duration of unemployment. I restrict attention here to the class of typical UI systems where benefits are de-

[6] V is always concave. But U might not always be. For simplicity, and following Chetty [2008] who shows that in simulations U is always concave, we assume U is always concave.

fined by a constant level b for a fixed period B[7]. Therefore choosing the optimal benefit schedule amounts to choosing potential duration B and benefit level b.

In this model, the first-order condition of the planner's problem leads to the standard Baily-Chetty formula. The trade-off it highlights between consumption smoothing benefits and moral hazard has been discussed extensively. Assessing the welfare effects of UI following the standard Baily-Chetty formula requires an estimation of the consumption smoothing benefits of UI, which can prove arduous. My purpose here is to show that, under the testable assumption that the Euler equation holds at the exhaustion point B, the first-order condition can be written as a simple function of statistics that can be estimated using solely UI administrative data. Proposition 1 begins by showing that the welfare gains of increasing benefit level or benefit duration can be expressed as simple functions of the elasticity of unemployment duration and paid unemployment with respect to UI benefits, and of the ratio of liquidity to moral hazard effects.

PROPOSITION 1. *At the optimum, if the credit-constraint is not binding at time B, the UI benefit level b is such that:*

$$1+\rho_1 = \omega_1 \frac{D_B}{T-D}(1+\varepsilon_{D_B}+\varepsilon_D \frac{D}{T-D}) \tag{1}$$

where $\rho_1 = -\left.\frac{\partial s_0}{\partial a}\right|_B / \left.\frac{\partial s_0}{\partial w}\right|_B$ *is the liquidity to moral hazard ratio in the effect of an increase of benefit level. And* $\omega_1 = \frac{B}{D_B - s_0(B-1)} - 1$.
ε_{D_B} *is the elasticity of the duration of paid unemployment with respect to the level of UI benefits and* ε_D *is the elasticity of the duration of total unemployment with respect to the level of UI benefits.*

Similarly, at the optimum, if the credit-constraint is not binding at time B, the UI potential duration B satisfies :

$$1+\rho_2 = \omega_2 \frac{D_B}{B\cdot(T-D)}(\varepsilon_{D_B,B}+\varepsilon_{D,B} \frac{D}{T-D}) \tag{2}$$

where $\rho_2 = -\frac{\partial s_0}{\partial a_B} / \frac{\partial s_0}{\partial w_B}$ *is the liquidity to moral hazard ratio in the effect of an increase of potential*

[7]A large theoretical literature has derived the full optimal time-path of UI benefits. See for instance Hopenhayn and Nicolini [1997], or Pavoni [2009].

duration. And $\omega_2 = \frac{1}{S(B)-s_0} - 1$.

$\varepsilon_{D_B,B}$ *is the elasticity of the duration of paid unemployment with respect to the potential duration of UI benefits and* $\varepsilon_{D,B}$ *is the elasticity of the duration of total unemployment with respect to the potential duration of UI benefits.*[8]

Proof: see appendix C.

The result of proposition 1 generalizes Chetty [2008] to the welfare gains of both benefit level and potential duration. The intuition is that the larger the behavioral response to a variation in UI benefits (captured by the elasticities on the right hand side of equations (1) and (2), the more costly it is for the government to provide UI. But if the liquidity effect is large compared to the moral hazard effect, it also means that a large share of the elasticity is driven by the existence of liquidity constraints, and therefore, the consumption smoothing benefits of UI are also large. Note that the intuition for the formula holds whether the credit constraint is slack or not. The interest here is that if the credit constraint is not yet binding at the exhaustion point (an assumption that can be tested as shown in the empirical section), the first-order condition takes a very simple form.

In the tradition of the sufficient statistics approach, proposition 1 has the advantage of offering local [9] policy recommendations, without estimation of the full structural model [10]. If the left-hand side of equation (1) is larger than the right-hand side, then there is a net welfare gain from increasing the level of benefits b, at a constant level of potential duration B[11]. For this type of approach to be useful though, the components of the welfare formula need to be statistics that can be easily estimable, and preferably at high frequency, to be able to make readily available policy recommendations. The interest of proposition 1 is that, as will become apparent in the empirical sections of the paper, all the statistics entering the formulas are estimable with administrative UI data at

[8] All the different elasticities are defined as follows: $\varepsilon_{D_B} = \frac{b}{D_B}\frac{dD_B}{db}$; $\varepsilon_D = \frac{b}{D}\frac{dD}{db}$; $\varepsilon_{D_B,B} = \frac{B}{D_B}\frac{dD_B}{dB}$; $\varepsilon_{D,B} = \frac{B}{D}\frac{dD}{dB}$

[9] Local here means in the neighborhood of the actual policy parameters, where the statistics entering the formula are estimated.

[10] Of course, out of sample predictions would require to estimate the primitives of the model.

[11] Similarly, if the left-hand side of equation (2) is larger than the right-hand side, then there is a net welfare gain from increasing the potential duration, at a constant level of benefits b.

high frequency using the regression kink design. In particular, following the result of proposition 2 below, the ratio of liquidity to moral hazard can be estimated, under some testable assumption, from responses of the exit rates to variations in benefit level and benefit duration.

An interesting corollary to proposition 1 concerns the determination of the relative welfare gains of increasing the benefit level or the potential duration of UI benefits. Traditionally, during recessions, governments tend to increase the potential duration of UI instead of the level of benefits. I provide a simple test for a benefit extension to welfare dominate an increase in benefit level.

COROLLARY 1. *An increase in the potential duration of benefits B will be welfare superior to an increase in the benefit level b if*

$$\frac{\partial s_0}{\partial B} + \frac{d\tau}{db}\Theta_2\omega_2 \leq \left.\frac{\partial s_0}{\partial b}\right|_B + \frac{d\tau}{db}\Theta_1\omega_1 \tag{3}$$

where $\frac{\partial s_0}{\partial B}$ *and* $\left.\frac{\partial s_0}{\partial b}\right|_B$ *are the effect on the exit rate at the beginning of a spell, of respectively, a variation in potential duration and of a variation in the benefit level.* Θ_2 *is the moral hazard effect of an increase in the potential duration of benefits and* Θ_1 *is the moral hazard effect of an increase in the benefit level.*

Proof: see appendix

Corollary 1 can be interpreted as a modified Baily-Chetty formula: if the response of the exit rate at the beginning of a spell to an increase in the potential duration of benefits is large (in absolute value) relative to the response to a change in benefit level, it means that the unemployed expect that the marginal utility of consumption while unemployed after B periods will be large relative to the marginal utility of consumption while unemployed in the first B periods[12]. So providing benefits at time B is more desirable. But these consumption smoothing benefits come at the cost of distorting incentives: the relative welfare gain of increasing the potential duration of benefits instead of the benefit level decreases with the size of the moral hazard effect of a benefit extension relative to that

[12] To understand the intuition here, it is useful to remember that the effect of a variation in benefit level at time any time t on optimal search at time 0 is given by $\frac{\partial s_0}{\partial b_t} = -\frac{\beta^t \prod_{i=1}^{t}(1-s_i)u'(c_t^u)}{\psi''(s_0)}$ and is therefore directly proportional to the (discounted) expected marginal utility of consumption if unemployed at time t.

of an increase in the benefit level.

The trade-off exemplified in Corollary 1 is reminiscent of the results of Shavell and Weiss [1979] and Shimer and Werning [2008] on the optimal path of benefits. In the absence of liquidity constraint, one can show from equation (3) that an extension of UI benefits will always welfare dominate an increase in the benefit level. This relates to the result of Shavell and Weiss [1979] that if agents can freely borrow and save and therefore the government cannot control the full sequence of consumption, it is optimal to have a constant path of benefits. But if the unemployed face liquidity constraints that limit their ability to maintain a smooth path of marginal utilities, the government indirectly controls the sequence of consumption of the unemployed, and faces a trade-off between the need for a declining path of benefits over time to preserve incentives and insurance against uncertain spell duration. The welfare gains from insurance are determined by the expected path of consumption at the start of a spell. In particular, the faster the marginal utility of consumption is expected to increase over the time of a spell, the more beneficial it is to increase the potential duration of benefits to insure the long term unemployed.

Once again, the interest of formula (3) is to offer readily available local policy recommendations concerning the optimal timing of benefits using statistics that can be estimated at potentially high frequency using administrative data, as shown in proposition 2.

Relating moral hazard and liquidity effects to estimable behavioral responses: The dichotomy between the purely distortionary effects of UI (moral hazard effect) and the liquidity effects of UI has been shown to be critical to assess the welfare impact of UI. But, to date, the dichotomy has been of little practical interest because of the difficulty to disentangle these two effects empirically. Apart from Chetty [2008], there has been no attempt to estimate the magnitude of liquidity effects, and common sense assumes that this would somehow require data on severance payments. Proposition 2 shows that, under the assumption that the liquidity constraint is not yet binding at the exhaustion of UI benefits, the moral hazard and liquidity effects can actually be disentangled simply by using estimates of the behavioral responses to a change in both benefit level and potential duration.

PROPOSITION 2. *If the borrowing constraint does not bind after B periods, the moral hazard effect Θ_1 is a linear combination of the effects on exit rate at the start of a spell of an increase in benefit duration and of an increase in benefit level:*

$$\frac{1}{B}\left.\frac{\partial s_0}{\partial b}\right|_B - \frac{1}{b}\frac{\partial s_0}{\partial B} = \Phi_1\Theta_1 \tag{4}$$

where $\Phi_1 = \frac{S(B)-\frac{D_B+s_0}{B}}{D_B-s_0(B-1)}$

Proof: see appendix C.

The intuition for this result is the following. If the Euler equation holds for at least B periods, it means that agents can freely transfer money across the first B periods. From the perspective of an unemployed in period zero, any increase in benefits in these B periods, be it at period t or t', is equivalent and commensurable to an increase in consumption while unemployed in period zero. The only difference is the probability of receiving this benefit, because of the difference in the expected survival rate at period t or t'. By reweighting the effect of a change in benefit level at time t or t' by these survival rates, we can make the liquidity effect equivalent (by giving the same dollar amount in expectation) and the difference in the two reweighted effect identifies the pure moral hazard[13].

Proposition 2 tells us that if we can estimate the responses of the exit rate at the beginning of a spell with respect to a change in both benefit level and potential duration, we have a simple way to assess how the overall behavioral response breaks down into liquidity and moral hazard effects. This result relies of course on our ability to test the assumption that the credit constraint is not yet binding after B periods. In section 4 I provide a simple test of this assumption using

[13] Note that the formula carries on for all points of support of the hazard function. So potentially, one could look at the evolution of liquidity effects over the time of an unemployment spell.

post-exhaustion behavior with administrative data. An important point to note here is that this assumption does not mean that the liquidity effect is zero. In other words, the fact that the credit constraint is not binding after B periods does not mean that the existence of a credit constraint does not affect the optimal consumption path chosen by the unemployed until time B.

2 Empirical strategy

Assessing the welfare effects of UI benefits rests critically on our ability to identify and estimate the behavioral responses of search effort to changes in UI benefits. The empirical challenge lies in the difficulty to find credibly exogenous and time invariant sources of variations in UI benefits. Most sources of variations used in the literature on US data come from changes in state legislation over time[14], with the issue that these changes might be endogenous to labor market conditions. I describe in this section how one can use the presence in most US states of kinked schedules in the relationship between previous earnings and both benefit level and benefit duration to estimate the responses of labor supply to UI benefits using administrative data on UI recipients. My empirical strategy has several important advantages. First, in contrast to studies using regional or time variation in UI benefits, the RK design holds market-level factors constant, such that I identify changes in the actual behavioral response, net of any market level factors that may change over time or across regions. Second, the RK design allows me to identify behavioral responses with respect to both benefit level and potential duration for the same workers in the same labor markets. With these estimates, one can recover the liquidity versus moral hazard ratio of the effect of UI benefits following proposition 2, and fully assess the welfare effects of an increase in both benefit level and benefit duration. Finally, my empirical strategy, based on the use of administrative data, delivers high frequency estimates of behavioral responses without the need for quasi-experimental policy reforms, which is critical for welfare recommendations based on sufficient statistics formula.

[14] See for instance Meyer [1990] or Card and Levine [2000].

2.1 Regression Kink Design

There has been recently a considerable interest for RK designs in the applied economics literature. References include Nielsen et al. [2010], Card et al. [2009], Dong [2010] or Simonsen et al. [2010]. The reason of this recent development is that in many settings, RK designs offer valid non parametric inference of the average treatment effect in the absence of instruments. Conditions for the validity of the RK design are stringent nevertheless, more stringent than in the RD design. RK designs also require a lot of statistical power to detect local changes in the slope of the conditional expectation function. Here, I consider a model where the treatment is continuous and is a known deterministic function of the running variable, as in Nielsen et al. [2010] or Card et al. [2009]. This type of setting can be thought of as a *sharp* design in the sense that everyone is a complier and obeys the same treatment assignment rule. But the identification strategy can be extended to classes of model with *fuzzy* design where the functional form for the treatment is unknown, as in Dong [2010] who consider a binary treatment. I am interested in the following model:

$$Y = y(b, D, W_1, W_2, \varepsilon)$$

where Y is a duration outcome, b (the level of UI benefits) and D (total potential duration of benefits) are two continuous regressors of interest, W_1, W_2 are two other potentially endogenous regressors, and ε is unobservable heterogeneity. Note that I allow for completely unrestricted non-additive heterogeneity. This very general non-parametric framework has the advantage of nesting a wide range of duration model such as the accelerated failure-time model or other semi-parametric duration models. In particular, I do not impose modeling assumptions that may not be empirically valid such as the proportional hazard assumption traditionally used in duration analysis. Note also that, similar to RD designs, other covariates are generally not needed for consistency in estimating the average (unconditional) treatment effect, though they may be useful for efficiency or for testing the validity of RKD assumptions. However, if desired, additional covariates Z could be included in the analysis by letting all the assumptions hold conditional upon the values Z may take on[15].

[15] In the estimation, I also considered models where I include covariates as additional regressors.

$H(.)$ is the c.d.f. of ε. I define two average marginal effects of b and D, α and β as:

$$\alpha = \int \frac{\partial y(.)}{\partial b} dH(\varepsilon|b, w_1) \quad \text{and} \qquad \beta = \int \frac{\partial y(.)}{\partial D} dH(\varepsilon|D, w_2)$$

These constructs are the effect of a marginal increase in b (resp. D) for b, w_1 (resp. D, w_2) fixed at their kink point value integrated on the distribution of the unobservable. This can be thought of as an average treatment effect (ATE) weighted by the ex ante probability of being at the kink given heterogeneity type.

The key element of the RK design is the fact that $b = b(W_1)$ (resp. $D = D(W_2)$) is a deterministic, continuous but kinked function of the endogenous assignment variable W_1 at $W_1 = k_1$ (resp. $W_2 = k_2$). Using this kink in the relationship between b and W_1 (resp. D and W_2), it is possible to identify α and β under two conditions. The first is a regularity condition: $\frac{\partial y(.)}{\partial b}$ (resp. $\frac{\partial y(.)}{\partial D}$) is continuous in b (resp in D) and $\frac{\partial y(.)}{\partial w_1}$ is continuous in w_1 for all b, w_1, ε (resp. $\frac{\partial y(.)}{\partial w_2}$ is continuous in w_2 for all D, w_2, ε). This condition states that the direct marginal effect of the assignment variable on the outcome should be smooth. The second condition is a smooth density condition. The c.d.f of W_1 (resp. W_2) conditional on ε $F_{W_1|\varepsilon}(W_1|\varepsilon)$ is twice continuously differentiable in W_1 at $W_1 = k_1$ (resp. $W_2 = k_2$) for all ε. This second condition requires that the derivative of the conditional probability density function is continuous for all ε at the kink so that density of the unobserved heterogeneity evolves smoothly with the assignment variable at the kink. Under these two conditions, we have:

$$\alpha = \frac{\lim_{w_1 \to k_1^+} \frac{\partial E[Y|W_1 = w_1]}{\partial w_1} - \lim_{w_1 \to k_1^-} \frac{\partial E[Y|W_1 = w_1]}{\partial w_1}}{\lim_{w_1 \to k_1^+} \frac{\partial B(w_1)}{\partial w_1} - \lim_{w_1 \to k_1^-} \frac{\partial B(w_1)}{\partial w_1}}$$

$$\beta = \frac{\lim_{w_2 \to k_2^+} \frac{\partial E[Y|W_2 = w_2]}{\partial w_2} - \lim_{w_2 \to k_2^-} \frac{\partial E[Y|W_2 = w_2]}{\partial w_2}}{\lim_{w_2 \to k_2^+} \frac{\partial D(w_2)}{\partial w_2} - \lim_{w_2 \to k_2^-} \frac{\partial D(w_2)}{\partial w_2}}$$

The two conditions are needed because a marginal increase in the assignment variable w_1 induces an effect on the outcome through b (because of the deterministic relationship between b and the assignment variable) but also through the direct effect of the assignment variable on the outcome and through the change in the distribution of the unobserved heterogeneity. Only if the latter two effects are smooth and cancel out by differencing on both sides of the kink can the change in the derivative of the conditional expectation function at the kink isolate the causal effect of b on the outcome.

Note that the assumptions needed for the validity of the RK design are somewhat stronger than for the validity of a RD design, since not only the conditional p.d.f. of the assignment variable but its derivative also need to be continuous for all unobservable individual types ε. These assumptions are always fundamentally untestable, i.e. whether each individual's ex ante density and its derivative are continuous is fundamentally untestable, since for each individual we only observe one realization. But first, knowledge of the institutional details are a good way of assessing the credibility of the RKD identification assumption. In the case of UI, manipulation of the assignment variable seems complicated and the local random assignment seems likely to hold. Very few people know the schedule of UI benefits while still employed. Moreover, to be able to perfectly choose ex ante one's position in the schedule of both benefit level and potential duration, it is necessary to know continuously one year in advance the date at which one gets fired and the schedule that shall apply then[16] and to optimize continuously not only one's highest-earning quarter but also the ratio of base period earnings to the highest-earning quarter. Second, it is always possible to check empirically for clear violations of the RKD assumptions. In particular, to assess the validity of the smooth density assumption, it is useful to check whether pre-determined covariates have a c.d.f that is twice continuously differentiable with respect to the assignment variable. I do so by estimating changes in the slope of the conditional expectation function of some pre-determined covariates like age, education or gender given the assignment variable. I also provide another test which consists in extending the approach of McCrary [2008] and test for the continuity of both the p.d.f of the assignment variable and of its first derivative around the kink.

[16] As shown in figures 1 and 2, the schedule changes rather frequently.

Estimation of α and β is straightforward. The denominator of the estimand is deterministic, and is the change in the slope of the schedule at the kink. The numerator is the change in the slope of the conditional expectation function of the outcome given the assignment variable at the kink. It can be simply estimated by running parametric polynomial models of the form:

$$E[Y|W=w] = \mu_0 + [\sum_{p=1}^{\bar{p}} \gamma_p (w-k)^p + \nu_p (w-k)^p \cdot D] \quad \text{where } |w-k| \leq h \tag{5}$$

where W is the assignment variable, $D = \mathbb{1}[W \geq k]$ is an indicator for being above the kink threshold, h is the bandwidth size, and the change in the slope of the conditional expectation function is given by ν_1.

Because the RK design fully controls for labor market conditions (that may be endogenously determined by the level of benefits) by netting out its effects across similar individuals at the kink, the estimated elasticities can be interpreted as micro-elasticities in the sense of Landais et al. [2010], i.e. a pure partial equilibrium elasticity, net of any equilibrium adjustments in labor market tightness.

To assess the welfare effects of UI benefits, I have shown in section 1 that one needs to estimate not only the elasticity of unemployment duration with respect to UI benefits, but also the effect of UI on the exit rate at the start of a spell. The advantage of the RKD setting is that it can easily be extended to the estimation of the effect of unemployment benefits on the hazard rate at different points of the hazard support.

Let $s_t = Pr[Y = t | Y \geq t, W = w]$ define the hazard rate at time t conditional on the assignment variable, I am interested in the average effect on the hazard rate of a continuous regressor b [17]:

$$\alpha_t = \frac{\partial s_t(Y|W=w)}{\partial b}$$

Under the assumption that $\frac{\partial s_t(Y|W=w)}{\partial w}|_{b=b(w)}$ is smooth, the logic of the RK design can be extended to identification of α_t and we have:

$$\alpha_t = \frac{\lim_{w \to k_1^+} \frac{\partial s_t(Y|W=w)}{\partial w} - \lim_{w \to k_1^-} \frac{\partial s_t(Y|W=w)}{\partial w}}{\lim_{w \to k_1^+} \frac{\partial b(w)}{\partial w} - \lim_{w \to k_1^-} \frac{\partial b(w)}{\partial w}}$$

Estimation of α_t is also straightforward. The denominator of the estimand is deterministic, and is the change in the slope of the schedule at the kink. The numerator is the change in slope at the kink of the hazard rate at time t conditional on the assignment variable. It can be simply estimated by running a linear probability model of the following form:

$$Pr[Y=t|Y \geq t, W=w] = \mu_{t,0} + [\sum_{p=1}^{\bar{p}} \gamma_{t,p}(w-k)^p + \nu_{t,p}(w-k)^p \cdot D] \quad \text{where } |w-k| \leq h \qquad (6)$$

where $\nu_{t,1}$ gives once again the numerator of the RK estimand for the effect of benefit level on the hazard rate at week t.

Note that the assumption that $\frac{\partial s_t(Y|W=w)}{\partial w}|_{b=b(w)}$ evolves smoothly at the kink is actually relatively strong regarding the selection process (into remaining unemployed) when unobserved heterogeneity θ also determines the exit rate out of unemployment $s_t(\{b_t\}_{t=0}^{B}, \theta)$. In fact, it implies that the heterogeneity effect is additively separable, in which case $\forall t$, $\frac{\partial^2 s_t}{\partial b_t \partial \theta} = 0$, meaning that the unobserved heterogeneity only acts as a shifter, independently of UI benefits. Once again, even though this smoothness assumption is fundamentally untestable, it is nevertheless always possible to check empirically for clear violations by looking for all t at the smoothness of the p.d.f of the assignment variable (conditional on still being unemployed after t weeks) around the kink, as

[17] The same logic applies to effect of potential duration D.

well as at the smoothness of the relationship between some covariates and the assignment variable (conditional on still being unemployed after t weeks) around the kink.

2.2 Data

The data used is from Continuous Wage and Benefit History (CWBH) UI records[18]. This is the most comprehensive, publicly available administrative UI data set for the US. CWBH data contains the exhaustive of all unemployment spells and wage records for five US states between 1978 and 1984[19]: Idaho, Louisiana, Missouri, New Mexico and Washington[20]. This enables me to replicate and successfully test for the validity of the RK design in many different settings and labor market conditions. Three other important advantages of the data are worth noting[21]. First, CWBH data provides accurate information on the level of benefits, potential duration, previous earnings and work history over time. Given the large degree of measurement error found in survey data, administrative data like the CWBH are the only reliable source if one wants to implement identification strategies such as the regression kink design used in this paper. Administrative data was also supplemented by a questionnaire given to new claimants in most states participating to the CWBH project, which gives additional information on socio-demographic characteristics of the claimants such as ethnicity, education, spouse's and dependents' incomes, capital income of the household, etc[22]. Second, since identification in the regression kink design relies on estimating changes in the slope of the relationship between an assignment variable and some duration outcomes of interest, the granularity of the CWBH data, which contains the exhaustive of unemployment spells, is a key advantage and smaller samples of UI recipients would in general not exhibit enough statistical power to detect any effect in a RK design. Finally, labor market conditions exhibit a lot of variation for the states and years for which CWBH data is available, which means that behavioral responses and welfare effects of UI can be estimated for very different labor market conditions. Figure B3

[18] I am especially grateful to Bruce Meyer and Patricia M. Anderson for letting me access the CWBH data.

[19] Records for Idaho begin in 1976.

[20] The CWBH also contains a small sample of records for Pennsylvania that I was not able to exploit.

[21] For further details on the CWBH dataset, see for instance Moffitt [1985a]

[22] Some of these questionnaire information are unfortunately not available for certain years depending on the state.

displays the evolution of monthly unemployment rates computed from the Current Population Survey in the five states for the time period available in the CWBH dataset. The data spans a period of low unemployment (1976 to 1979) followed by two recessions (January to July 1980 and July 1981 to November 1982). Following the 1981-1982 recession, the US unemployment rate surged above 10% and reached higher levels than during the Great Recession. In this respect, the CWBH data offers a truly interesting comparison with the current situation of the US labor market. I report in table A2 in appendix A descriptive statistics for the CWBH sample. It is interesting to note that the composition of the UI recipients in the CWBH is relatively close to that of UI recipients during the Great Recession[23]. A notable difference, though, is the relatively lower fraction of very long term unemployed during the 1981-83 recession than during the Great Recession, as pointed out by Aaronson et al. [2010], which may be partly due to a change in labor supply responses at the extensive margin for female workers[24].

Unemployment Insurance claims are observed at weekly frequencies in the administrative data so that all duration outcomes are measured and expressed in weeks. I focus on several duration outcomes. The duration of paid unemployment, which corresponds to the number of weeks a claimant receives unemployment compensation for a given spell. The duration of claimed unemployment corresponds to the number of weeks a claimant is observed in the administrative data for a given unemployment spell. This duration differs from the duration of paid unemployment. First, because most states have instated waiting periods, which means that after a claim has been filed, there is a minimum period during which the claimant cannot receive any UI compensation. Second, because a lot of spells exhibit interruptions in payment with the claimant not collecting any check for a certain number of weeks without being observed in the wage records. The third duration outcome of interest is the duration of the initial spell as defined in Spiegelman et al. [1992] The initial spell starts at the date the claim is filed and ends when there is a gap of at least two weeks in the receipt of UI benefits. Finally, the duration of total non-employment is also an important outcome, since its elasticity is a necessary statistics to compute the welfare effects of UI. Unfortunately, the

[23] For an interesting comparison, see for instance Table 2.1 in Krueger and Mueller [2011]

[24] Women seem to be less likely to exit the labor force during the Great Recession than during previous recessions.

duration of total non-employment cannot easily be computed with administrative UI data since unemployed individuals traditionally leave the dataset after exhausting their benefits. In Washington state though, the wage records matched to the UI records contain information about reemployment dates so that I was able to compute non-employment durations.

2.3 Institutional Background

The identification strategy relies on the presence of kinks in the schedule of UI benefits in US states. In this section, I describe the main features of the states UI legislation. In almost all US states, UI benefits depends on the labor market activity of the claimant in the period before becoming unemployed. This period is usually defined as the base period, and is traditionally the last four completed calendar quarters immediately preceding the start of the claim. The weekly benefit amount b received by a compensated unemployed is a fixed fraction τ_1 of his highest-earning quarter (hqw) in the base period[25] up to a maximum benefit amount b_{max}:

$$b = \begin{cases} \tau_1 \cdot hqw & \\ b_{max} & \text{if} \quad \tau_1 \cdot hqw > b_{max} \end{cases}$$

Figure 1 plots the evolution of the weekly benefit amount schedule in Louisiana for the time period available in the CWBH data. The schedule applies based on the date the UI claim was filed, so that a change in the maximum weekly benefit amount does not affect the weekly benefit amount of ongoing spells. In Louisiana, τ_1 is equal to $1/25$ which guarantees a constant replacement ratio of 52% of the highest-earning quarter up to the kink, where the replacement ratio decreases. The number of weeks a claimant can collect UI benefits is determined by two rules. First, there is a maximum duration D_{max} that cannot be exceeded, usually 26 weeks. But the total amount of benefits that a claimant is able to collect for a given benefit year is also subject to a ceiling, which is usually determined as a fraction τ_2 of total earnings in the base period bpw. So the total amount

[25] Some states, such as Washington, use the average of the two highest-earning quarters in the base period. For details about states' legislation and sources, see appendix.

of benefits collected is defined as:

$$B = min(D_{max} \cdot b, \tau_2 \cdot bpw)$$

This ceiling in the total amount of benefits determines the duration of benefits, since duration $D = \frac{B}{b}$ is simply the total amount of benefits divided by the weekly benefit amount. Duration of benefits can therefore be summarized as[26]:

$$D = \begin{cases} D_{max} \\ \tau_2 \cdot \frac{bpw}{min(\tau_1 . hqw, b_{max})} & \text{if} \quad \tau_2 \cdot \frac{bpw}{min(\tau_1 \cdot hqw, b_{max})} \leq D_{max} \end{cases}$$

Duration is thus also a deterministic kinked function of previous earnings. To analyze independently the effects of duration and of the benefit amount in the regression kink design, it is useful to break down the sample in different subgroups. Figure B4 in appendix B summarizes the kinked schedules of the weekly amount and potential duration of UI benefits for Louisiana for all the different subgroups.

First, for claimants who hit the maximum weekly benefit amount, $b = b_{max}$, there is a kink in the relationship between potential duration and base period earnings bpw at $bpw = D_{max} \cdot \frac{b_{max}}{\tau_2}$

$$D = \begin{cases} D_{max} \\ \frac{\tau_2}{b_{max}} \cdot bpw & \text{if} \quad bpw \leq D_{max} \cdot \frac{b_{max}}{\tau_2} \end{cases}$$

The schedules of b and D for this subgroup is displayed on the left of panel B in figure B4. For claimants who are below the maximum weekly benefit amount, $b < b_{max}$, (right of panel B in figure B4) there is a kink in the relationship between potential duration and the ratio of base period

[26]Idaho is the only state in the CWBH data with different rules for the determination of benefit duration. In Idaho, as explained in the appendix, there is no ceiling on the total benefit amount for a given benefit year, but the potential duration is a step function of the ratio bpw/hqw of the base period earnings to the highest quarter earnings.

earnings to the highest-earning quarter at $\frac{bpw}{hqw} = D_{max} \cdot \frac{\tau_1}{\tau_2}$

$$D = \begin{cases} D_{max} & \\ \frac{\tau_2}{\tau_1} \cdot \frac{bpw}{hqw} & \text{if } \frac{bpw}{hqw} \leq D_{max} \cdot \frac{\tau_1}{\tau_2} \end{cases}$$

Finally, if $\frac{bpw}{min(hqw, \frac{b_{max}}{\tau_1})} \leq D_{max} \cdot \frac{\tau_1}{\tau_2}$, then:

$$D = \tau_2 \cdot \frac{bpw}{min(\tau_1 . hqw, b_{max})}$$

For these claimants, whose schedules are displayed on the left of panel A in figure B4, potential duration is always inferior to the maximum duration D_{max} but the relationship between duration and highest quarter earnings hqw exhibits an upward kink at $hqw = \frac{b_{max}}{\tau_1}$, which is also the point where the relationship between the weekly benefit amount b and hqw is kinked. When estimating the independent effect of b on unemployment duration in the regression kink design, I drop these observations and focus only on individuals with maximum potential duration ($D = D_{max}$) to avoid having two endogenous regressors kinked at the same point. The schedules for this subgroup is shown on the right of panel A in figure B4.

The rules for the determination of benefit duration discussed above constitute the basis of the UI benefit system (Tier I) that applies in each state. During recessions, and depending on state labor market conditions, two additional programs superimpose on Tier I to extend the duration that UI benefits are available. The first program is the permanent standby Extended Benefit program, federally mandated but administered at the state level (Tier II). This program provides with an additional duration of 50% of regular state duration up to a total of 39 weeks when the state unemployment rate reaches a certain trigger. When the EB program is in action, the slope of the relationship between previous earnings and benefit duration is steeper but the location of the kink is identical as shown for instance in figure 2. [27]

[27] Some specificities of EB program changed in 1981. Before 1981, two triggers existed: a national trigger, and a state trigger. In the Omnibus Budget Reconciliation Act of 1981, Congress voted to eliminate the national trigger entirely (effective July 1, 1981) and to permit the states to establish an optional trigger when the unemployment rate

On top of the EB program, federal extensions are usually enacted during recessions (Tier III). During our period of analysis, the Federal Supplemental Compensation (FSC) program was in action from September 1982 to March 1985. The FSC program had four different phases with additional duration of 50% to 65% of state regular duration with maximum depending on state labor market conditions[28]. The FSC introduced additional kinks in the relationship between previous earnings and benefit duration as shown in figure 2 in the case of Louisinia[29]. Most importantly, benefit extensions create non-stationarity in the potential duration of benefits over the duration of a spell, which creates challenges for inference in the RK design, as I discuss in section 3.2.

3 Effect of UI benefits on unemployment duration

I present in this section results of the estimation of the elasticity of unemployment duration with respect to both UI benefit level and UI potential duration. These elasticities are key inputs in the welfare formulas of proposition 1. The objective of this section is also to assess the validity of the RK design to estimate these elasticities. I propose and run several tests aimed at assessing both the validity of the identifying assumptions, and the robustness of the RK estimates. I also take advantage of the large variations in labor market conditions across states and over time to investigate the evolution of labor supply responses to UI over the business cycle.

reaches 6 percent, rather than 5 percent. The mandatory trigger rate was also raised.

[28]For details on the FSC, see appendix and Corson et al. [1986]

[29]The figure is a simplified summary of the many different schedules that applied in Louisiana between 1979 and 1983. Within each phase of the FSC for instance, maximum durations changed several times based on state labor market conditions. See table III.1 in Corson et al. [1986] for complete details.

3.1 Benefit level

I begin by presenting the results of the analysis of the effect of UI benefit level on unemployment duration. In the analysis, I divide for each state all the unemployment spells in subperiods based on the evolution of the UI schedule as well as of labor market conditions. There are two main considerations behind the choice of subperiods. Grouping unemployment spells over a larger period of time has the advantage of providing with a larger number of observations at the kink for statistical power. The pooled analysis will therefore yield more efficient estimates. But, this efficiency gain comes at a cost, because of the pooling of observations from different schedules when the maximum benefit amount changes frequently over time. For each unemployment spell, I center the highest quarter of earnings at the kink point in the schedule that is applicable given the date the claim was filed. If the maximum benefit amount increases from b_{max1} to b_{max2}, then the change in slope at the kink remains unaffected but the level of benefit at the kink is higher and the pooled estimate represent an average of the marginal effects at b_{max1} and b_{max2}. Another potential issue of choosing longer subperiods is the presence of high inflation rates at the beginning of the period of analysis which creates an attenuation bias on the estimates. Because of these potential concerns, I also present below checks for the sensitivity of the results to the choice of the number and length of sub-periods.

Graphical Evidence

I begin by showing graphical evidence in support of the RKD assumptions. First, I plot densities of the assignment variable in order to detect potential manipulation of the assignment variable at the kink point. Figure 3 shows the number of spells observed in each bin of $250 of highest quarter of earnings[30] centered at the kink point in Louisiana for two subperiods. The first period from january 1979 to september 1981 is a period of relatively low unemployment in Louisiana (monthly unemployment rate of 7.0% on average). The second period from september 1981 to december 1983 is a period of very high unemployment in Louisiana with a monthly unemployment rate of 10.8% on

[30] The choice of the bin size in our graphical analysis is done using the formal test of excess smoothing recommended by Lee and Lemieux [2010] in the RD setting. A bin size of $250 is the largest that passes the test for all states and outcomes of interest.

average. The two histograms show no signs of discontinuity in the relationship between the number of spells and the assignment variable at the kink point. To confirm this graphical diagnosis, I also performed McCrary tests as is standard in the Regression Discontinuity Design literature.The estimate for the log change in height and its bootstrapped standard error are displayed directly on both histograms and confirm that we cannot detect a lack of continuity at the kink for both periods. This test is of course only a partial one because, first, as explained above, the assumption of continuity of the ex ante individual density is fundamentally untestable, and second, because it does not provide evidence on the continuity of the derivative of the conditional density at the kink. But the spirit of the McCrary test can be simply extended to test for violation in the continuity of the derivative, as done in Card et al. [2009]. The idea is to regress the number of observations N_i in each bin on polynomials of the average highest quarter of earnings in each bin (centered at the kink) $(w-k)$ and the interaction term $(w-k)\cdot 1_{[W\geq k]}$. The coefficient on the interaction term for the first order polynomial (testing for a change in slope of the p.d.f) reported on both graphs is insignificant which supports the assumption of a continuous derivative of the conditional density at the kink.

A key testable implication of a valid RK design is that the conditional expectation of any covariate should be twice continuously differentiable at the kink. This can be visually tested by plotting the mean values of covariates in each bin of the assignment variable as done in figure 4 for the first sub period in Louisiana. The four panels of figure 4 all suggest that the covariates evolve smoothly at the kink, in support of the identification assumptions of the RK design. Formal tests can also be performed by running polynomial regressions of the form described in equation 5. Results are described in the next subsection.

The pattern for the outcome variables offers a striking contrast with that of covariates, as shown in figure 5 which display the evolution of the mean values in each bin of the main outcome of interest, the duration of UI claims, against the assignment variable centered at the kink, for all five states, for the first sub period in each state[31]. There is a sharp visible change in the slope of the relationship between the duration of UI claims and the assignment variable at the kink point of the benefit schedule for all five states[32]. This provides supportive evidence for the identification of an effect of benefit level on unemployment duration in the RK design.

Estimation Results

Table 1 shows the results for the baseline specification of equation 5 in the linear case for Louisiana and for the two sub periods 1979 to 1981 and 1981 to 1983. In each column, I report the estimate of the weighted average treatment effect $\widehat{\alpha} = -\frac{\widehat{\nu_1}}{\tau_1}$, with robust standard errors. Each estimate is done using nominal schedules, but the $\widehat{\alpha}$ are rescaled to 2010 dollars and they should be interpreted as the marginal effect of an extra dollar of 2010 in weekly benefit amount on the average duration (in weeks) of the outcome. I also report the elasticity with respect to the benefit level ($\varepsilon_b = \widehat{\alpha} \cdot \frac{b_{max}}{\overline{Y_1}}$, where $\overline{Y_1}$ is mean duration at the kink point) and its robust standard error, as well as the p-values from a Goodness-of-Fit test that consists in comparing the polynomial model to the same polynomial model plus a series of bin dummies. The results are consistent across the three duration outcomes of interest, with an estimated elasticity of between .36 and .41 for the first period and .51 and .6 for the second period. In each case, the linear specification is not considered too restrictive compared to the model including bin dummies as suggested by the large p-values of the Goodness-of-Fit test. For covariates, to the contrary, I cannot detect evidence of a significant change in the slope of the conditional expectation at the kink for any of the two periods.

In table 2 panel A, I analyze the sensitivity of the results to the choice of the polynomial order.

[31] Results for other important related duration outcomes of interest, the duration that UI benefits are paid, and the duration of initial spell, are displayed in figures B5 and B6 and reveal the exact same patterns.

[32] It is interesting to note that for Missouri, the change in slope seems to be smaller, which is due to a smaller change in slope in the benefit schedule, where τ_1 is equal to 1/20, instead of 1/25 in most other states. Besides, the relationship between unemployment duration and highest quarter of earnings seems to be slightly increasing on the right of the kink in Missouri, contrary to other states, where it is decreasing. This might be due to the very low level of the kink in the distribution of previous earnings compared to other states, since in Missouri, both τ_1 and b_{max} are very small. Because of this, liquidity effects might be stronger on the right side of the kink in Missouri than in other states, and higher previous earnings lead to higher unemployment duration.

I display the same results as in Table 1 for a linear, a quadratic, and a cubic specification[33]. I also report the Aikake Information Criterion (AIC) for all specifications. The estimates for α are quite similar across the different specifications. Standard errors of the estimates nevertheless increase quite substantially with higher order for the polynomial. The AIC suggest that the quadratic specification is always dominated but the linear and the cubic specification are almost equivalent, and none of them is too restrictive based on the p-values of the Goodness-of-Fit test. Table 2 panel B explores the sensitivity of the results to the choice of the bandwidth level. Results are consistent across bandwidth sizes, but the larger the bandwidth size, the less likely is the linear specification to dominate higher order polynomials. Overall though, it should be noted that the RKD does pretty poorly with very small samples, and therefore is a quite demanding in terms of bandwidth size compared to a regression discontinuity design. In practice, I found that the precision of the estimates would fall quite substantially when reducing bandwidth sizes below 1500.

An additional concern is that using relatively long sub periods with nominal schedules may lead to an attenuation bias because inflation causes an extra nominal dollar in weekly benefit amount to be worth less at the end than at the beginning of the sub period. To examine the robustness of the results to this concern, I present results using a larger number of sub-periods in table 3. Estimates of α are clearly in line with the baseline, ranging between .025 and .055. The drawback of using shorter sub-periods is that the relationship between the assignment variable and the outcome becomes noisier. Even though the change in the slope is quite precisely estimated in each of the five sub-periods, the p-values of the Goodness-of-Fit test are smaller, indicating that the polynomial specifications have more difficulty fitting the data.

Because the total duration of non-employment matters for the government's budget constraint, the elasticity of the duration of total non-employment is also a necessary statistics for assessing the welfare effects of UI, as shown in proposition 1. In table 4, I display estimates of the elasticity of all duration outcomes, including the duration of total non-employment, in Washington,

[33]For all three specifications, the bandwidth is set at 2500.

the only state for which we observe reemployment dates from wage records in the CWBH data. Interestingly, the marginal effect of a change in benefit level on the duration of non-employment is very similar to the effect on the duration of UI claims or on the duration of paid UI. But the duration of non-employment being usually quite longer than the duration of paid UI, the elasticity of non-employment duration is relatively lower than the elasticity of paid UI spells.

One important contribution of this paper is to provide a thorough assessment of the validity of the regression kink design. I therefore provide three additional tests for the robustness of the RKD estimates, intended to constitute the basis for a set of good practices when implementing RKD estimation. For the sake of brevity, most of the details of these tests are given in the appendix.

The first two tests deal with the issue of functional dependence between the forcing variable and the outcome of interest. A key identifying assumption of the RK design is that, conditional on b, this relationship is smooth at the kink. But in practice, it could be that the relationship between the forcing variable and the outcome (in the absence of a kink in the schedule of b) is either kinked or simply quadratic. Then, the RKD estimates are likely to be picking up this functional dependence between y and w_1 instead of the true effect of b on y. One way to control for this type of issue would be to compare two groups of similar individuals with different UI schedules, so that kinks would be at different points of support of the forcing variable. As shown in appendix B, under the assumption that the functional dependence between y and w_1 is the same for the two groups, the average treatment effect can be identified and estimated in a "double-difference regression kink design". To implement this strategy, the idea is to use the presence of variations in the maximum benefit amount over time, that shift the position of the kink across the distribution of the forcing variable (as shown in figure 1). The problem though is that, taken separately, each variation in max_b is too small to give enough statistical power to detect changes in slopes because the bandwidths are too small, and as previously pointed out, the drawback of the RKD is to be quite demanding in terms of bandwidth size. The idea therefore is to compare periods that are further away in time. The obvious drawback of this option is that the identifying assumption is less likely to hold as one compares periods that are further away in time. In particular, one may worry about the high inflation rates during this period. It is important to note here that the maximum benefit amount increased in Louisiana a lot faster than inflation (40% between September 1979 and Sept 1982 and total inflation was less than 20% during that period), so that there is a clear and important change in the schedule in *real* terms [34]. Figure B1 in appendix shows the relationship between the duration of paid unemployment and the forcing variable in 1979 and 1982. Interestingly, there is a kink in this relationship in 1979 at the level of the 1979-kink in the schedule, and this kink disappears in 1982, when a new kink appears right at the level of the 1982-kink. Furthermore, in the interval between the 1979 and 1982 kinks, there is a change in slope in the relationship between the duration of unemployment and the forcing variable. This evidence is strongly supportive of the validity of the RK design. Table B1 reports the double-difference RKD estimates of the effect of benefit level corresponding to the evidence of figure B1. The point estimates are perfectly in line with the baseline RKD estimates of table 1. The DD-RKD strategy being a lot more demanding, the precision of the estimates is nevertheless quite reduced compared to the baseline RKD strategy.

Another way to test for the functional dependence between earnings and the outcome is to run RKD estimates using as the forcing variable a placebo, i.e. a proxy for previous earnings, that would not be too correlated with the highest quarter of earnings. In the CWBH data, the variable that is best suited for this strategy is the reemployment wage. Table B2 explores the robustness of the RKD results using the post unemployment wage as a placebo forcing variable instead of the pre-unemployment highest quarter of earnings. Results show that we cannot detect any effect in these placebo specifications which confirm that the baseline RKD estimates are not just an artifact picking up a functional dependence between earnings and unemployment duration.

Another series of tests that should constitute the basis of any RKD analysis are non-parametric or semi-parametric tests inspired by the literature on the detection of structural breakpoints in time series analysis, following for instance Bai and Perron [2003]. I carry out here a straightforward

[34] To further alleviate this concern, I also control for quadratic in *real* highest quarter of earnings in the DD-RKD specifications and find similar results.

test that consists in trying to detect the location of the kink by looking for the kink point that would minimize the residual sum of squares or equivalently maximize the R-squared[35]. Details of the test are given in appendix B. I report in figure B2 the evolution of the R-squared as I change the location of the kink point in specification (5). The evolution of the R-squared as one varies the location of the kink points provides evidence in support of the validity of the RKD design. For both periods, the R-squared increases sharply as one moves closer to the actual kink point and then decreases sharply, supportive of the existence of a kink around 0. Despite their bad small sample properties, I recommend that these non-parametric or semi-parametric tests are always performed when running RKD estimation, to make sure that the estimates are not picking up some spurious breakpoints in the relationship between the forcing variable and the outcome of interest.

Comparison to other studies & cyclical behavior

I replicate the RKD estimation procedure for all states and periods. Overall, estimates are consistently between .1 and .6 with an average of .31[36]. To get a sense of the validity of the RK design, it is useful to compare the RKD estimates to existing estimates in the literature. My estimates are on the lower end of the spectrum when compared to traditional benchmarks in the literature on US data[37]. Estimation of the effect of UI benefit level in this literature has however always been struggling with the endogeneity issue due to the joint determination of UI benefits and previous earnings. Most empirical studies on US data therefore use proportional hazard models and add controls for previous earnings[38]. In table B3 in appendix, I report the estimates of Cox proportional hazard models on the CWBH data[39], which enables me to compare my results to the widely cited benchmark of Meyer [1990], who used a smaller sample of the same CWBH records. Table

[35] I conduct here a simple grid search but these tests can become computationally burdensome when looking for several breakpoints or for more complicated models, in which case the use of more efficient algorithms is recommended, as in Bai and Perron [2003].

[36] This is the average elasticity of the duration of initial spell for all 5 states and periods, where each period of analysis is defined as the entire period for which the benefit schedule is left unchanged. This represents a total of 26 different estimates. The standard deviation is .2.

[37] See for instance the survey in Holmlund [1998] or Krueger and Meyer [2002].

[38] See for instance estimates in Chetty [2008], Kroft and Notowidigdo [2011] or Spinnewijn [2010].

[39] All the details of the estimation procedure are given in appendix B.

B3 shows that the estimates of Meyer [1990], who found an elasticity of .56[40], can be fully replicated using his specification. The drawback of these estimates is that they do not fully address the endogeneity issue due to the joint determination of UI benefits and previous earnings. Meyer [1990] only controls for previous wages using the log of the base period earnings. Interestingly, if one adds a richer set of non parametric controls for previous earnings to mitigate the concern of endogeneity, and fully controls for variations across labor markets by adding time fixed effects interacted with state fixed effects, the results converge to the RKD estimates and the elasticity goes down to around .3. The reason is that, as one controls more efficiently for the functional dependence between unemployment duration and previous earnings, the only identifying variation in benefit level that is left comes from the kink in the benefit schedule, and the model naturally converges to the identification strategy of the RKD. Overall, I find this evidence to be supportive of the validity of the RK design.

Following the Great Recession, a recent literature has been interested in estimating how labor supply responses to UI vary over the business cycle in order to assess the optimality of UI rules that are contingent on the state of the labor market (Schmieder et al. [2012], Kroft and Notowidigdo [2011]). I take advantage of the large variations in labor market conditions across states and over time in the CWBH data to investigate how the RKD estimates vary with indicators of (state) labor market conditions[41]. I correlate the RKD estimates with the average monthly unemployment rate from the Current Population Survey prevailing in the state for each period. Results suggest that increases in the state unemployment rate are associated with a slight decrease in the estimated elasticity of unemployment duration with respect to the UI benefit level. In my preferred specification, the results imply that the elasticity varies between .38 (.09) when the state unemployment rate is at 4.5% (minimum in the CWBH data) and .25 (.10) when the unemployment rate is at 11.8% (the max in the CWBH data). Overall, this evidence supports the idea of a small cyclicality of

[40] See Meyer [1990], Table VI, column (7). Coefficient estimates for log(b) in the proportional hazard models of table B3 can be interpreted as the elasticity of the hazard rate s with respect to the weekly benefit level. However, under the assumption that the hazard rate is somewhat constant, these elasticities can be easily compared to the RKD elasticities of unemployment duration, since $D \approx 1/s$ so that $\varepsilon_D \approx -\varepsilon_s$

[41] All the details on the analysis of the cyclical behavior of the estimates are once again given in appendix B.

the (partial equilibrium) labor supply responses to UI, and is in line with the evidence of Kroft and Notowidigdo [2011] for the US, although the cyclicality of the estimates is somewhat larger in their analysis. One needs to acknowledge that the standard errors on the estimated coefficient is rather large and the results of this exercise should be interpreted with some caution[42].

3.2 Benefit Duration

Dealing with benefit extensions

The advantage of the RKD design is that the schedule of both the benefit level and the potential duration of UI are deterministic and kinked allowing for non-parametric estimation of the effect of both the benefit level and the potential duration of UI on unemployment duration. However, the presence of frequent changes in the schedule of potential duration complicates the estimation of the effect of potential duration in the CWBH sample. These frequent changes are due first to the federal extensions of the FSC program following the 1981 recession, but also to the functioning of the EB program before the Omnibus Budget Reconciliation Act of 1981: because of the existence of two triggers (a national trigger, and a state trigger), and because of the lower level of unemployment required for these triggers to be activated, the number of EB sequences was much larger before 1981 than it is today[43]. These frequent changes in the schedule of potential duration are a concern for identification because a fundamental requirement of the RK design is that the

[42] In table B3, columns (4) to (6) , I also investigate how the effect of the log benefit correlates with state unemployment conditions in the standard Cox proportional hazard model, and find similar results, with the estimated elasticity decreasing slightly between .36 for the bottom quartile of the distribution of state×month unemployment rates in the CWBH data and .27 for the top quartile of unemployment rates.

[43] In Louisiana for instance the schedule changed 11 times between January 1979 and December 1983. When the sample begins with spells starting as of 01/14/1979, only Tier I is in effect. Then the national EB trigger goes on from 7/20/1980 to 1/24/1981, starting a period of EB in Louisiana. From 01/24/1981 to 09/12/1981, only Tier I is in effect again, but the state EB trigger goes on after 09/12/1981, which starts another period of EB. Before this new period of EB is over, FSC-I comes in effect starting 09/12/1982, and therefore FSC-I and EB apply. After 10/20/1982, the state trigger on EB goes off and only FSC-I remains in action. On 01/09/1983, FSC-II begins, and on 01/23/1983, the state EB trigger goes on again. On 03/20/1983 the maximum duration of the FSC-II program in Louisiana is increased to 16 weeks. On 03/31/1983 the FSC-III program comes into effect, and at the same date, the maximum duration for the Tier I program (standard state UI) is reduced from 28 to 26 weeks. On 06/19/1983 the maximum duration of the FSC-III extension goes down to 12 weeks. On 10/19/1983 the FSC-IV extension program begins, but its rules and its maximum duration in Louisiana are the same as for the FSC-III.

unemployed anticipate the stationarity of the schedule during the whole duration of their spell. Only observations for which the schedule did not change from the beginning of the spell to the end of the potential duration can be kept in the estimation sample for estimating the effect of potential duration on actual unemployment duration. In Louisiana for instance, when I restrict the sample to spells with a stationary schedule throughout the whole potential duration of the spell, I am left with only 3 sub periods: the first sub period contains all spells beginning between 01/14/1979 and 01/31/1980, the second contains all spells beginning between 09/12/1981 and 05/01/1982, and finally the third sub period contains all spells beginning after 06/19/1983 to 31/12/1983. The small sample size issue of having to split the data in stationary sub periods is reinforced by the necessity to break down observations according to their weekly benefit amounts, since individuals with $b = b_{max}$ and $b \leq b_{max}$ face different schedules[44]. Given state UI parameters, sample size at the kink can become to small for inference. Because of these constraints, the number of estimates for the effect of potential duration is more limited than for the effect of benefit level.

Figure 6 shows the density at the kink in Louisiana for the three sub periods with stable potential duration schedule. In all three sub periods, the number of observations in the estimation sample around the kink is four to five times smaller than for the estimation of the effect of benefit level. The histograms show no signs of discontinuity in the relationship between the number of spells and the assignment variable at the kink point, apart in the second sub-period, where there seems to be a slight discontinuity, which might be attributed to the smaller sample size. I also test the RK design assumption of a twice differentiable conditional density at the kink more formally, as in section 3.1. The second key assumption for the validity of the RK design, namely that the conditional expectation of any covariate should be twice continuously differentiable at the kink, seems also confirmed by graphical evidence. Figure 7 plots the mean values of covariates in each bin of the assignment variable for one particular sub-period and all four panels suggest that the covariates evolve smoothly at the kink. Note that because of a smaller sample size, a smaller bin

[44]Note also that for individuals hitting the maximum weekly benefit amount $b = b_{max}$, the location of the kink changes every time the statutory maximum weekly benefit amount is increased which further reduces the estimation sample size of observations with stationary schedule.

size is recommended to avoid excess smoothing when using formal tests for the choice of the optimal bin size. This graphical diagnosis is also confirmed for each sub-period by formal tests for the existence of a kink in the relationship between covariates and the assignment variable in table 5.

The strategy followed in figure 7 can be once again replicated for the outcome variables of interest. Figure 8 plots the mean values of the duration of UI claims in each bin of the assignment variable for the 3 sub-periods of analysis in Louisiana. In contrast with figure 7, figure 8 shows clear signs of a kink in the relationship between the assignment variable and the duration of initial spell at the kink. But the smaller sample size at the kink makes the relationship between the outcome and the assignment variable a little noisier visually than in the case of the kink in the benefit level schedule depicted in figure 5.

Estimation Results

Estimation of the ATE of potential duration in the RK design is similar to that of benefit level, and relies on the estimation of the numerator of the RK estimand with polynomial regressions of the form described in equation 5. Table 5 presents the results for the average treatment effect $\widehat{\beta}$ with robust standard errors for Louisiana. For each of the three sub periods with stable schedules[45], I report the estimates of the preferred polynomial specification based on the Aikake Information Criterion. The effect of an additional week of UI on average duration is consistently around .2 to .5 for all duration outcomes and sub-periods of interest. The linear specification is always preferred and is never rejected by the Goodness-of-Fit test as indicated by the reported p-values. For covariates in columns (4) to (8), to the contrary, the same estimation procedure does not reveal any kink in the relationship with the assignment variable, which supports the validity of the RK design.

The estimates of an increase of .2 to .3 weeks of unemployment with each additional week of UI are in line with previous estimates in the US such as Moffitt [1985b], Card and Levine [2000],

[45] For the third sub period, the 12 weeks maximum duration of FSC-III and FSC-IV introduces a small second kink in the schedule, visible in figure 2, but due to a lack statistical power to detect its effect, I focus on estimation of the effect of the larger kink.

and Katz and Meyer [1990]. They are slightly higher than existing estimates in Europe using RD designs such as Schmieder et al. [2012] for Germany. This could be due to much longer baseline durations in European UI systems. In Schmieder et al. [2012] for instance, baseline potential durations, at which the effect of an extension of UI are estimated, are between 12 to 24 months, which is 2 to 4 times longer than in the US.

How are the estimates presented here informative about the effect of UI extensions in the Great Recession? UI institutions have little changed since the late 1970s: replacement rates and baseline durations of state UI programs are more or less the same. Nevertheless, institutional settings were different, and in particular, the relative generosity of safety nets for the long term out-of-work has declined significantly in the 1990s with a complete overhaul of welfare programs. A consequence is that elasticities are potentially slightly greater today because the continuation value of unemployment past the UI exhaustion point is lower than in the CWBH data. Rothstein [2011], however, finds very small effects of UI extensions during the Great Recession, but his identification strategies might be picking up equilibrium effects in the labor market, which might be lower during recessions in the presence of negative job search externalities as suggested in Landais et al. [2010].

4 Moral hazard, liquidity and welfare calibrations

The previous section has shown that the RK design can deliver robust and timely estimates of labor supply effects of UI benefits. But, to be able to calibrate the welfare implications of UI, one needs to estimate the consumption smoothing benefits of UI, or, equivalently, as shown in section 1, the ratio of liquidity to moral hazard effects in labor supply responses to UI. Proposition 2 has shown that, under the assumption that the liquidity constraint is not yet binding at exhaustion, this ratio can be identified by comparing labor supply responses to an increase in the benefit level versus an increase in the potential duration of UI. I now show how can once again use the RK design to produce timely estimates of the welfare effects of UI.

To implement empirically this calibration strategy, one needs to be able to compute total non employment duration (D), as well as survival rates after exhaustion ($S(B)$). In the CWBH data, Washington is the only state for which this information is available through the matched UI records-wage records. But, in practice, any UI administration could implement these calibrations since all UI administrations link UI records with wage records to compute UI eligibility. To compute the liquidity to moral hazard ratio, one needs to estimate at the same time the effect of benefit level and that of potential duration. I therefore focus on the longest period (July 1980 to July 1981) for which we have a stationary schedule in Washington for both benefit level and potential duration.

4.1 Test for the slackness of the liquidity constraint using post benefit exhaustion behavior

The result of proposition 2 relies on the assumption that the liquidity constraint is not yet binding at the exhaustion point B. I begin by providing a simple test for this assumption. The intuition for the test is simple. If the liquidity constraint is binding, it means that the unemployed can no longer deplete their asset; they are hand-to-mouth, and therefore, benefits that they have received in the past do not have any effect on their future behavior. If to the contrary, exit rates after the exhaustion point are affected by benefits received before exhaustion, it means that agents can still transfer part of their consumption across time periods. To see this more formally, recall that the effect of benefit at time B on search at time $B+1$, when the Euler equation holds and the liquidity constraint is not binding, is given by:

$$\frac{\partial s_{B+1}}{\partial b_B} = \frac{u''(c^u_B)}{u'(c^u_{B+1}) - v'(c^e_{B+1})} \leq 0$$

$\frac{\partial s_{B+1}}{\partial b_B}$ is inversely proportional to the liquidity effect. In other words, when the Euler equation holds and agents can transfer money freely across periods, an increase in benefits earlier during the spell reduces the probability of exiting unemployment because it increases asset level. But when the agents can no longer smooth consumption perfectly or have little asset to transfer across periods, the denominator (which is directly proportional to the consumption smoothing benefits of UI) increases and $\frac{\partial s_{B+1}}{\partial b_B}$ tends to be small in absolute value. When agents hit the borrowing constraint, they become hand-to-mouth and set consumption equal to income every period, in which case the Euler equation does not hold any more and $\frac{\partial s_{B+1}}{\partial b_B} = 0$.

The implementation of the test relies on the comparison of exit rates after benefit exhaustion. To identify $\frac{\partial s_{B+1}}{\partial b_B}$, the idea is to compare the exit rates conditional on still being unemployed after the maximum exhaustion point of two individuals, one having been given exogenously one more week of covered UI than the other. Once again, the RK design can be used to implement the test, taking advantage of the kink in the schedule of the potential duration of benefits, which creates variations in the number of weeks that individuals can collect UI before time B, or equivalently in the total amount of benefits that individuals can collect before time B. I run regressions of the form of equation (6) where the outcome is the probability of exiting unemployment between 40 and 60 weeks[46], conditional on still being unemployed after 39 weeks (the maximum duration of benefits in Washington between July 1980 and July 1981). The assignment variable is the ratio of base period earnings to highest quarter of earnings, that determines the potential duration of UI. The RKD identifies $\partial s_{B+1}/\partial B$ that I then divide by the benefit amount b to get $\frac{\partial s_{B+1}}{\partial b_B}$[47]. As explained in section 2.1, when dealing with hazard rates, identification requires some assumptions regarding the selection process in case some unobserved heterogeneity θ also determines the exit rate out of unemployment $s_t(\{b_t\}_{t=0}^{B}, \theta)$. Under the assumption that the heterogeneity effect is additively separable, in which case $\frac{\partial^2 s_B}{\partial b_B \partial \theta} = 0$, then $\frac{u''(c_B^u)}{u'(c_{B+1}^u) - v'(c_{B+1}^e)}$ is point identified. I ran tests of smoothness of the relationship between observable covariates at the kink and the assignment variable conditional on still being unemployed after 39 weeks, and could not detect significant

[46] Because of the small number of observations, I am forced to choose a rather large interval to increase the precision of the estimates.

[47] I assume here that a marginal change in the potential duration of benefits B normalized by the benefit amount b is the same as a marginal change in b_B. This would be the case if B could be increased by a fraction of period. This simplification does not affect the validity of the test but only the interpretation of the coefficient in column (1) of table 6.

changes in slope, indicative of the validity of the identifying assumption.

Results are reported in column (1) of table 6. Having received one extra dollar of benefits before 39 weeks reduces the exit rate out of unemployment after exhaustion by a statistically significant .19 percentage point. This means that benefits received before the exhaustion point still have a negative effect on exit rates after the exhaustion point, or in other words, that the liquidity constraint is not yet binding at the exhaustion point. Note that *per se*, this statistics is interesting in the sense that it is inversely related to the consumption smoothing benefits of UI at the exhaustion point. The lower this statistics, the larger the liquidity effect of UI benefits at exhaustion. It would therefore be interesting to be able to replicate this type of test to look at the evolution of this statistics over the business cycle.

4.2 Liquidity effects and calibrations

To calibrate the welfare effects of UI, following proposition 1, I need estimates of the elasticities of paid unemployment duration and of total non-employment duration, as well as estimates of the liquidity to moral hazard ratio. In table 6, I give in column (2) and (3) RKD estimates of the elasticities for the period of interest in Washington. An interesting point to note is that ε_{D_B}, the elasticity of UI duration with respect to potential duration is much larger than the elasticity of non-employment duration with respect to potential duration ε_D. The reason is that, because $D_B = \sum_{t=0}^{B-1} S(t)$, we have that $\frac{\partial D_B}{\partial B} = \sum_{t=0}^{B-1} \frac{\partial S(t)}{\partial B} + S(B)$, which means that the effect of a change in potential duration on the average duration of UI claims is the sum of the mechanical effect of truncating the distribution of spells at a later point in time $S(B)$ and a behavioral response. The difference between the elasticity of paid UI duration and non-employment duration suggests that the mechanical effect accounts for a large share of the total effect of potential duration on paid UI duration, and that the pure behavioral response is much smaller. This confirms the results of Schmieder et al. [2012] for Germany.

Estimation of liquidity and moral hazard effects:

The estimation of liquidity and moral hazard effects follows from the application of the result of proposition 2. In practice, I estimate separately in the regression kink design the effect of an increase in benefit level ($\frac{\partial s_0}{\partial b}\Big|_B$) and of an increase in potential duration ($\frac{\partial s_0}{\partial B}$) on the hazard rate out of unemployment at the beginning of a spell[48]. Proposition 2 requires that we estimate the effect of benefit level and potential duration for the same individuals. To ensure that the characteristics of individuals at both kinks (in benefit level and potential duration) are the same, I use a re-weighting approach described in appendix B. Column (4) of table 6 reports ($\frac{1}{B}\frac{\partial s_0}{\partial b}\Big|_B - \frac{1}{b}\frac{\partial s_0}{\partial B}$), the difference between the RKD estimate of the effect of benefit level (divided by the potential duration) and the RKD estimate of the effect of potential duration (divided by the benefit level) on s_0. Standard errors for all statistics in column (4) are bootstrapped with 40 replications[49]. By a simple application of proposition 2, this difference is then divided by $\Phi_1 = \frac{S(B)-\frac{D_B+s_0}{B}}{D_B-s_0(B-1)}$ to compute the moral hazard effect Θ_1 of an increase in benefit level and the ratio of liquidity to moral hazard ρ_1 in the effect of an increase in benefit level. I use the observed average survival rates and durations for the full period July 1980 to July 1981 in Washington and for individuals at the kink of benefit level in order to compute Φ_1.

The estimate reported in column (4) suggests the existence of substantial liquidity effects, with a ratio of liquidity effect to moral hazard effect of 44%. This estimate is however smaller than the figures reported in Chetty [2008], who finds a ratio of roughly 1.5 using data on severance payments. The great advantage of the RKD strategy is to be able to estimate liquidity effects from administrative UI data directly, without the need for information on severance payments or for consumption data. The assumptions for the validity of the identification strategy pursued here are however important to keep in mind. First, it relies on important assumptions about the optimiza-

[48] To increase the precision of the estimates, I choose to define s_0 as the probability of exiting unemployment in the first 4 weeks. Shorter definitions for period 0 yield similar results but the standard errors on the estimates of the effect of potential duration increase sharply.

[49] To be precise, I merge observations from both samples, the one at the benefit level kink and the one at the potential duration kink, and draw with replacement 50 different samples from that merged sample. I then replicate the full estimation procedure from these 50 samples to compute the standard errors on ($\frac{1}{B}\frac{\partial s_0}{\partial b}\Big|_B - \frac{1}{b}\frac{\partial s_0}{\partial B}$), Θ_1 and ρ_1.

tion abilities of unemployed individuals. The unemployed must be rational and forward-looking. If individuals were perfectly myopic for instance, the Euler equation would not hold. The test about the slackness of the liquidity constraint seems to indicate a certain degree of consumption smoothing over time, ruling out perfect myopia. But evidence in the labor market (see for instance DellaVigna and Paserman [2005]) indicates that job seekers may exhibit a lot of impatience. Even though our identification strategy is valid independently of the value of the discount factor, it rules out the possibility of forms of impatience such as hyperbolic (beta-delta) discounting. My identification strategy also necessitates that individuals have very precise information about their benefit level and potential duration of UI. This seems to be the case nowadays, unemployed individuals receiving in most states at the beginning of their claim a summary of their rights, with the amount of their weekly benefits and total duration of benefits in weeks[50]. Finally, my identification strategy postulates that unemployed individuals are able to form rational expectations about their survival rates and expected duration of unemployment at the start of a spell. Evidence in the labor market also suggests that unemployed individuals may actually exhibit biased perceptions about their unemployment risks (Spinnewijn [2010]). It is unfortunately difficult to know to what extent such biased beliefs are likely to affect my estimates, since the moral hazard estimate is at the same time an increasing function of the expected duration of unemployment and a decreasing function of the expected survival rate at exhaustion. In other words, biased beliefs would not affect my estimate if the bias is a simple shifter of the survival curve. If this is not the case, one would need to compare the full (biased) expected survival curve to the true survival curve to know how these biased perceptions affect the moral hazard and liquidity estimates.

Calibrations

I now use these estimates to calibrate the welfare effects of UI. To calibrate $D_B/(T-D)$, which is equivalent to the Insured Unemployment Rate (IUR), I use the total number of paid unemployed divided by the total number of employees paying payroll taxes in the wage records in Washington for the period July 1980 to July 1981. I find $D_B/(T-D) \approx 3.9\%$. Similarly, I calibrate

[50] Unfortunately, I was not able to find a copy of UI benefit summary for the period covered by the CWBH, and could not confirm that such information was already present at the time.

$D/T-D \approx 8.5\%$ as the average unemployment rate in Washington during the period computed from CPS[51]. From the CWBH data in Washington, I get that $\omega_1 = \frac{B}{D_B - s_0(B-1)} - 1 \approx 17$. Plugging the estimated elasticities of column (2) of table 6 into the formula of proposition 1, I get the right-hand side of the optimal formula $\omega_1 \frac{D_B}{T-D}(1+\varepsilon_{D_B}+\varepsilon_D \frac{D}{T-D}) \approx 1.14$. With a ratio of liquidity to moral hazard $\rho_1 \approx .44$, it means that the left-hand side of the formula ($1+\rho_1 \approx 1.44$) is greater than the right-hand side. This indicates that increasing the benefit level from its current level would be welfare increasing.

Similarly, one can calibrate the formula for the welfare effects of the potential duration of UI. Under the approximation that $\rho_2 \approx \rho_1$, and given that in the CWBH data, $\omega_2/B \approx 14.2$, we get that the right-hand side of equation (2) is approximately equal to 1.29, which is slightly lower than the left-hand side of the formula. Once again, the result of this calibration suggest that a small increase in the potential duration of UI would be welfare increasing.

These calibrations show that the size of the liquidity effects is critical to assess the welfare impact of UI. In the absence of liquidity effects ($\rho_1 = \rho_2 = 0$), the behavioral responses to UI would be entirely driven by moral hazard, and the right-hand side of the formula in both equations (1) and (2) would be greater than the left-hand side. The RKD strategy pursued here offers a simple way to investigate the presence and size of liquidity effects, but this exercise also clearly demonstrates the need for a deeper understanding and identification of the consumption smoothing benefits of UI.

Overall, my results confirm the evidence in Chetty [2008] that liquidity effects are substantial, and that an increase in the replacement rate and duration of UI might be welfare increasing. It is important however to remember that these policy recommendations are only valid locally, at

[51] The way I calibrate the ratios $D_B/(T-D)$ and $D/T-D$ relies on the assumption, implicit in the model, that each state UI agency balances its own budget every period. This assumption is somewhat restrictive, since the federal government subsidizes state UI agencies in practice. In particular, half of the cost of EB extensions is paid by the federal budget.

the value of the policy parameters at which the statistics entering the formula are estimated. Extrapolating the optimal level of benefit and duration of UI from these statistics would require the implausible assumption that all statistics would remain unchanged if we were to modify the policy parameters[52]. Moreover, my calibrations are also local in the sense that the empirical strategy identifies the average liquidity effect and behavioral responses at the kink, and might not be valid for the full spectrum of the earnings distribution. But the advantage of calibrating the welfare formula using the regression kink design as described in this paper, is that the formula can technically be tested in real time, so that any UI administration could easily estimate the welfare effects of the small adjustments that are usually done in UI legislation such as a change in the maximum benefit amount.

These calibrations demonstrate the interest and the validity of the RKD to analyze the welfare implications of UI, since the RKD provides a robust and promising empirical design to study many behavioral responses to unemployment benefits. Yet, the calibrations presented here are obtained in a very stylized version of the labor market and rely on some important assumptions that are worth mentioning. First, throughout the paper, I have assumed perfect take-up of UI. Evidence shows that the take-up rate of UI is actually significantly lower than 100%. As shown in Kroft [2008], in the presence of responses to UI at the extensive margin with endogenous take-up costs, social multiplier effects arise and the optimal replacement rates can be substantially higher than in traditional models with responses only along the intensive margin[53]. More importantly, models in the tradition of Baily [1978] and Chetty [2006] such as the one presented here take a pure partial equilibrium view of the labor market, with an infinitely elastic labor demand. The unemployment problem is represented as a pure labor supply story, with no effect of UI on labor market equilibrium through labor demand effects. As shown in Landais et al. [2010], in equilibrium search-and-matching models of the labor market, partial equilibrium labor supply responses

[52] However, we can gauge from the calibrations that the optimal level and duration of UI benefit are not substantially higher, since the welfare gains of increasing the benefit level ($\frac{dW}{db}$)or potential duration ($\frac{dW}{dB}$) of UI are relatively small.

[53] Another limitation of the analysis in terms of policy instruments is that UI is the only instrument to facilitate both intertemporal smoothing and smoothing across states. A natural alternative to resolve credit market failures would be the provision of loans or UI savings accounts.

to UI are no longer sufficient to compute the optimal trade-off between insurance and moral hazard, and one needs to estimate equilibrium employment responses as well. Finally, another aspect of the model is the assumption of stationarity of labor market conditions. Relaxing the assumption of deterministic labor market conditions would not affect qualitatively the results of the model, but would complicate the empirical strategy since one would need to have information about how unemployed individuals expect labor market conditions to evolve over the time of their unemployment spell.

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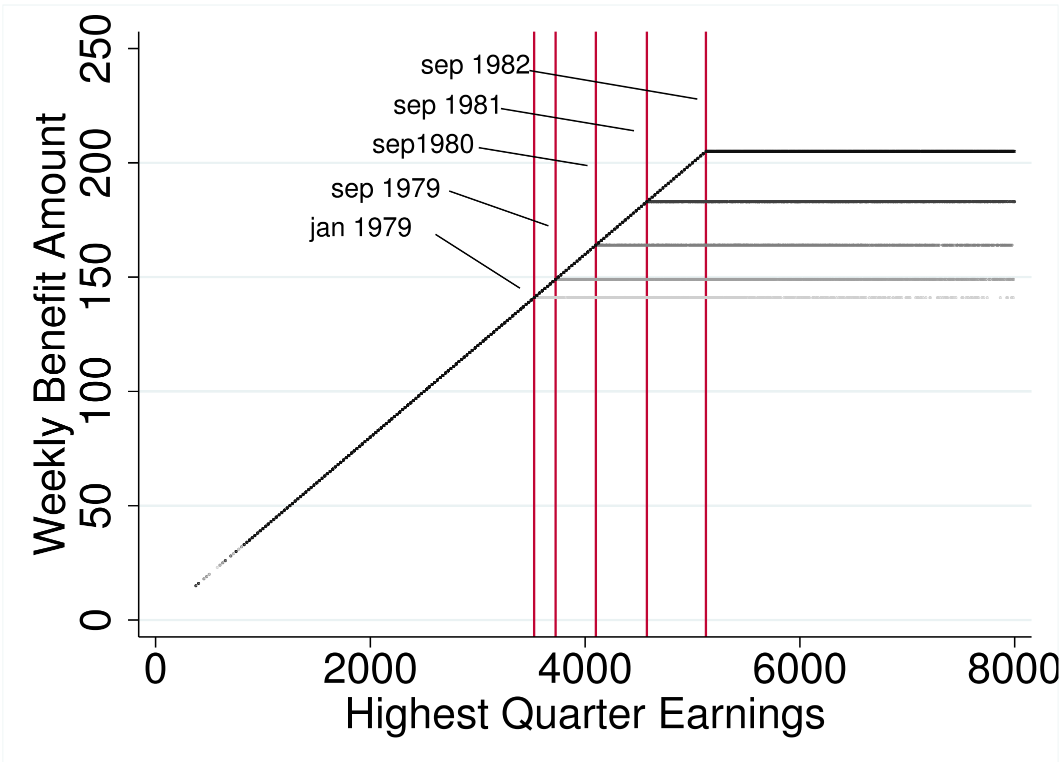
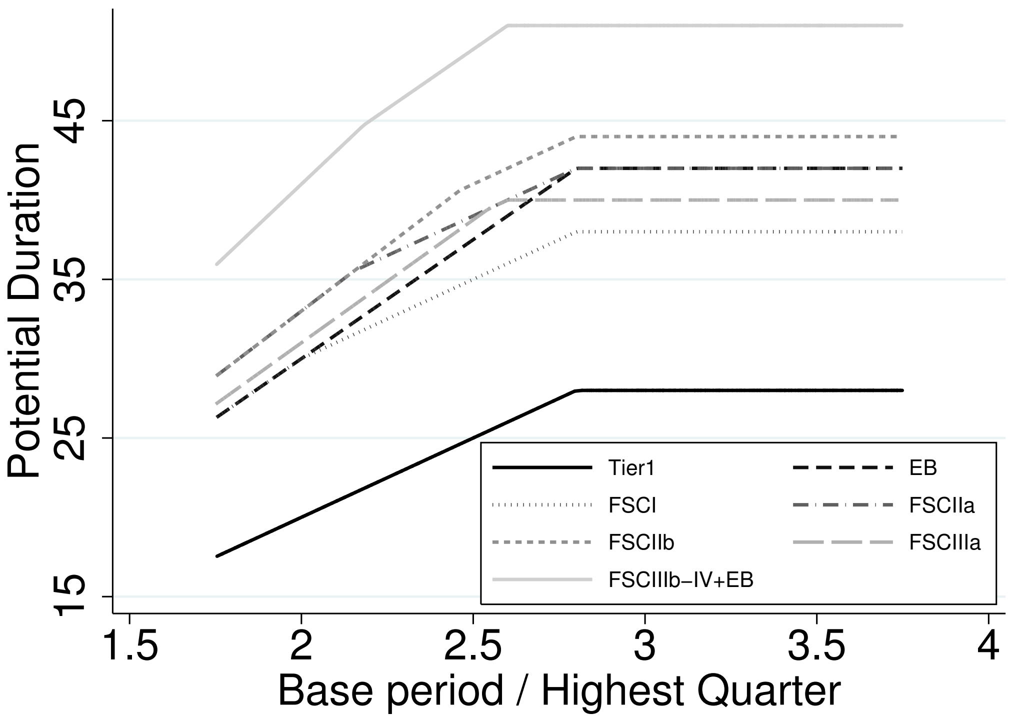
Figure 1: LOUISIANA: SCHEDULE OF UI WEEKLY BENEFIT AMOUNT, JAN1979-DEC1983



Sources: Louisiana Revised Statutes RS 23:1592 and yearly *Significant Provisions of State Unemployment Insurance Laws* 1976 to 1984, Dpt of Labor, Employment & Training Administration.
Notes: The graph shows the evolution of the schedule of the weekly benefit amount (WBA) as a deterministic and kinked function of the highest quarter of earnings in Louisiana. The schedule applies based on the date the UI claim was filed, so that a change in the maximum weekly benefit amount does not affect the weekly benefit amount of ongoing spells.

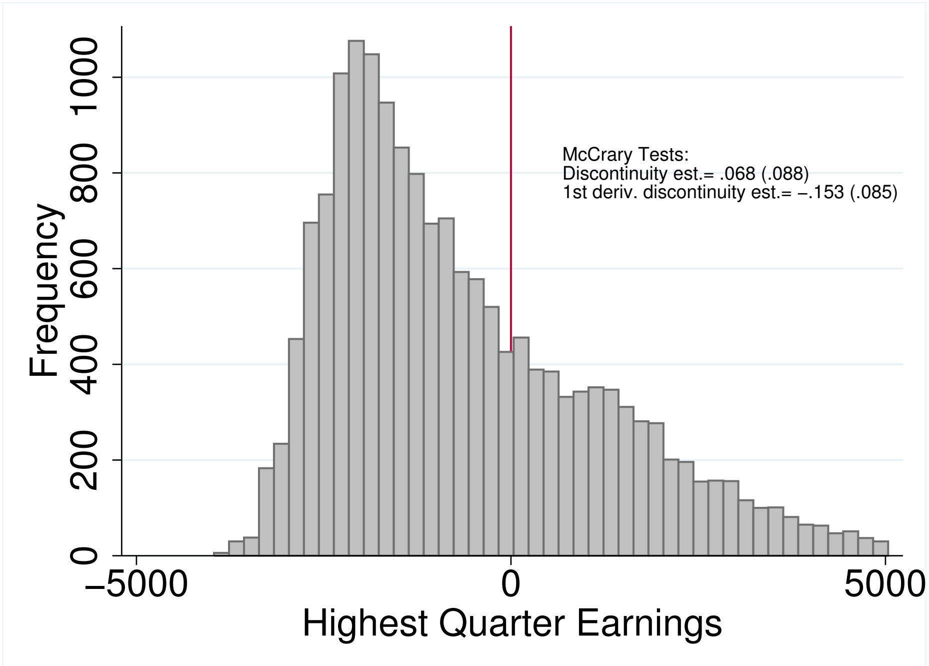
Figure 2: LOUISIANA: SCHEDULE OF UI POTENTIAL DURATION, JAN1979-DEC1983



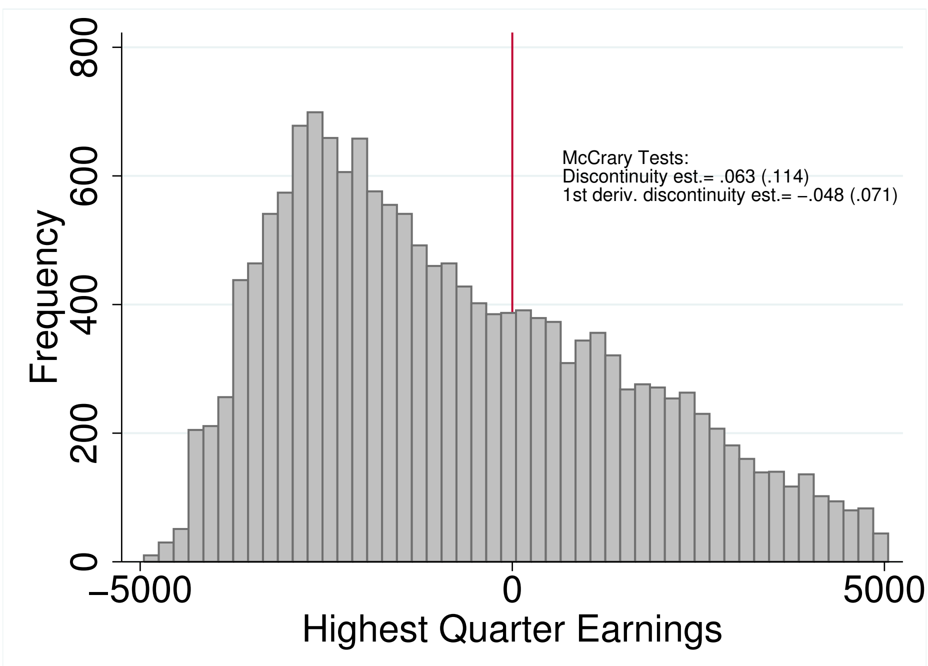
Sources: Louisiana Revised Statutes RS 23:1592 and weekly state trigger notice reports
Notes: The graph shows the evolution of the schedule of the potential duration of UI benefits as a deterministic and kinked function of the ratio of base period earnings to highest quarter of earnings in Louisiana. The schedule applies based on the date of the week of certified unemployment so that changes in the schedule do usually affect ongoing spells. Specific eligibility rules also apply to qualify for the different phases of the FSC.

Figure 3: LOUISIANA: NUMBER OF OBSERVATIONS IN EACH BIN OF HIGHEST QUARTER EARNINGS

A. JAN 1979 - SEPT 1981

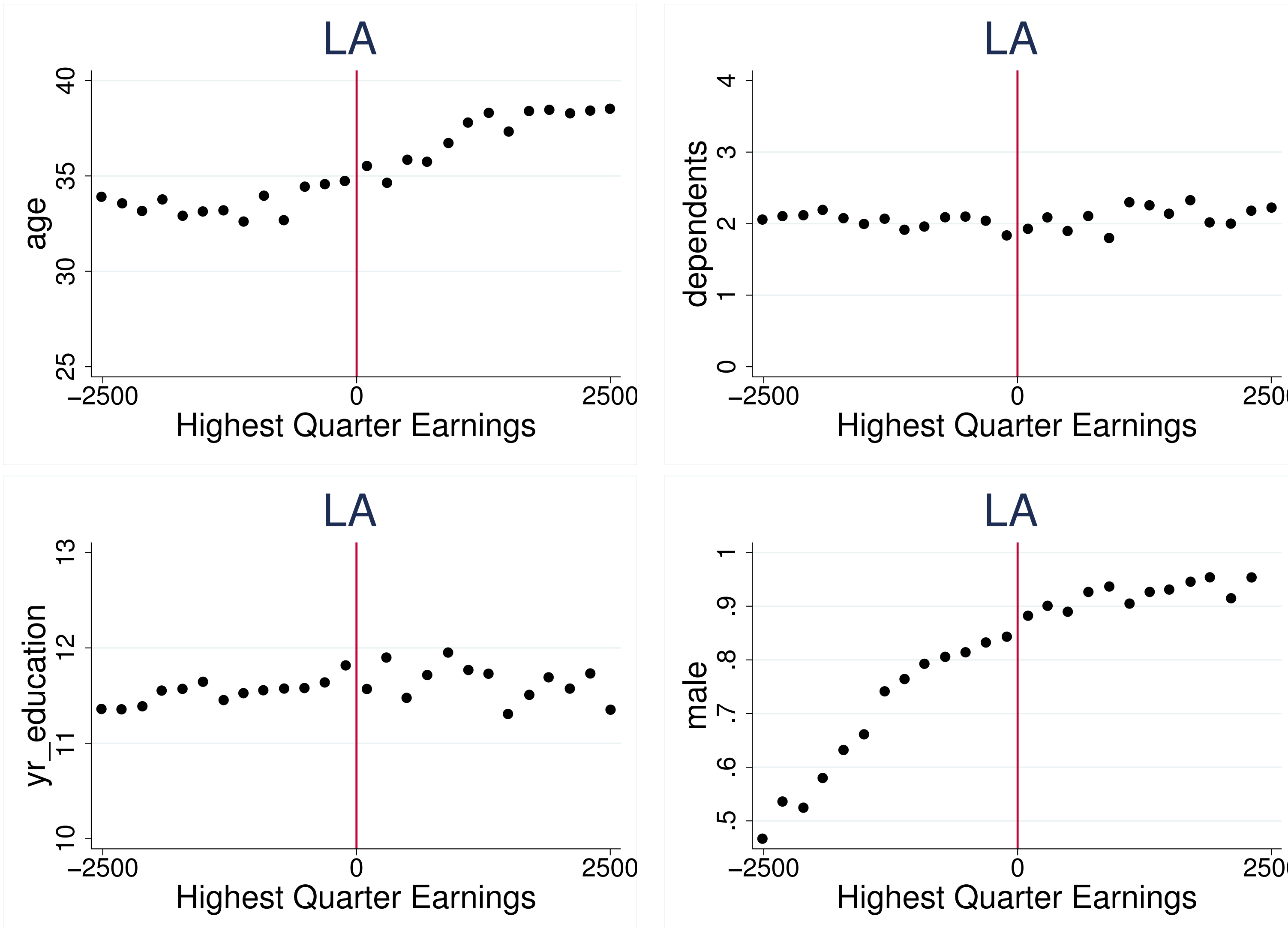


B. SEPT 1981 - DEC 1983



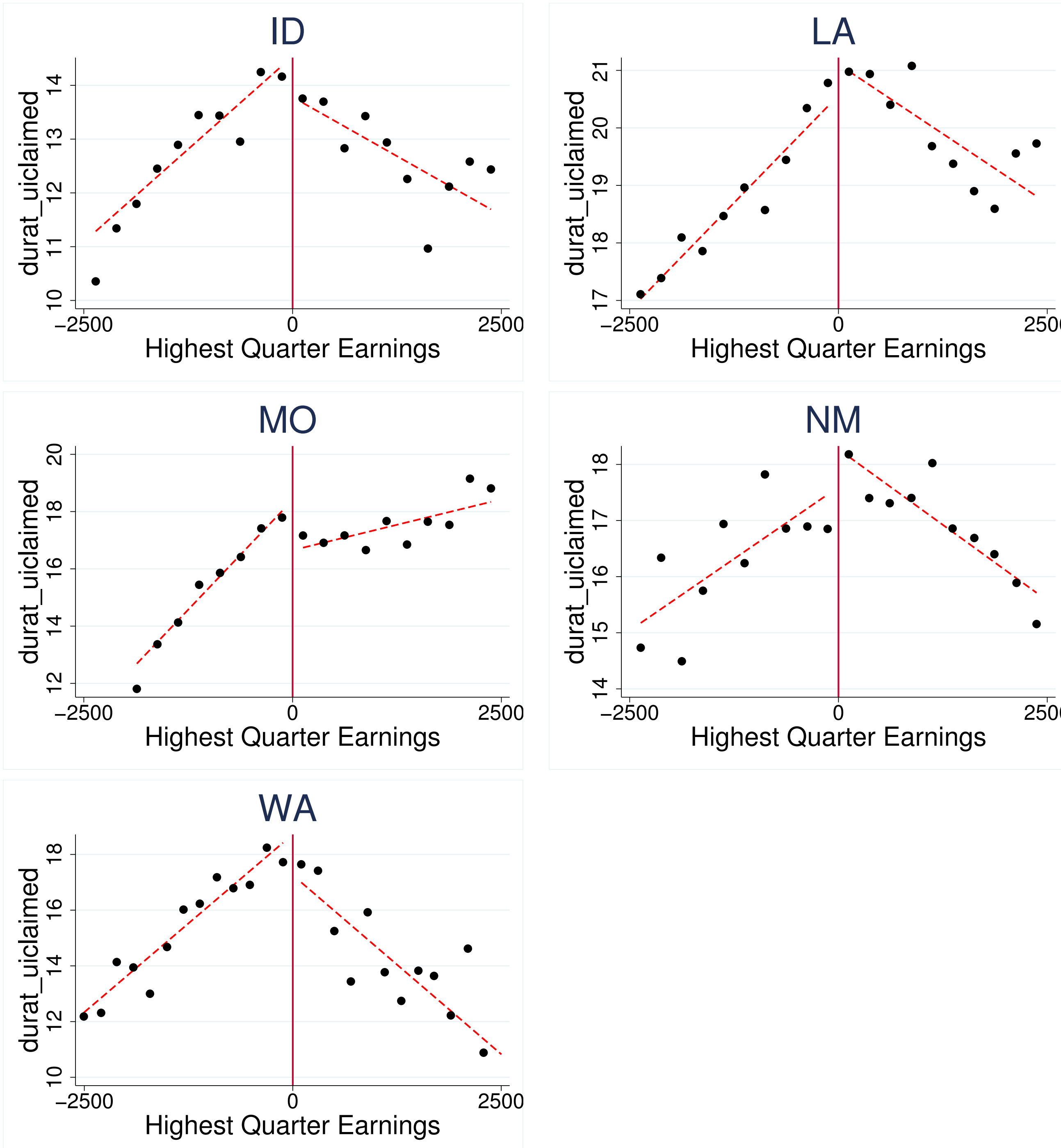
Notes: The graph shows the p.d.f of highest quarter of earnings, which is the assignment variable in the RK design for the estimation of the effect of benefit level. The assignment variable is centered at the kink. The binsize is 250 and passes the test of excess smoothing recommended in Lee and Lemieux [2010]. I also display two tests of the identifying assumptions of the RKD. The first is a standard McCrary test of the discontinuity of the p.d.f of the assignment variable. I report here the log difference in height of the p.d.f at the kink. The second is a test for the continuity of the first derivative of the p.d.f. I report here the coefficient estimate of the change in slope of the p.d.f in a regression of the number of individuals in each bin on polynomials of the assignment variable interacted with a dummy for being above the kink. See text for details.

Figure 4: COVARIATES VS HIGHEST QUARTER EARNINGS, LOUISIANA JAN 1979- SEP 1981



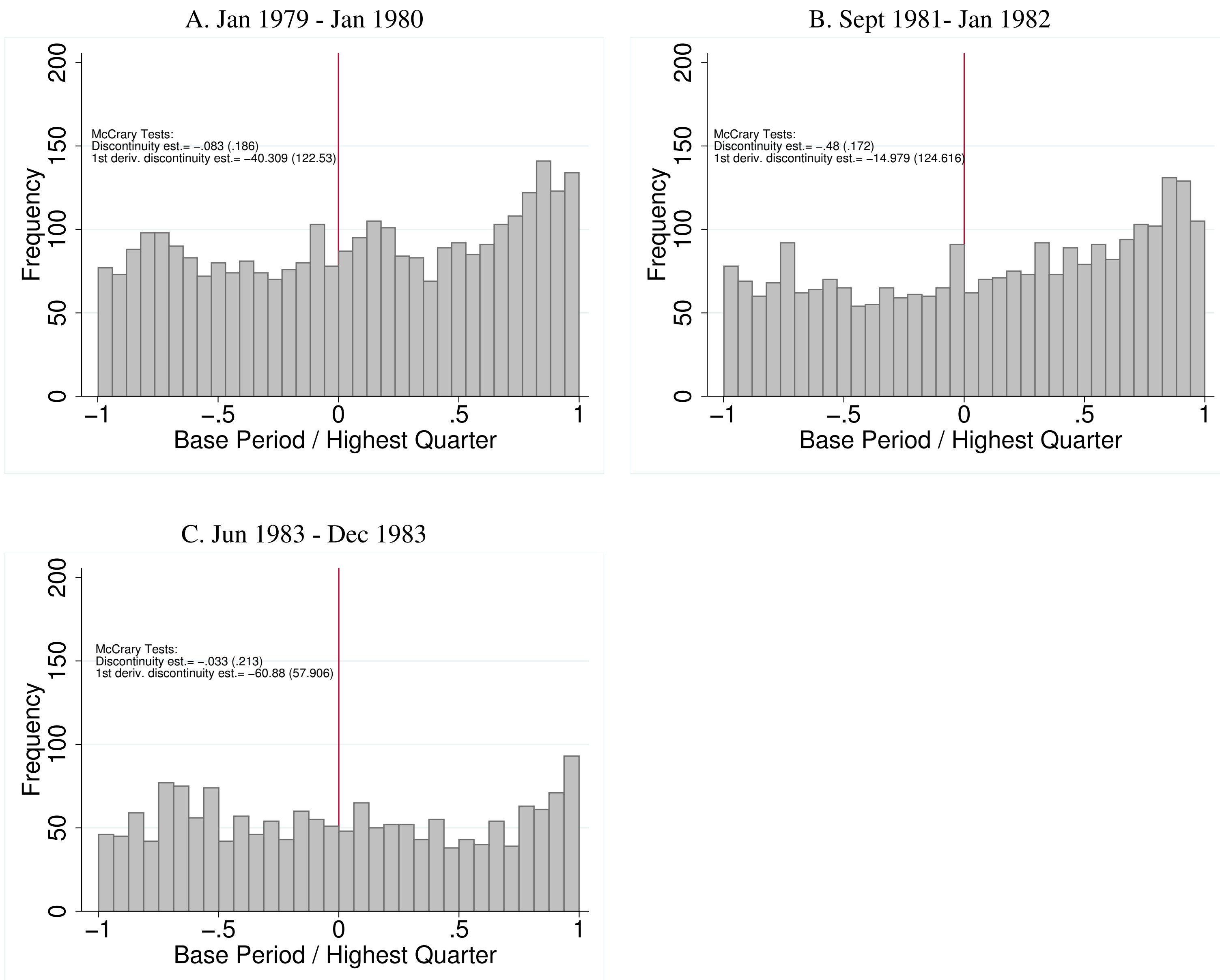
Notes: The graph shows for the first sub-period of analysis in Louisiana the mean values of the covariates in each bin of $250 of highest quarter of earnings, which is the assignment variable in the RK design for the estimation of the effect of benefit level. The assignment variable is centered at the kink. The graph shows evidence of smoothness in the evolution of covariates at the kink, in support of the RKD identification assumptions. Formal tests of smoothness are displayed in table 1.

Figure 5: RKD EVIDENCE OF THE EFFECT OF BENEFIT LEVEL: DURATION OF UI CLAIMS VS HIGHEST QUARTER EARNINGS FOR ALL 5 STATES



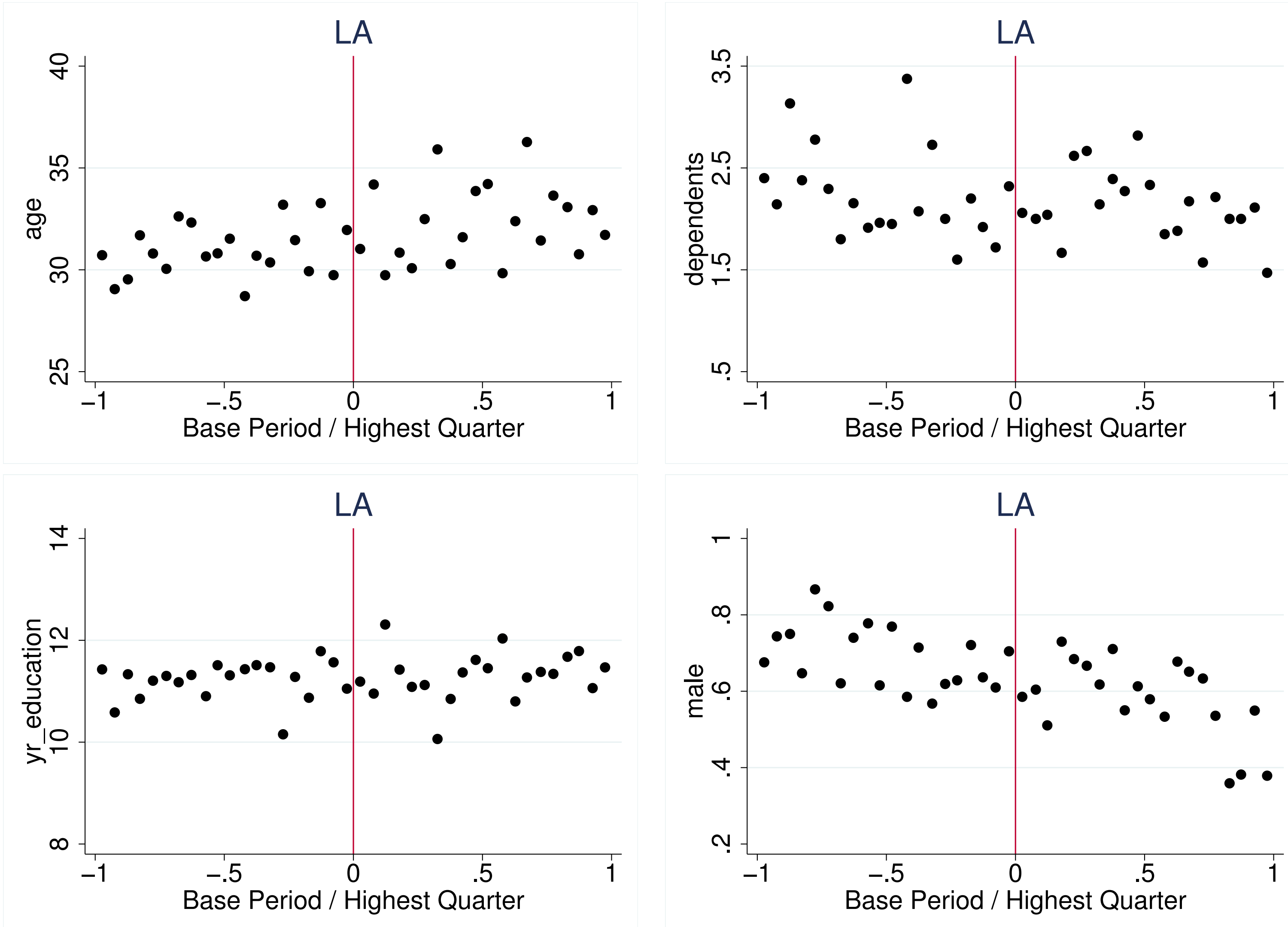
Notes: The graph shows for the first sub-period of analysis in each state the mean values of the duration of UI claims in each bin of $250 of highest quarter of earnings, which is the assignment variable in the RK design for the estimation of the effect of benefit level. The assignment variable is centered at the kink. The graph shows evidence of a kink in the evolution of the outcome at the kink. Formal estimates of the kink using polynomial regressions of the form of equation 5 are displayed in table 1. The red lines display predicted values of the regressions in the linear case allowing for a discontinuous shift at the kink.

Figure 6: LOUISIANA: NUMBER OF OBSERVATIONS IN EACH BIN OF THE RATIO BASE PERIOD / HIGHEST QUARTER EARNINGS



Notes: The graph shows the p.d.f of the ratio of base period to highest quarter earnings (centered at the kink), which is the assignment variable in the RK design for the estimation of the effect of potential duration. The binsize is .05 and passes the bin test of excess smoothing of Lee and Lemieux [2010]. The three sub-periods are chosen so that all individuals face a stable schedule for potential duration during the entire length of their potential duration.

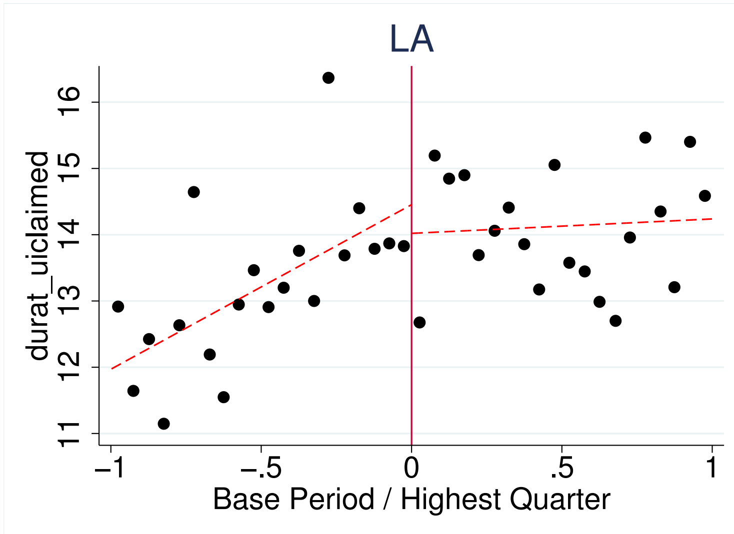
Figure 7: COVARIATES VS RATIO BASE PERIOD / HIGHEST QUARTER EARNINGS IN LOUISIANA FOR JUN 1983 - DEC 1983



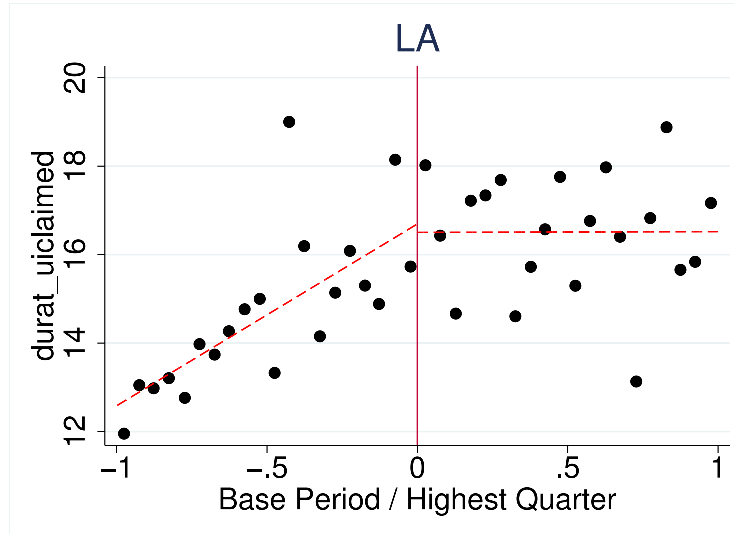
Notes: The graph shows for the last sub-period of analysis of potential duration in Louisiana the mean values of the covariates in each bin of .05 of the ratio of base period to highest quarter earnings, which is the assignment variable in the RK design for the estimation of the effect of potential duration. The assignment variable is centered at the kink. The graph shows evidence of smoothness in the evolution of covariates at the kink, in support of the RKD identification assumptions. Formal tests of smoothness are displayed in table 5.

Figure 8: RKD for the Effect of Potential Duration: Duration of UI claims vs Assignment Variable in Louisiana for 3 Periods

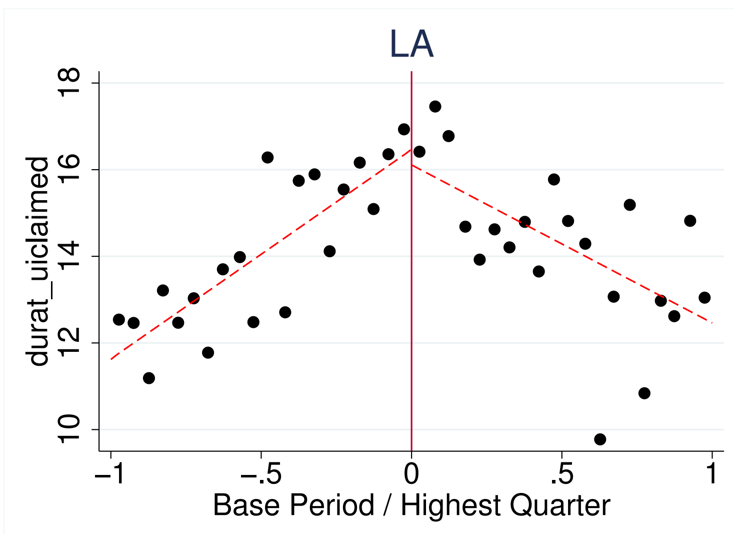
A. Jan 1979 - Jan 1980



B. Sept 1981- Apr 1982



C. Jun 1983 - Dec 1983



Notes: The graph shows for the three sub-periods of analysis of potential duration in Louisiana the mean values of the duration of initial spell in each bin of .05 of the assignment variable centered at the kink. The graph shows evidence of a kink in the evolution of the outcome at the kink. Formal estimates of the kink are displayed in table 5. The red lines display predicted values in the linear case allowing for a discontinuous shift at the kink.

Table 1: BASELINE RKD ESTIMATES OF THE EFFECT OF BENEFIT LEVEL, LINEAR SPECIFICATION, BANDWIDTH=2500, LOUISIANA JAN 1979 - DEC 1983

	(1) Duration of Initial Spell	(2) Duration UI Claimed	(3) Duration UI Paid	(4) Age	(5) Years of Education	(6) Male	(7) Dependents
	Period 1: Jan 1979- Sept 1981						
α	.036	.041	.038	-.013	-.001	-.001	-.006
	(.009)	(.009)	(.009)	(.103)	(.023)	(.003)	(.004)
$\varepsilon_b = \frac{dY}{db} \cdot \frac{b}{Y}$	.382	.421	.366				
	(.095)	(.095)	(.087)				
p-value	.968	.917	.948	.188	.346	.01	.462
N	8073	8073	8073	8036	7449	7983	4814
	Period 2: Sept 1981- Dec 83						
α	.053	.047	.048	.018	.001	-.001	-.004
	(.01)	(.01)	(.01)	(.098)	(.002)	(.003)	(.002)
$\varepsilon_b = \frac{dY}{db} \cdot \frac{b}{Y}$	.604	.552	.515				
	(.116)	(.115)	(.107)				
p-value	.396	.706	.442	.426	.085	.481	.414
N	6899	6899	6899	6852	6268	6807	3128

Notes: Duration outcomes are expressed in weeks. α is the RK estimate of the average treatment effect of benefit level on the outcome. Standard errors for the estimates of α are in parentheses. The elasticity of the three duration outcomes with respect to the UI benefit level $\varepsilon_b = \widehat{\alpha} \cdot \frac{b_{max}}{\overline{Y_1}}$, where $\overline{Y_1}$ is mean duration at the kink point, are also reported. P-values are from a test of joint significance of the coefficients of bin dummies in a model where bin dummies are added to the polynomial specification in equation 5.

Table 2: SENSITIVITY ANALYSIS OF THE RKD ESTIMATES, EFFECT OF BENEFIT LEVEL, LOUISIANA SEPT 81- DEC 83

	(1)	(2)	(3)		(4)	(5)	(6)
	A. Sensitivity to Poly Order				**B. Sensitivity to Bandwidth**		
	Duration of Initial Spell	Duration UI Claimed	Duration UI Paid		Duration of Initial Spell	Duration UI Claimed	Duration UI Paid
	Poly Order=1				**Bandwidth=1500**		
α	.053	.047	.048	α	.063	.05	.162
	(.01)	(.01)	(.01)		(.022)	(.021)	(.224)
p-value	.396	.706	.442	p-value	.405	.61	.277
AIC	53847.4	53323.4	53555.8	Opt. poly	1	1	3
N	6899	6899	6899	N	3972	3972	3972
	Poly Order=2				**Bandwidth=2500**		
α	.092	.075	.091	α	.063	.047	.072
	(.041)	(.039)	(.04)		(.104)	(.01)	(.102)
p-value	.478	.729	.549	p-value	.291	.706	.38
AIC	53849.5	53326.5	53558.1	Opt. poly	3	1	3
N	6899	6899	6899	N	6899	6899	6899
	Poly Order=3				**Bandwidth=4500**		
α	.063	.074	.072	α	.099	.076	.094
	(.104)	(.1)	(.102)		(.047)	(.046)	(.046)
p-value	.291	.551	.38	p-value	.2	.363	.208
AIC	53845.1	53324.0	53554.0	Opt. poly	3	3	3
N	6899	6899	6899	N	10024	10024	10024

Notes: The table explores the sensitivity of the results to the choice of the polynomial order (panel A) and of the bandwidth (panel B) for the regression specification in equation 5. In panel A, the bandwidth level is equal to 2500 for all specifications. α is the RK estimate of the average treatment effect of benefit level on the outcome. Standard errors for the estimates of α are in parentheses. P-values are from a test of joint significance of the coefficients of bin dummies in a model where bin dummies are added to the polynomial specification in equation 5. AIC is the Aikake Information Criterion.

Table 3: BASELINE RKD ESTIMATES OF THE EFFECT OF BENEFIT LEVEL WITH MORE SUB-PERIODS, LOUISIANA JAN 1979 - DEC 1983

		(1) Duration of Initial Spell	(2) Duration UI Claimed	(3) Duration UI Paid
Jan-Sep 79	α	.024	.028	.026
		(.018)	(.019)	(.018)
	p-value	.19	.146	.264
	N	1898	1898	1898
Sep 79-Sep 80	α	.043	.048	.043
		(.015)	(.015)	(.015)
	p-value	.224	.104	.166
	N	3399	3399	3399
Sep 80-Sep 81	α	.035	.038	.037
		(.015)	(.015)	(.014)
	p-value	.049	.023	.035
	N	2776	2776	2776
Sep 81-Sep 82	α	.051	.04	.05
		(.018)	(.017)	(.017)
	p-value	.108	.19	.176
	N	2905	2905	2905
Sep 82-Dec 83	α	.055	.052	.047
		(.012)	(.012)	(.012)
	p-value	.597	.739	.513
	N	3994	3994	3994

Notes: The table explores the sensitivity of the results to the number of sub-periods of analysis. α is the RK estimate of the average treatment effect of benefit level on the outcome. Standard errors for the estimates of α are in parentheses. P-values are from a test of joint significance of the coefficients of bin dummies in a model where bin dummies are added to the polynomial specification in equation 5. The displayed estimates are for the optimal polynomial order chosen to minimize the Aikake Information Criterion.

Table 4: Washington: Estimates of the Effect of Benefit Level on Unemployment and Non-Employment Duration

	Duration Initial Spell	Duration UI Claimed	Duration UI Paid	Non-Employment Duration
	Period 1: July 1979- July 1980			
α	.085	.078	.087	.088
	(.018)	(.017)	(.018)	(.022)
ε_b	.68	.69	.657	.419
	(.147)	(.152)	(.136)	(.104)
Opt. Poly	1	1	1	1
p-value	.162	.197	.198	.327
N	3485	3485	3485	3485
	Period 2: July 1980- July 1982			
α	.07	.059	.077	.056
	(.017)	(.016)	(.017)	(.02)
ε_b	.583	.546	.591	.278
	(.138)	(.146)	(.128)	(.097)
Opt. Poly	1	1	1	1
p-value	.987	.991	.985	.968
N	3601	3601	3601	3601
	Period 3: July 1982- Dec 1983			
α	.054	.035	.055	.059
	(.021)	(.02)	(.021)	(.022)
ε_b	.37	.263	.351	.281
	(.146)	(.153)	(.137)	(.105)
Opt. Poly	1	1	1	1
p-value	.022	.036	.009	.183
N	4275	4275	4275	4275

Notes: Duration outcomes are expressed in weeks. α is the RK estimate of the average treatment effect of the UI benefit level on the outcome. Standard errors for the estimates of α are in parentheses. P-values are from a test of joint significance of the coefficients of bin dummies in a model where bin dummies are added to the polynomial specification in equation 5. The optimal polynomial order is chosen based on the minimization of the Aikake Information Criterion.

Table 5: BASELINE RKD ESTIMATES OF THE EFFECT OF POTENTIAL DURATION, LOUISIANA

	(1) Duration of Initial Spell	(2) Duration UI Claimed	(3) Duration UI Paid	(4) Age	(5) Years of Education	(6) Male	(7) Dependents
	Period 1: Jan 1979 - Jan 1980						
β	.216	.185	.222	-.107	.014	.004	-.013
	(.119)	(.12)	(.117)	(.167)	(.032)	(.006)	(.026)
p-value	.685	.596	.65	.163	.123	.519	.072
N	3107	3107	3107	3091	2839	3078	1952
Opt. Poly	1	1	1	1	1	1	1
	Period 2: Sep 1981 - Apr 1982						
β	.3	.299	.272	.071	.013	-.007	-.016
	(.103)	(.099)	(.099)	(.113)	(.024)	(.004)	(.025)
p-value	.593	.546	.488	.416	.118	.31	.427
N	2659	2659	2659	2644	2415	2624	951
Opt. Poly	1	1	1	1	1	1	1
	Period 3: Jun 1983 - Dec 1983						
β	.502	.456	.457	-.004	-.003	-.028	-.092
	(.087)	(.081)	(.084)	(.096)	(.025)	(.017)	(.082)
p-value	.746	.837	.747	.837	.492	.234	.264
N	1750	1750	1750	1738	1586	1731	935
Opt. Poly	1	1	1	1	1	2	2

Notes: Duration outcomes are expressed in weeks. β is the RK estimate of the average treatment effect of potential duration on the outcome. Standard errors for the estimates of α are in parentheses. P-values are from a test of joint significance of the coefficients of bin dummies in a model where bin dummies are added to the polynomial specification in equation 5. The optimal polynomial order is chosen based on the minimization of the Aikake Information Criterion.

Table 6: RKD ESTIMATES OF BEHAVIORAL RESPONSES TO UI, TESTS FOR THE SLACKNESS OF THE LIQUIDITY CONSTRAINTS, AND LIQUIDITY EFFECT ESTIMATES, WASHINGTON, JUL 1980 - JUL 1981

	(1)	(2)	(3)	(4)
	Test for slackness of the liquidity constraint	**Effect of benefit level**	**Effect of potential duration**	**Liquidity and moral hazard estimates**
$\frac{\partial s_{B+1}}{\partial b_B}$	-.0019			
	(.00082)			
	[.337]			
ε_{D_B}		.689	1.361	
		(.114)	(.685)	
		[.842]	[.382]	
ε_D		.356	.446	
		(.076)	(.434)	
		[.893]	[.163]	
$(\frac{1}{B}\frac{\partial s_0}{\partial b}\Big\|_B - \frac{1}{b}\frac{\partial s_0}{\partial B}) \times 10^3$				-.068
				(.01)
Θ_1				.0023
				(.00029)
ρ_1				.440
				(.018)
N	529	5772	2047	7819

Notes 1: For all columns, standard errors for the estimates are in parentheses. P-values are reported between brackets and are from a test of joint significance of the coefficients of bin dummies in a model where bin dummies are added to the polynomial specification in equation 5. The optimal polynomial order is chosen based on the minimization of the AIC. The bandwidth for the RK estimate of benefit level is 2500 (assignment variable: highest quarter of earnings) and .75 for the RK estimate of the potential duration (assignment variable: ratio of base period to highest quarter of earnings).
Notes 2: This table shows how to use the RKD to estimate all the statistics entering the formula of proposition (1) to calibrate the welfare effects of UI. Column (1) begins by testing for the slackness of the liquidity constraint. It reports the RK estimate of $b \cdot \frac{\partial s}{\partial b_B}$, the effect of one additional dollar of UI before 39 weeks on the exit rate of unemployment after exhaustion, between 40 weeks and 60 weeks. The estimates suggest that the Euler equation holds and that variations in benefits prior to exhaustion affect exit rate of unemployment after the exhaustion point. Column (2) reports the RKD estimate of the elasticity of UI duration (ε_{D_B}) and of the elasticity of non-employment duration (ε_D) with respect to benefit level. Column (3) reports the RKD estimate of the same elasticities with respect to potential duration. Column (4) reports the liquidity effect estimates following the strategy detailed in section 4.2. $(\frac{1}{B}\frac{\partial s_0}{\partial b}\Big|_B - \frac{1}{b}\frac{\partial s_0}{\partial B})$ is the difference between the RKD estimate of the effect of benefit level (divided by the potential duration) and the RKD estimate of the effect of potential duration (divided by the benefit level) on s_0 defined as the exit rate out of unemployment in the first 4 weeks of unemployment. To ensure that the characteristics of individuals at both kinks (in benefit level and potential duration) are the same, I use a reweighing approach described in appendix B. Following proposition 2, this difference is then used to compute the moral hazard effect Θ_1 of an increase in benefit level and the ratio of liquidity to moral hazard ρ_1 in the effect of an increase in benefit level. For the three statistics of column (4), bootstrapped s.e. with 50 replications are in parentheses. See text for additional details.

Appendix. NOT FOR PUBLICATION

Appendix A: State UI Information

Information on state UI laws come from the *Significant Provisions of State Unemployment Insurance Laws*, published bi-annually by the US Dept of Labor, Employment and Training Administration. I consulted state laws and state employment agencies for more detailed information on benefit schedule variations[54].

Idaho

In Idaho, the fraction of highest quarter of earnings to compute the weekly benefit amount is $1/26$ for the whole period 1976 to 1984.

Maximum benefit amount
The maximum benefit amount in Idaho in January 1976 is $b_{max} = \$90$.
It was then increased seven times until December 1983:
\$99 for claims filed after 04jul1976
\$110 for claims filed after 01jul1977
\$116 for claims filed after 01jul1978
\$121 for claims filed after 01jul1979
\$132 for claims filed after 01jul1980
\$145 for claims filed after 01jul1981
\$159 for claims filed after 20jun1982.

Minimum benefit amount
The minimum benefit amount in Idaho in January 1976 is $b_{min} = \$17$.
It was then increased twice until December 1983:
\$36 for claims filed after 01jul1980
\$45 for claims filed after 01jan1984.

Duration of Benefits
Idaho has a special determination rule for potential duration described in table A1.

[54] CWBH has exhaustive information in Georgia on unemployment spells and wage records. But because of the parameters of the UI system in Georgia, the RK design was inoperable. $\tau_1 = 1/25$, $D_{max} = 26$, $\tau_2 = 1/4$ so that $D_{max} \cdot \frac{\tau_1}{\tau_1} > 4$ always larger than $\frac{bpw}{hqw}$ for all individuals on the left side of the benefit level kink. I don't have any observation with only kink in benefit level at the kink.

Table A1: Determination of Potential Duration 1st tier UI Idaho: 1976-1984

Ratio of bqw/hpw		UI Duration	
At Least...	Less Than...	before Jul 1st 1983	after Jul 1st 1983
1.25	1.50	10	
1.50	1.750	12	10
1.750	2.00	14	12
2.00	2.250	16	14
2.250	2.500	18	16
2.500	2.750	20	18
2.750	3.000	22	20
3.000	3.250	24	22
3.250	3.500	26	24
3.500	–	26	26

Louisiana

In Louisiana, the fraction of highest quarter of earnings to compute the weekly benefit amount is $1/25$ for the whole period 1979 to 1984.

Maximum benefit amount

The maximum benefit amount in Louisiana in January 1979 is $b_{max} = \$141$.
It was then increased four times until December 1983:
\$149 for claims filed after 02sep1979
\$164 for claims filed after 07sep1980
\$183 for claims filed after 06sep1981
\$205 for claims filed after 05sep1982

Minimum benefit amount

The minimum benefit amount in Louisiana from January 1979 until December 1983 is always \$10.

Duration of Benefits

The fraction of base period earnings to determine the total amount of benefits payable for a given benefit year is 2/5. The maximum duration of benefits was set at 28 weeks. It was reduced to 26 weeks for claims filed after 03apr1983.

Missouri

In Missouri, the fraction of highest quarter of earnings to compute the weekly benefit amount is $1/20$ from the beginning of the period covered by the CWBh data (January 1978) until December 2nd, 1979 when it becomes .045.

Maximum benefit amount

The maximum benefit amount in Missouri in January 1978 is $b_{max} = \$85$.
It was then increased only once until December 1983:
$105 for claims filed after02dec1979.

Minimum benefit amount

The minimum benefit amount in Missouri from January 1979 until December 1983 is always $15.

Duration of Benefits

The fraction of base period earnings to determine the total amount of benefits payable for a given benefit year is 1/3. The maximum duration of benefits is 26 weeks for the whole period covered by the CWBH data.

New Mexico

In New Mexico, the fraction of highest quarter of earnings to compute the weekly benefit amount is $1/26$ for the whole period covered by the CWBh data (January 1980 to December 1983).

Maximum benefit amount

The maximum benefit amount in New Mexico in January 1980 is $b_{max} = \$106$.
It was then increased three times until December 1983:
$105 for claims filed after02dec1979.
$117 for claims filed after 01jan1981
$130 for claims filed after 01jan1982
$142 for claims filed after 01jan1983

Minimum benefit amount

The minimum benefit amount in New Mexico in January 1980 is $22.
It was then increased to: $24 for claims filed after 01jan1981
$26 for claims filed after 01jan1982
$29 for claims filed after 01jan1983

Duration of Benefits

The fraction of base period earnings to determine the total amount of benefits payable for a given benefit year is 3/5. The maximum duration of benefits is 26 weeks for the whole period covered by the CWBH data.

Washington

In Washington, the weekly benefit amount is computed as a fraction of the average of the two highest quarters of earnings. The fraction to compute the weekly benefit amount is $1/25$ for the whole period covered by the CWBh data (June 1979 to December 1983).

Maximum benefit amount

The maximum benefit amount in Washington in June 1st, 1979 is $b_{max} = \$128$.
It was then increased to:
$137 for claims filed after 25jun1979
$150 for claims filed after 06jul1980
$163 for claims filed after 01jul1981
$178 for claims filed after 01jul1982
$185 for claims filed after 01jul1983

Minimum benefit amount

The minimum benefit amount in in Washington in June 1979 is always $17.
It was then increased to: $41 for claims filed after 06jul1980
$45 for claims filed after 01jul1981
$49 for claims filed after 01jul1982
$51 for claims filed after 01jul1983

Duration of Benefits

The fraction of base period earnings to determine the total amount of benefits payable for a given benefit year is 1/3. The maximum duration of benefits is 30 weeks for the whole period covered by the CWBH data.
Note that until February 26, 1983, the state of Washington provides for 13 weeks of State-funded additional benefits for individuals who have exhausted their regular and Federal-State Extended Benefits[55]. However, no additional benefit period was paid while a Federal program was in effect.

[55] The additional benefits correspond to an *ad hoc* program which is triggered on only if the Governor determines it necessary.

EB trigger dates

Information on national and state triggers and trigger dates comes from the weekly trigger notice reports of the Bureau of Labor Statistics. Note that in the weekly trigger notice reports, there are sometimes some slight adjustments ex-post because of lags in the computation of the IUR triggers. I therefore rely on ex post trigger notices where the starting and ending dates of each episodes of EB are indicated.

National Trigger Dates
Until the Omnibus Budget Reconciliation Act of 1981, (effective July 1st 1981), the EB system had two triggers. A national trigger and state specific triggers. During the period 1976 to 1981, the national trigger was on three times, from 2/23/1975 to 7/2/1977, from 8/28/1977 to 01/28/1978, and from 7/20/1980 to 1/24/1981, automatically triggering periods of EB in all US states.

Idaho Trigger Dates
During the period 1976 to 1984, and on top of national EB periods, the EB trigger for Idaho was on four times: from 4/30/1978 to 7/29/1978, from 2/25/79 to 6/6/1979, from 2/17/80 to 7/18/81, and finally from 10/18/81 to the end of the period covered by the CWBH data.

Louisiana Trigger Dates
During the period 1979 to 1984, and on top of national EB periods, the EB trigger for Louisiana was on three times: from 7/20/1980 to 1/24/1981, from 9/12/1981 to 10/23/1982, and finally from 1/23/83 to the end of the period covered by the CWBH data.

Missouri Trigger Dates
During the period 1978 to 1984, and on top of national EB periods, the EB trigger for Missouri was on twice: from 6/1/80 to 7/25/1981, and from 3/26/1982 to 6/19/82.

New Mexico Trigger Dates
During the period 1980 to 1984, and on top of national EB periods, the EB trigger for New Mexico was on only once from 8/29/82 to 11/27/82

Washington Trigger Dates
During the period 1979 to 1984, and on top of national EB periods, the EB trigger for Washington was on without interruption from 7/6/1980 to 7/2/83.

Table A2: DESCRIPTIVE STATISTICS FOR FULL CWBH SAMPLE

	Idaho			Louisiana			Missouri			New Mexico			Washington		
	Mean	s.d.	N	Mean	s.d.	N	Mean	s.d.	N	Mean	s.d.	N	Mean	s.d.	N
	Duration Outcomes (wks)														
Initial spell	13.9	12.4	33365	14	10.6	34077	12.2	10.9	28665	14	12.6	27004	17.6	15.4	41992
wks UI paid	11.7	10.7	33365	13.8	10.4	34077	12.5	11.3	28665	13.4	12.8	27004	16.2	14.8	41992
wks UI claim	15.8	12.2	33365	15.1	10.4	34077	15.4	11.8	28665	15.8	12.6	27004	18.9	15.4	41992
	Earnings and Benefits ($2010)														
bpw	25136	22164	33365	26993	19446	34077	23733	17334	28665	23334	17132	27004	31232	20380	41992
hqw	9827	16405	33365	9581	6441	34077	8211	5830	28665	8252	5382	27004	8982	5321	41992
wba	262.4	86.3	33365	304.8	117.1	34077	225	51.4	28665	230	69.5	27004	286.7	94.7	41992
potential duration Tier I	20	5.5	33365	25	4.4	34077	22.1	5.2	28665	25.7	1	27004	27	4.2	41992
	Covariates														
age	30.2	12.7	33361	34.6	12.7	33850	34.8	12.7	28651	33.7	11.4	26924	34.2	11.9	41955
male	.666	.471	33361	.683	.465	33624	.609	.488	28663	.651	.477	27002	.627	.484	41972
educ. (yrs)	12	2.2	17774	11.4	2.7	31272	11.3	2.2	1867	11.7	2.5	26482	12.4	2.4	41702
dependents	2	1.6	18781	2	1.6	17325	2	1.6	21746	2.2	1.7	25534	1.7	1.5	28834
censored	.165	.362	33365	.128	.323	34077	.151	.382	28665	.162	.336	27004	.107	.289	41992

Notes: The initial spell, as defined in Spiegelman et al. [1992], starts at the date the claim is filed and ends when there is a gap of at least two weeks in the receipt of UI benefits. The duration of paid UI corresponds to the number of weeks a claimant receives unemployment compensation. The duration of a UI claim is the number of weeks a claimant is observed in the administrative data for a given unemployment spell. bpw is the base period earnings, and hqw is the highest quarter of earnings. wba is the weekly benefit amount of UI. Potential duration Tier I is the potential duration of the regular state UI program. In Missouri, information on education level is almost always unavailable.

Appendix B: Additional Results, Figures and Tables

RKD in Double-Difference

One main issue with the identifying assumptions of the RK design concerns the functional dependence between the forcing variable and the outcome of interest. It could be that the relationship between the forcing variable and the outcome is either kinked or quadratic. Then estimates are likely to be picking up this functional dependence between y and w_1.

A simple way to understand the issue is to remember the basic intuition behind the RK design. The model that I am interested in is $y = f(b, w_1, \varepsilon)$, where I want to get an estimate of f_1'. In this model, we have: $\frac{dy}{dw_1} = f_1' \frac{\partial b}{\partial w_1} + f_2' + f_3' \frac{\partial \varepsilon}{\partial w_1}$. The RKD assumes that f_2' and f_3' are the same on both sides of the kink (smoothness assumptions). Then, it follows that

$$\frac{\underset{k^+,k^-}{\Delta} \frac{dy}{dw_1}}{\underset{k^+,k^-}{\Delta} \frac{\partial b}{\partial w_1}}$$

identifies f_1', because $\underset{k^+,k^-}{\Delta} f_2' = 0$ and $\underset{k^+,k^-}{\Delta} f_3' = 0$.
If the assumption of smoothness in the functional dependence between the forcing variable and the outcome is violated, meaning that $\underset{k^+,k^-}{\Delta} f_2' \neq 0$ then, identification is not possible in the standard RKD. But if we have two sets of observations A and B for which we are willing to assume that $\underset{k^+,k^-}{\Delta} f_2'$ is the same, and for these two groups

$$\underset{k^+,k^-}{\Delta} \frac{\partial b}{\partial w_1}$$

is different, then f_1' is identified by α_{DD}, where:

$$\alpha_{DD} = \frac{\underset{A,B}{\Delta} \underset{k^+,k^-}{\Delta} \frac{dy}{dw_1}}{\underset{A,B}{\Delta} \underset{k^+,k^-}{\Delta} \frac{\partial b}{\partial w_1}} \tag{7}$$

Such an identification strategy is reminiscent of double-difference strategies. In practice it consists in comparing the change in slope at point k in the relationship between the outcome and the forcing variable for two identical groups of observations, but one of the two groups is subject to a kink in the schedule of b at k, and the other group is not.

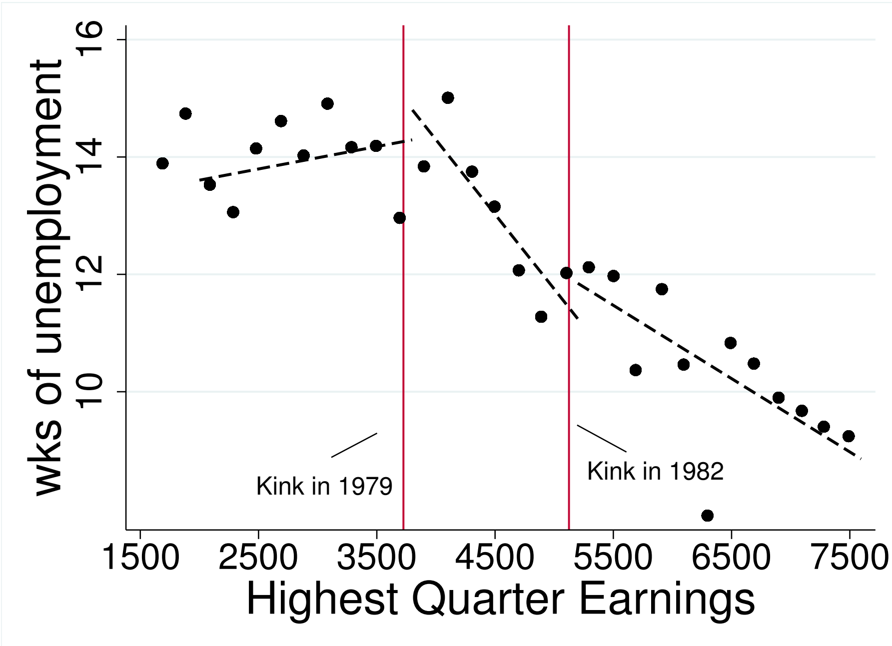
To implement this strategy, the idea is to use the presence of variations in the maximum benefit amount over time, that shift the position of the kink across the distribution of the forcing variable (as shown in figure 1). The problem though is that, taken separately, each variation in max_b is too small to give enough statistical power to detect changes in slopes because the bandwidths are too small, and as previously pointed out, the drawback of the RKD is to be quite demanding in terms of bandwidth size. The idea therefore is to compare periods that are further away in time.

The obvious drawback of this option is that the identifying assumption is less likely to hold as one compares periods that are further away in time. In particular, one may worry about the high inflation rates during this period. It is important to note here that the maximum benefit amount increased in Louisiana a lot faster than inflation (40% between September 1979 and Sept 1982 and total inflation was less than 20% during that period), so that there is a clear and important change in the schedule in *real* terms [56]. Figure B1 shows the relationship between the duration of paid unemployment and the forcing variable in 1979 and 1982. Interestingly, there is a kink in this relationship in 1979 at the level of the 1979-kink in the schedule, and this kink disappears in 1982, when a new kink appears right at the level of the 1982-kink. Furthermore, in the interval between the 1979 and 1982 kinks, there is a change in slope in the relationship between the duration of unemployment and the forcing variable. This evidence is strongly supportive of the validity of the RK design.

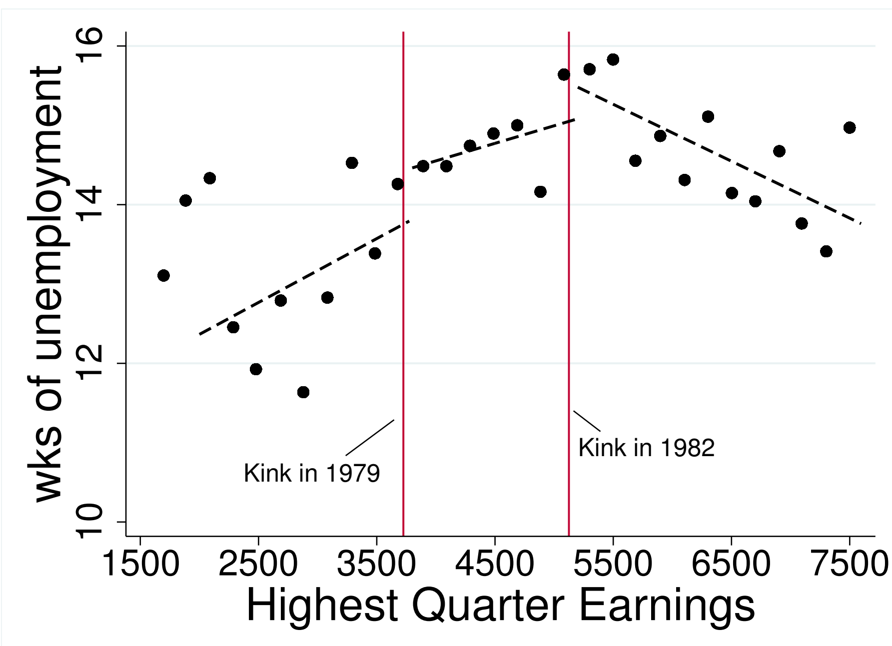
[56] To further alleviate this concern, I also control for quadratic in *real* highest quarter of earnings in the DD-RKD specifications and find similar results.

Figure B1: RKD in Double-Difference using variations in the maximum benefit level, Louisiana, 1979 vs 1982

A. 1979



B. 1982



Notes: The graph shows the average value of the duration of paid unemployment in each bin of the forcing variable in 1979 (panel A) and 1982 (panel B). The maximum benefit amount has been increased by more than 40% during the period, shifting the position of the kink in the schedule across the distribution of the forcing variable, as shown by the two red bars indicating the position of the kink for the two periods. The change in slope between the two periods in the interval between the two kinks is indicative of an effect of *b* on *y*, and can be used to identify the average treatment effect of *b* in a double-difference RKD. See text for details.

Table B1: DOUBLE-DIFFERENCE RKD ESTIMATES OF THE EFFECT OF BENEFIT LEVEL USING VARIATIONS IN THE MAXIMUM BENEFIT LEVEL, LOUISIANA, 1979 VS 1982

	(1)	(2)	(3)	(4)	(5)	(6)
	Duration of Initial Spell	Duration UI Claimed	Duration UI Paid	Duration of Initial Spell	Duration UI Claimed	Duration UI Paid
	A. 1979 Kink			**B. 1982 Kink**		
α_{DD}	.064	.088	.051	.065	.069	.05
	(.035)	(.035)	(.035)	(.034)	(.034)	(.034)
h_-	2500	2500	2500	1400	1400	1400
h_+	1400	1400	1400	2500	2500	2500
Opt. Poly	1	1	1	1	1	1
N	6495	6495	6495	4744	4744	4744

Notes: The table reports the results of the implementation of a Double-Difference RKD using variations in the maximum benefit amount over time, as described in the previous subsection. α_{DD} is the Double-Difference RKD estimate of the average treatment effect of benefit level as described in equation (7). It consists in comparing the change in slope at point k in the relationship between the outcome and the forcing variable for two identical groups of observations, but one of the two groups is subject to a kink in the schedule of b at k, and the other group is not. Standard errors for the estimates of α_{DD} are in parentheses. There are two sets of DD-RKD estimates, one for each kink. For the 1979-kink, I compare the change in slope in the duration of unemployment spells at the level of the 1979-kink in the forcing variable for the unemployed in 1979 (who had a schedule of benefit kinked at that point) against the unemployed in 1982 (who had a continuous schedule of benefits at that point). For the 1982-kink, I compare the change in slope in the duration of unemployment spells at the level of the 1982-kink in the forcing variable for the unemployed in 1982 (who had a schedule of benefit kinked at that point) against the unemployed in 1979 (who had a continuous schedule of benefits at that point). h_- and h_+ are the sizes of the lower and upper bandwidth. The optimal polynomial order is chosen based on the minimization of the AIC.

Placebo forcing variable

Another way to test for the existence of a kinked or quadratic functional dependence between earnings and unemployment duration is to use a placebo forcing variable. The placebo needs to be a good proxy for lifetime earnings, but must not be too correlated with the highest quarter of earnings that determines the benefit level. Table B2 explores the robustness of the RKD results by using the post unemployment wage as a placebo forcing variable instead of the pre-unemployment highest quarter of earnings. The post unemployment wage used is the wage for the first quarter of full employment after an unemployment spell. Post unemployment wages are available only for spells starting after September 1979 in Louisiana. Post unemployment wages are correlated with lifetime earnings but are not too much correlated with the highest quarter of earnings that determines the benefit level. Therefore, this table explores to what extent the baseline results are driven by some functional dependence between earnings and unemployment duration and shows that we cannot detect any effect in these placebo specifications using post unemployment wages as a forcing variable.

Table B2: ROBUSTNESS: RKD ESTIMATES OF THE EFFECT OF BENEFIT LEVEL USING POST UNEMPLOYMENT WAGE AS THE FORCING VARIABLE, LOUISIANA

	(1) Duration of Initial Spell	(2) Duration UI Claimed	(3) Duration UI Paid
		Sep 79-Sep 80	
α	-.024	-.022	-.02
	(.046)	(.045)	(.045)
Opt. Poly	1	1	1
		Sep 80-Sep 81	
α	-.025	-.019	-.019
	(.026)	(.026)	(.026)
Opt. Poly	1	1	1
		Sep 81-Sep 82	
α	.026	.031	.019
	(.034)	(.033)	(.033)
Opt. Poly	1	1	1
		Sep 82-Dec 83	
α	.01	.009	.005
	(.024)	(.024)	(.023)
Opt. Poly	1	1	1

Notes: The table explores the robustness of the RKD results by using the post unemployment wage as a placebo forcing variable instead of the pre-unemployment highest quarter of earnings. The post unemployment wage used is the wage for the first quarter of full employment after an unemployment spell. Post unemployment wages are available only for spells starting after September 1979 in Louisiana. Post unemployment wages are correlated with lifetime earnings but are not too much correlated with the highest quarter of earnings that determines the benefit level. Therefore, this table explores to what extent the baseline results are driven by some functional dependence between earnings and unemployment duration and shows that we cannot detect any effect in these placebo specifications using post unemployment wages as a forcing variable. α is the RK estimate of the average treatment effect of benefit level on the outcome. Standard errors for the estimates of α are in parentheses. The displayed estimates are for the optimal polynomial order chosen to minimize the Aikake Information Criterion.

Non-parametric tests for the the existence and location of a kink

An important concern in the RKD is that the estimates are picking up some spurious breakpoints in the relationship between the forcing variable and the outcome of interest. Despite their usually bad small sample properties, I recommend that non-parametric or semi-parametric tests for the detection and location of structural breakpoints are always performed when running RKD estimation, following the tests existing in the time series analysis literature, like for instance Bai and Perron [2003]. The number of tests that one can implement is large, but will usually fall within one of two categories. Tests for the existence of one or several breakpoints. And tests trying to detect the location of these breakpoints. By essence, testing for the statistical significance of the RKD estimates can be seen as falling into the first category. One could nevertheless envisage testing for the existence of more than one breakpoint, in order to make sure that the RKD estimates are not driven by the existence of multiple kinks in the relationship between the outcome and the forcing variable. An example of such tests can be found in Bai and Perron [1998].

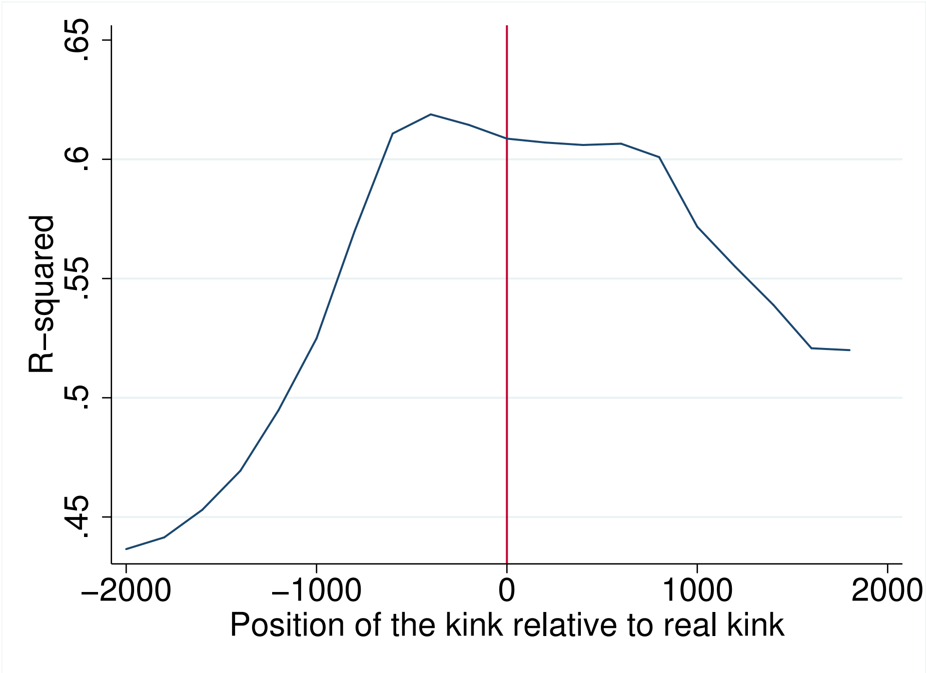
Here, I carry out a straightforward test that falls in the second category. I intend to make sure that the real location of the kink in the schedule is the location that would be detected if one were to look for the location of the kink in the data without knowing where the kink actually stands. The test simply consists in running the RKD specification of equation (5) for a large number of virtual kink points k, and then in looking at the kink point that minimizes the residual sum of squares or equivalently that maximizes the R-squared[57]. Because of the large variance of unemployment durations across individuals, I collapse the observations in bins of \$50 of the assignment variable in order to reduce the residuals sum of squares to begin with[58]. I report in figure B2 the evolution of the R-squared as I change the location of the kink point in specification (5). The evolution of the R-squared as one varies the location of the kink points provides evidence in support of the validity of the RKD design. For both periods, the R-squared increases sharply as one moves closer to the actual kink point and then decreases sharply, supportive of the existence of a kink around 0. For the first period, the kink point that maximizes the R-squared is situated \$370 to the left of the real kink point, but as one may infer from figure B2, one cannot actually reject the hypothesis that the kink point is actually at 0. For the second period, the kink point that maximizes the R-squared is situated \$200 to the right of the real kink point, but once again one cannot actually reject the hypothesis that the kink point is actually at 0. I interpret these results as strong evidence in support of the validity of the RK design.

[57] I conduct here a simple grid search but these tests can become computationally burdensome when looking for several breakpoints or for more complicated models, in which case the use of more efficient algorithms is recommended, as in Bai and Perron [2003]

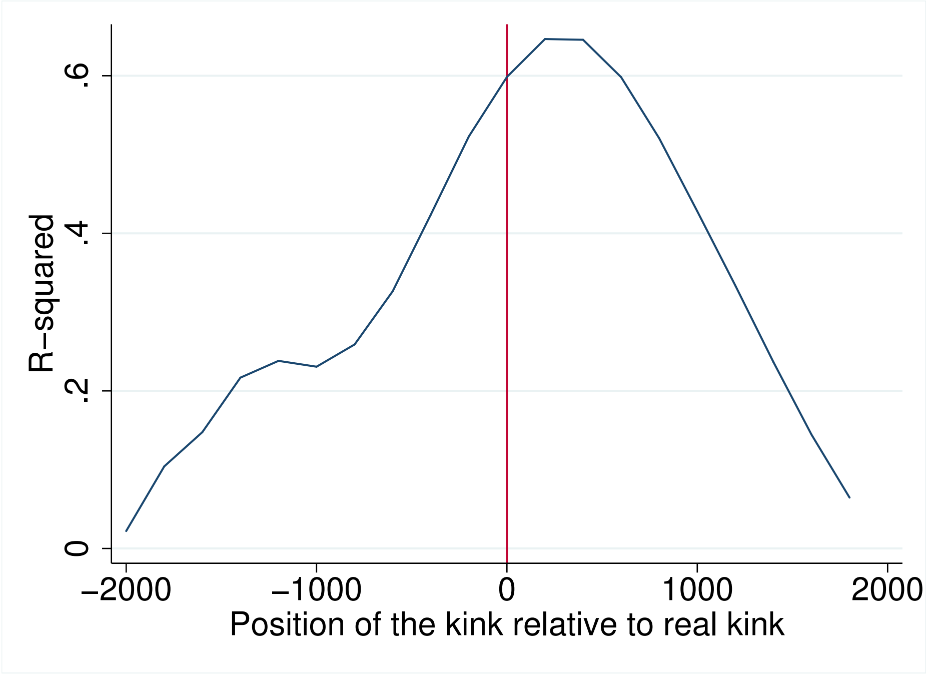
[58] This procedure increases the power of the test considerably.

Figure B2: R-SQUARED AS A FUNCTION OF THE LOCATION OF THE KINK POINT IN RKD SPECIFICATION (5), LOUISIANA

A. JAN 1979 - SEPT 1981



B. SEPT 1981 - DEC 1983



Notes: The graph shows the value of the R-squared as a function of the location of the kink point in RKD specification (5). The assignment variable is centered at the actual kink point in the benefit schedule so that virtual kink points are expressed relative to the real kink point in the schedule. Inspired by non-parametric tests for the detection of structural breakpoints in time series analysis, I conduct a grid search to look for the kink point that maximizes the R-squared. See text for details.

Proportional hazard models

To get a sense of the validity of the RK design, it is useful to compare the RKD estimates to the estimates of more standard empirical strategies widely used in the existing literature. Most empirical studies on US data use proportional hazard models. In table B3, I report the estimates of Cox proportional hazard models on the CWBH data which enables me to compare my results to the widely cited benchmark of Meyer [1990], who used a smaller sample of the same CWBH records.

This table estimates the effect of UI weekly benefits levels b on the hazard rate of leaving UI using the CWBH complete data for the 5 US states . I fit standard Cox proportional hazard models. All specifications include controls for gender, ethnicity, marital status, year of schooling, a 6-pieces exhaustion spline and state fixed effects. u denotes the state unemployment rate. log(b) denotes the log-weekly UI benefit amount. p25 and p75 denote the 25th and 75th percentile of unemployment rates (among all state×quarter in our data).

Coefficient estimates for log(b) in the proportional hazard models can be interpreted as the elasticity of the hazard rate s with respect to the weekly benefit level. Under the assumption that the hazard rate is somewhat constant, these elasticities can be easily compared to the RKD elasticities of unemployment duration, since $D \approx 1/s$ so that $\varepsilon_D \approx -\varepsilon_s$.

Column (1) replicates the specification of Meyer [1990], Table VI, column (7). Note that Meyer [1990] was using a much smaller sample of the same CWBH records. The estimates show that the result of Meyer [1990], who found an elasticity of .56, can be fully replicated using his specification. The drawback of these estimates is that they do not fully address the endogeneity issue due to the joint determination of UI benefits and previous earnings. Meyer [1990] only controls for previous wages using the log of the base period earnings. Column (2) further adds non-parametric controls for previous earnings and experience. Column (3) further adds year×state fixed effects. Interestingly, if one adds this richer set of non parametric controls for previous earnings to mitigate the concern of endogeneity, and fully controls for variations across labor markets by adding time fixed effects interacted with state fixed effects, the results converge to the RKD estimates and the elasticity goes down to around .3. The reason is that, as one controls more efficiently for the functional dependence between unemployment duration and previous earnings, the only identifying variation in benefit level that is left comes from the kink in the benefit schedule, and the model naturally converges to the identification strategy of the RKD. Overall, I find this evidence to be supportive of the validity of the RK design.

Columns (4) to (6) investigate the cyclicality of the partial equilibrium labor supply elasticities in the standard proportional hazard model to analyze the robustness of the results of table B4. Columns (4) and (5) add the interaction of log(UI) and high unemployment dummies (unemployment rate above the median across all US states in the same quarter in column (4) and unemployment rate above 8% in column (5)). Column (6) adds the interaction of log(b) with quartiles for the level of unemployment (quartiles defined across all state×quarter cells in our sample).

Table B3: SEMI-PARAMETRIC ESTIMATES OF HAZARD RATES

	(1) Meyer [1990]	(2)	(3)	(4)	(5)	(6)
log(b)	-0.587***	-0.274***	-0.320***	-0.341***	-0.323***	
	(0.0394)	(0.0365)	(0.0368)	(0.0374)	(0.0370)	
State unemployment rate	-0.0550***	-0.0552***	-0.0207	-0.0226	-0.0251	-0.105***
	(0.00518)	(0.00519)	(0.0142)	(0.0143)	(0.0153)	(0.0209)
log(b)$\times$ (u>median)				0.0248**		
				(0.00812)		
log(b)$\times$(u> .08)					0.00527	
					(0.00685)	
log(b)$\times$(u<p25)						-0.363***
						(0.0376)
log(b)$\times$(p25<u<median)						-0.353***
						(0.0371)
log(b)$\times$(median<u<p75)						-0.292***
						(0.0371)
log(b)$\times$(u>p75)						-0.274***
						(0.0378)
Non-param controls for previous wage & experience	NO	YES	YES	YES	YES	YES
Year$\times$state F-E	NO	NO	YES	YES	YES	YES
# Spells	39852	39852	39852	39852	39852	39852
Log-likelihood	-136305.0	-136364.8	-135976.0	-135971.4	-135975.7	-135946.2

Notes: Standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01.
This table estimates the effect of UI weekly benefits levels b on the hazard rate of leaving UI using the CWBH complete data for 5 US states from the late 1970s to early 1980s. I fit Cox proportional hazard models. All specifications include controls for gender, ethnicity, marital status, year of schooling, a 6-pieces exhaustion spline and state fixed effects. u denotes the state unemployment rate. log(b) denotes the log-weekly UI benefit amount. p25 and p75 denote the 25th and 75th percentile of unemployment rates (among all state$\times$quarter in our data). Column (1) replicates the specification of Meyer [1990], Table VI, column (7) (Meyer [1990] was using a much smaller dataset). Column (2) further adds non-parametric controls for previous earnings. Column (3) further adds year$\times$state fixed effects. Columns (4) and (5) add the interaction of log(b) and high unemployment dummies (unemployment rate above the median across all US states in the same quarter in column (4) and unemployment rate above 8% in column (5)). Column (6) adds the interaction of log(b) with quartiles for the level of unemployment (quartiles defined across all state$\times$quarter cells in our sample).

Cyclical behavior:

Following the Great Recession, a recent literature has been interested in estimating how labor supply responses to UI vary over the business cycle in order to assess the optimality of UI rules that are contingent on the state of the labor market (Schmieder et al. [2012], Kroft and Notowidigdo [2011]). I take advantage of the large variations in labor market conditions across states and over time in the CWBH data to investigate how the RKD estimates vary with indicators of (state) labor market conditions. I correlate the RKD estimates with the average monthly unemployment rate from the Current Population Survey prevailing in the state for each period[59]. Results are displayed in table B4. In all specifications, I weight the observations[60] by the inverse of the standard error (of the elasticity)[61]

Column (1) to (3) correlates the estimated elasticity with the unemployment rate for all three duration outcomes. In all three columns, the coefficient on the state unemployment rate is very small (around -.02 and not significantly different from zero), which means that a 1 percentage point increase in the unemployment rate is associated with a .02 percentage point decrease in the estimated elasticity. This result implies that elasticity varies between .38 (.09) when the state unemployment rate is at 4.5% (minimum in the CWBH data) and .25 (.10) when the unemployment rate is at 11.8% (the max in the CWBH data). This evidence is in line with the evidence of Kroft and Notowidigdo [2011] for the US, though the cyclicality of the estimates is somewhat larger in their analysis. One needs to acknowledge though that the standard errors on the estimated coefficient is rather large and the result of this type of exercise should always be interpreted with caution.

The estimates are not affected by the inclusion of state fixed effects as shown in column (4). In column (5), I add more observations by estimating the RKD model for subsets of the labor force in each state and sub-period. Here, I estimate the RKD elasticity for young (below 40) and old (above 40 years old) workers separately, but one can think of other partitions of the labor market, as long as: 1) unemployment rates can be computed for these sub-labor markets, 2) variation in unemployment rate across these sub-labor markets is large enough, and 3) each sub-labor market is large enough in order to estimate RKD elasticities with enough precision. Adding several estimates within state and sub-periods has two advantages. First, it increases the statistical power of the analysis, and more importantly, it enables me to control for the level of the policy parameters at which the elasticity is estimated. Each RKD elasticity is of course by nature endogenous to the level of the maximum benefit amount and the potential duration at which it is estimated, and these parameters vary for each state and sub-period. Results in column (5) show that partitioning the data into a larger number of sub-labor markets does not affect the result. The coefficient of the correlation between the unemployment rate in the sub-labor market and the RKD elasticity is still negative, and somewhat smaller in absolute value, though the amount of variation over time in each sub-labor market when controlling for sub-labor market fixed effects (here for age group

[59]To know to what extent variations in labor market conditions across states are a good proxy for business cycle fluctuations is another question. I tend to prefer in table B4 specifications with state fixed effects so that all variation in labor market conditions is variation over time, which mimics more clearly the concept of business cycles.

[60]Each observation is a RKD elasticity estimate of unemployment duration with respect to the UI benefit level for a state and sub period.

[61]Weighting reduces substantially the standard errors on the estimates of the correlation of the elasticity with labor market conditions, without affecting the point estimates.

fixed effects) is rather limited.

In table B3, columns (4) to (6) , I also investigate how the effect of the log benefit correlates with state unemployment conditions in the standard Cox proportional hazard model, and find similar results, with the estimated elasticity decreasing slightly as the state unemployment rate increases.

Construction of weights for the reweighted approach estimation in liquidity effects and moral hazard estimates

To make sure that our comparison of the effect of benefit level and potential duration using the two deterministic and kinked benefit schedules is not mixing heterogenous individuals, we re-weight the observations in the sample for the RKD estimates of $\left.\frac{\partial s_0}{db}\right|_B$ (sample 1) to match the distribution of observable characteristics of observations in the sample for the RKD estimates of $\frac{\partial s_0}{dB}$ (sample 2). To generate these weights, for each period, I merge observations from both samples. I then estimate a probit model of the probability that a given observation in this merged sample belongs to sample 1. The predictors in this regression are gender, age, age squared, education in years, and dummies for 5 main industries. Using predicted propensity score p, I then weight each observation in the RKD regressions with the weight $\omega = p/(1-p)$

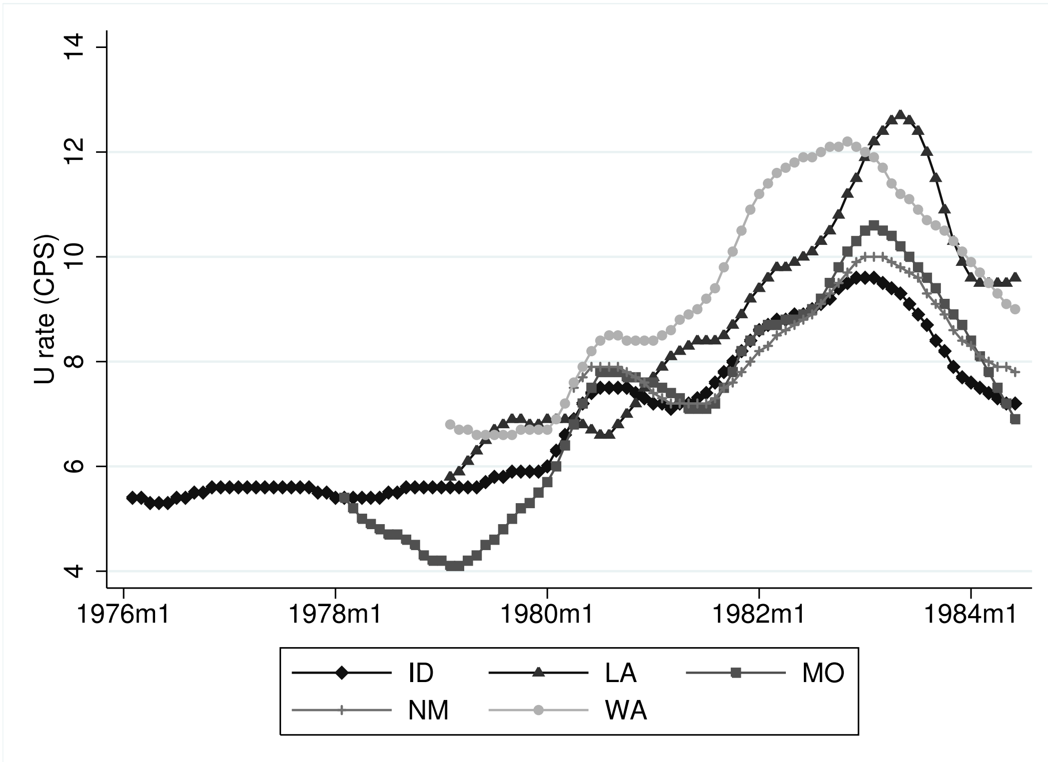
Table B4: CYCLICAL BEHAVIOR OF THE RKD ESTIMATES OF THE EFFECT OF BENEFIT LEVEL

	(1)	(2)	(3)	(4)	(5)
	Average Treatment Effects				
	ε_b	ε_b	ε_b	ε_b	ε_b
	Initial Spell	UI Paid	UI Claimed	Initial Spell	
U	-0.0195	-0.0293	-0.0259	-0.0289	-0.00576
	(0.0262)	(0.0263)	(0.0239)	(0.0303)	(0.0445)
Kink (K$2010)					-0.111
					(0.170)
Potential Duration					-0.00950
					(0.0177)
State F-E				×	×
Age Group F-E					×
Inverse s-e weights	×	×	×	×	×
N	26	26	26	26	52

Notes: Standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01.
Each observation is a RKD estimate of the elasticity of unemployment duration with respect to the UI benefit level for a state and sub period. Initial spell refers to the elasticity of the duration of the initial unemployment spell as defined above. UI paid refers to the elasticity of the duration that UI is paid, and UI claimed refers to the elasticity of the duration of the UI claim. U is the average monthly state unemployment rate from CPS and in column (5) U is the average monthly state unemployment rate from CPS for each age group (the young, below 40, and the older workers, above 40 years old). Unemployment rates are expressed in percentage points, so that the results in column (1) for instance should be interpreted as follows: a 1 percentage point increase in the unemployment rate is associated with a .019 percentage point decrease in the estimated elasticity.

Additional Figures

Figure B3: UNEMPLOYMENT RATES IN CWBH STATES 1976-1984



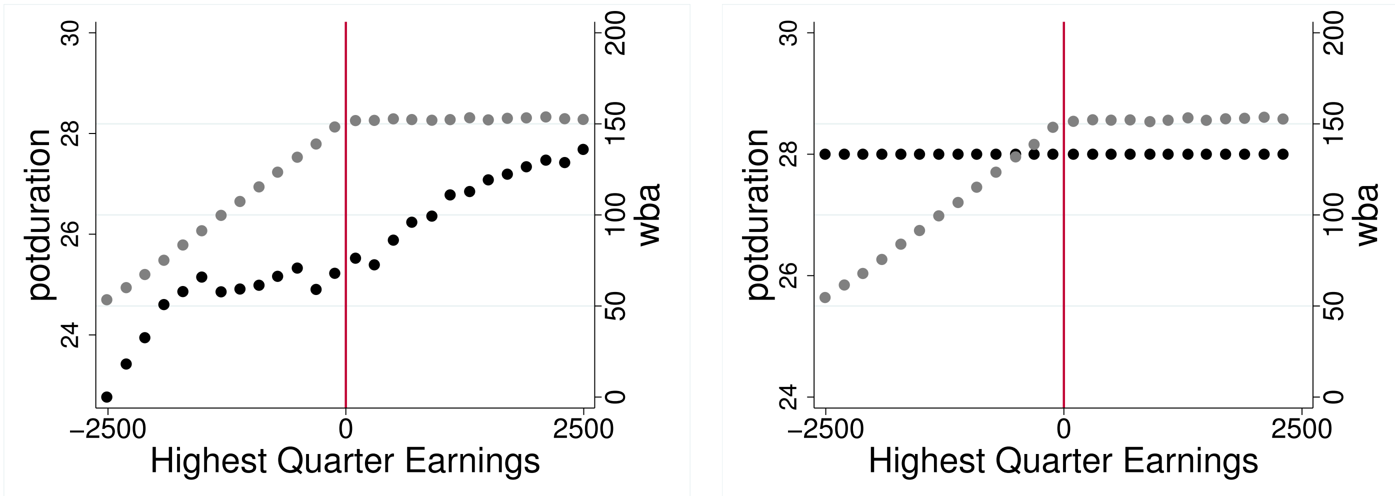
Sources: Current Population Survey

Notes: The graph shows the evolution of the monthly unemployment rate in the 5 states with the universe of unemployment spells available from the CWBH data. The CWBH data for the 5 states covers period of low unemployment as well as the two recessions of 1980 and 1981-82 with two-digit national unemployment rates, which gives the opportunity to examine the evolution of behavioral responses to UI over the business cycle.

Figure B4: UI BENEFIT SCHEDULE: WEEKLY BENEFIT AMOUNT (GREY) & POTENTIAL DURATION(BLACK), LOUISIANA

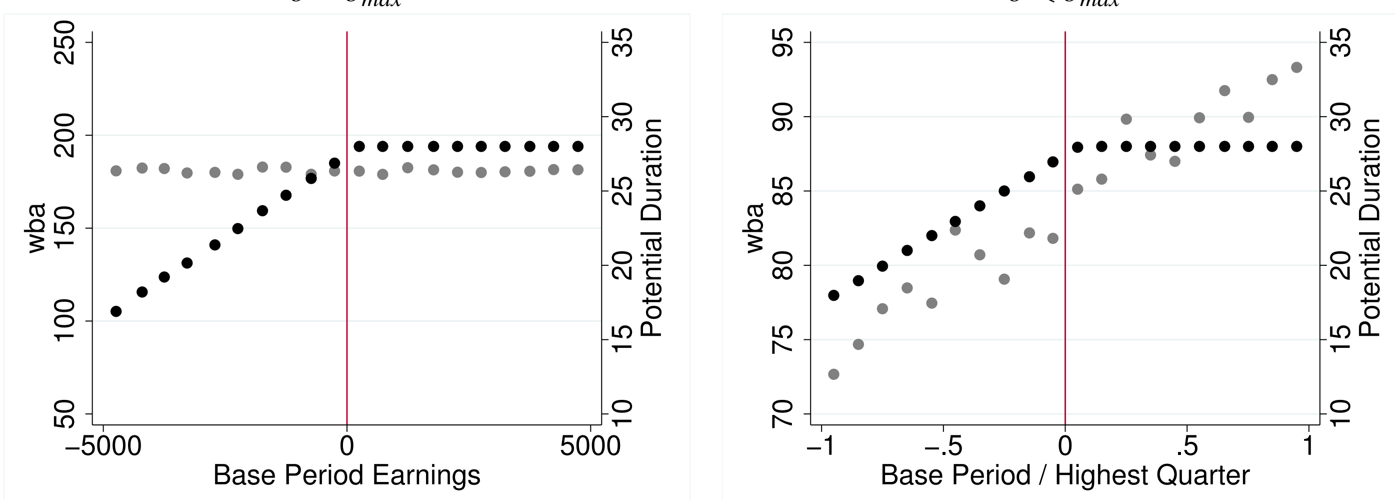
A. WBA as a kinked function of Highest Quarter Earnings

Full Sample $\qquad$ $D = D_{max}$



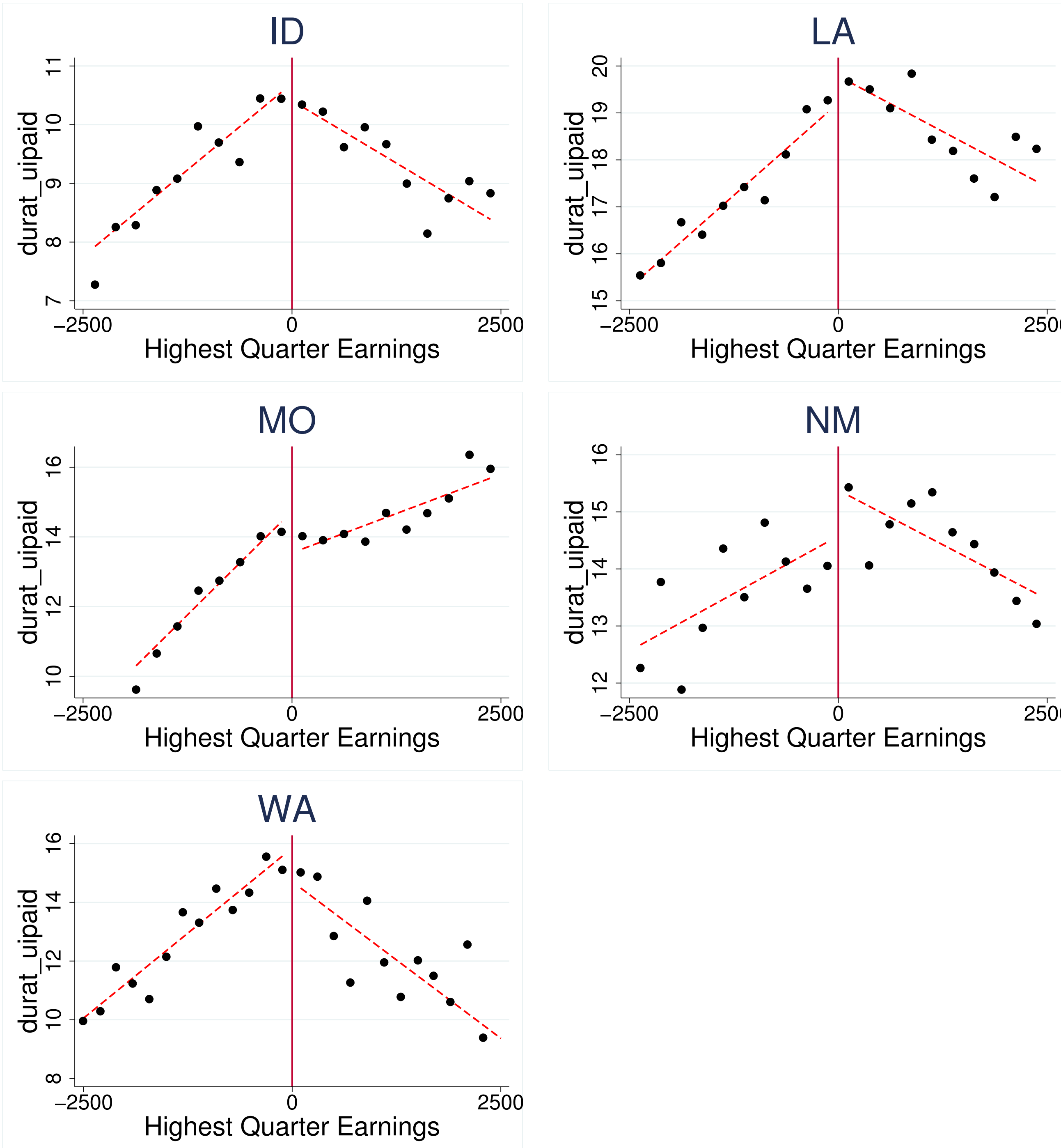
B. Potential Duration as a kinked function of Previous Earnings

$b = b_{max}$ $\qquad$ $b < b_{max}$



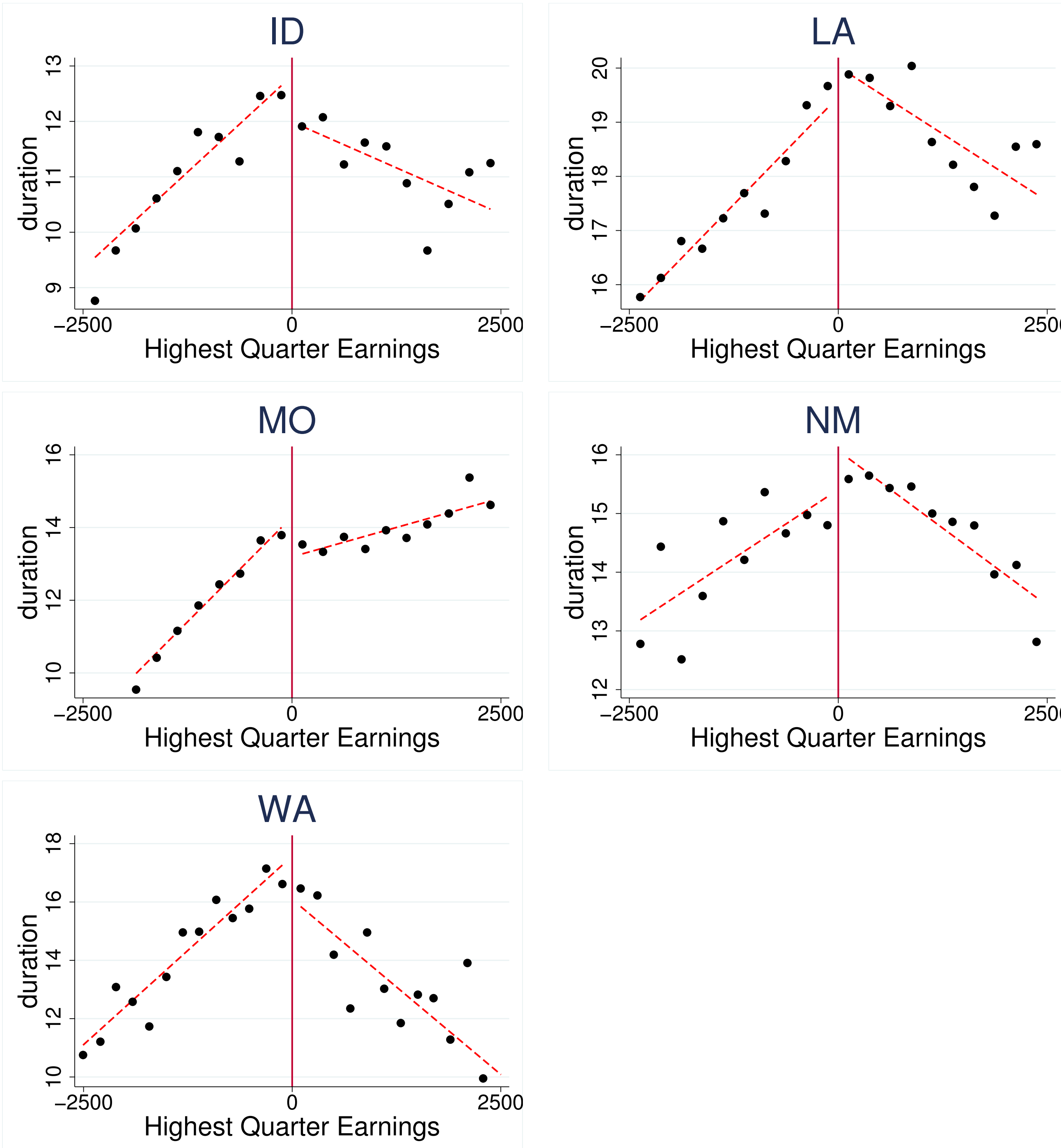
Notes: The graph shows the weekly benefit amount (wba: grey dots) and potential duration (potduration: black dots) of Tier I observed in the CWBH data for Louisiana for 1979 to 1983. Each dot is the average value in the corresponding bin of the assignment variable. Panel A shows that the weekly benefit amount is a kinked function of the highest quarter of earnings. Panel B shows that potential duration is a kinked function of the base period earnings for individuals with $b = b_{max}$ (left) and of the ratio of base period to highest quarter earnings for individuals with $b < b_{max}$ (right).

Figure B5: RKD EVIDENCE OF THE EFFECT OF BENEFIT LEVEL: DURATION UI PAID VS HIGHEST QUARTER EARNINGS FOR ALL 5 STATES



Notes: The graph shows for the first sub-period of analysis in each state the mean values of the duration of paid UI in each bin of $250 of highest quarter of earnings, which is the assignment variable in the RK design for the estimation of the effect of benefit level. The assignment variable is centered at the kink. The graph shows evidence of a kink in the evolution of the outcome at the kink. Formal estimates of the kink using polynomial regressions of the form of equation 5 are displayed in table 1. The red lines display predicted values of the regressions in the linear case allowing for a discontinuous shift at the kink.

Figure B6: RKD evidence of the Effect of Benefit Level: Duration of Initial Unemployment Spell vs Highest Quarter Earnings for All 5 States



Notes: The graph shows for the first sub-period of analysis in each state the mean values of the duration of initial spell in each bin of $250 of highest quarter of earnings, which is the assignment variable in the RK design for the estimation of the effect of benefit level. The assignment variable is centered at the kink. The graph shows evidence of a kink in the evolution of the outcome at the kink. Formal estimates of the kink using polynomial regressions of the form of equation 5 are displayed in table 1. The red lines display predicted values of the regressions in the linear case allowing for a discontinuous shift at the kink.

Appendix C: Proofs and Results

Timing of the model: enter unemployment at period $t = 0$. At the beginning of every period, if the individual is still unemployed, she chooses search effort. Once search effort realized, she chooses consumption. The value function of finding a job at time t is:

$$V(A_t) = \max_{A_{t+1} \geq L} u(A_t - A_{t+1} + w_t - \tau) + \beta V(A_{t+1})$$

The value function of being unemployed at time t is:

$$U(A_t) = \max_{A_{t+1} \geq L} u(A_t - A_{t+1} + b_t) + \beta J(A_{t+1})$$

$$J(A_t) = \max_{s_t} s_t \cdot V(A_t) + (1 - s_t) \cdot U(A_t) - \psi(s_t)$$

s.t.

$$u(c_t^u) \geq 0$$
$$u(c_t^e) \geq 0$$

We assume that $\psi(.)$ is increasing and convex.

Optimal search:

$$\psi'(s_t) = V(A_t) - U(A_t) \tag{8}$$

Euler equations:

$$\forall t \quad u'(c_t^e) = \begin{cases} \beta u'(c_{t+1}^e) \\ u'(w - \tau) \ \text{ if } A_t = L \end{cases}$$

$$\forall t \quad u'(c_t^u) = \begin{cases} \beta[s_{t+1} u'(c_{t+1}^e) + (1 - s_{t+1}) u'(c_{t+1}^u)] \\ u'(b_t) \ \text{ if } A_t = L \end{cases}$$

Therefore, if the credit constraint is not binding at time t we have that:

$$\forall t \ \ u'(c_0^e) = \beta^t u'(c_t^e) \tag{9}$$

$$\begin{aligned} \forall t \ \ u'(c_0^u) &= \sum_{j=1}^{t} \left(\prod_{i=1}^{j-1} (1 - s_i) s_j\right) \beta^j u'(c_j^e) + \beta^t \prod_{i=1}^{t} (1 - s_i) u'(c_t^u) \\ &= \sum_{j=1}^{t} f_1(t) u'(c_0^e) + \beta^t S(t) u'(c_t^u) \\ &= F_1(t) u'(c_0^e) + \beta^t S(t) u'(c_t^u) \end{aligned} \tag{10}$$

where $f(t) = \prod_{i=0}^{t-1} (1 - s_i) s_t$ is the probability that the unemployment spell lasts exactly t periods and $f_1(t) = \prod_{i=1}^{t-1} (1 - s_i) s_t$ is the probability that the unemployment spell lasts exactly t periods conditional on being still unemployed at the beginning of period 1. Similarly, $\prod_{i=0}^{t} (1 - s_i) = S(t)$, is the survival rate at time t and $\prod_{i=1}^{t} (1 - s_i) = S_1(t)$is the survival rate conditional on being still unemployed at period 1. $F(t) = 1 - S(t) = \sum_{s=0}^{t} f(s)$ is the probability that the length of a spell is inferior or equal to t and $F_1(t)$ is the same probability conditional on being still unemployed at period 1.

Effect of benefit level at time t on optimal search:

$$\frac{\partial s_t}{\partial b_t} = -\frac{u'(c_t^u)}{\psi''(s_t)}$$

Effect of benefit level at time $t+j$ on optimal search at time t:

$$\frac{\partial s_t}{\partial b_{t+j}} = -\frac{\beta^j \prod_{i=1}^{j}(1 - s_{t+i})u'(c_{t+j}^u)}{\psi''(s_t)}$$

We define the effect on any variable Z of a change in the constant benefit level b for a finite period of potential duration of UI benefits B as:

$$\left.\frac{\partial Z}{\partial b}\right|_B = \sum_{i=0}^{B-1} \frac{\partial Z}{\partial b_i}$$

Decomposition of the effect of an increase in benefit level at time t into the moral hazard and liquidity effects:
From 8, we have that:

$$\frac{\partial s}{\partial A_t} = \frac{u'(c_t^e) - u'(c_t^u)}{\psi''(s_t)}$$

$$\frac{\partial s}{\partial w_t} = \frac{u'(c_t^e)}{\psi''(s_t)}$$

so that:

$$\frac{\partial s}{\partial b_t} = \frac{\partial s}{\partial A_t} - \frac{\partial s}{\partial w_t} \tag{11}$$

which is the Chetty (2007) decomposition of the effect of benefits between the liquidity and moral hazard effect.

Similarly, the effect on search effort at time 0 of a change in the constant benefit level b for a finite period of potential duration of UI benefits B can also be written as the sum of two components, a moral hazard and a liquidity effect:

$$\left.\frac{\partial s_0}{\partial b}\right|_B = \overbrace{\left.\frac{\partial s_0}{\partial a}\right|_B}^{\text{liquidity effect}} - \underbrace{\left.\frac{\partial s_0}{\partial w}\right|_B}_{\text{moral hazard effect}} \tag{12}$$

where $\left.\frac{\partial s_0}{\partial a}\right|_B = \sum_{i=0}^{B-1} \frac{\partial s_0}{\partial a_i}$ is the effect of a change in the level of an annuity that pays \$$a$ every period and $\frac{\partial s_0}{\partial w}\Big|_B = \sum_{i=0}^{B-1}\frac{\partial s_0}{\partial w_i}$

Planner's problem:

The social planner chooses the UI benefit system to maximize expected utility subject to a balanced-budget constraint:

$$\max_{b,B,\tau} W_0 = (1-s_0)U(A_0) + s_0 V(A_0) - \psi(s_0)$$
$$\text{subject to} \quad D_B \cdot b = (T-D)\tau$$

Proof of proposition 1 in the case of benefit level b:

$$\frac{dW_0}{db} = (1-s_0)\Big[\frac{\partial U_0}{\partial b}\Big|_B - \frac{\partial U_0}{\partial w}\Big|_B \frac{d\tau}{db}\Big] + s_0\Big[\underbrace{\frac{\partial V_0}{\partial b}\Big|_B}_{=0} - \frac{\partial V_0}{\partial w}\Big|_B \frac{d\tau}{db}\Big]$$

From 8, we have that:

$$\forall y,\ \frac{\partial s_0}{\partial y}\Big|_B = \frac{1}{\psi''(s_0)}\Big[\frac{\partial V_0}{\partial y}\Big|_B - \frac{\partial U_0}{\partial y}\Big|_B\Big]$$

So that:

$$\frac{dW_0}{db} = -(1-s_0)\psi''(s_0)\,\frac{\partial s_0}{\partial b}\Big|_B - \frac{d\tau}{db}\Big((1-s_0)\,\frac{\partial U_0}{\partial w}\Big|_B + s_0\,\frac{\partial V_0}{\partial w}\Big|_B\Big) \tag{13}$$

We also know that: $\forall t,\ \ \frac{\partial V_0}{\partial w_t} = \beta^t u'(c_t^e)$ so that :

$$\begin{aligned} \frac{\partial V_0}{\partial w}\Big|_B &= \sum_{t=0}^{B-1}\beta^t u'(c_t^e) \\ &= Bu'(c_0^e) \quad \text{if the credit constraint does not bind at time } B \end{aligned} \tag{14}$$

And, similarly: $\forall t,\ \ \frac{\partial U_0}{\partial w_t} = \sum_{j=1}^{t} f_1(j)\beta^t u'(c_t^e)$ so that :

$$\begin{aligned} \frac{\partial U_0}{\partial w}\Big|_B &= \sum_{t=1}^{B-1} F_1(t)\beta^t u'(c_t^e) \\ &= \sum_{t=1}^{B-1} F_1(t)u'(c_0^e) \quad \text{if the credit constraint does not bind at time } B \end{aligned} \tag{15}$$

And therefore, if the credit constraint does not bind at time B

$$
\begin{aligned}
(1-s_0)\left.\frac{\partial U_0}{\partial w}\right|_B &= \sum_{t=1}^{B-1}(1-s_0)F_1(t)u'(c_0^e) \\
&= \sum_{t=1}^{B-1}F_0(t)u'(c_0^e) \\
&= (B-D_B-s_0)u'(c_0^e) \qquad (16)
\end{aligned}
$$

where we use the fact that $\sum_{t=0}^{B-1}S(t)=D_B$, the average duration of unemployment truncated at B.

Note that the moral hazard effect of an increase in b can also be expressed as a simple function of $u'(c_0^e)$ if the credit constraint is not binding at time B:

$$
\begin{aligned}
\left.\frac{\partial s_0}{\partial w}\right|_B &= \frac{1}{\psi''(s_0)}\left[\left.\frac{\partial V_0}{\partial w}\right|_B - \left.\frac{\partial U_0}{\partial w}\right|_B\right] \\
&= \frac{(D_B-s_0(B-1))u'(c_0^e)}{(1-s_0)\cdot\psi''(s_0)} \qquad (17)
\end{aligned}
$$

Using (12), (14), (16) and (17), we can rewrite (13) such that:

$$
\frac{dW_0}{db} = -(1-s_0)\psi''(s_0)\Big[\Big(\left.\frac{\partial s_0}{\partial a}\right|_B - \left.\frac{\partial s_0}{\partial w}\right|_B\Big) + \frac{d\tau}{db}\Big(\left.\frac{\partial s_0}{\partial w}\right|_B\cdot(B/(D_B-s_0(B-1))-1)\Big)\Big]
$$

We get from the government budget constraint that:

$$
\frac{d\tau}{db} = \frac{D_B}{T-D}(1+\varepsilon_{D_B}+\varepsilon_D\frac{D}{T-D})
$$

where $\varepsilon_{D_B}=\frac{b}{D_B}\frac{dD_B}{db}$ is the elasticity of the duration of paid unemployment with respect to the benefit level and $\varepsilon_D=\frac{b}{D}\frac{dD}{db}$ is the elasticity of the duration of total unemployment with respect to the benefit level.

Therefore, if the credit constraint is not yet binding at time B, the first-order condition $\frac{dW_0}{db}=0$ takes a simple form:

$$
1+\rho_1 = (\frac{B}{D_B-s_0(B-1)}-1)\frac{D_B}{T-D}(1+\varepsilon_{D_B}+\varepsilon_D\frac{D}{T-D}) \qquad (18)
$$

where $\rho_1 = -\frac{\left.\frac{\partial s_0}{\partial a}\right|_B}{\left.\frac{\partial s_0}{\partial w}\right|_B}$ is the liquidity to moral hazard ratio in the effect of an increase of benefit level. When the lefthand side of 18 is superior to the righthand side, it is socially desirable to increase the benefit level b, at the given level of potential duration B.

Proof of proposition 1 in the case of potential duration B:

To analyze marginal changes in B, I assume that a marginal change in the potential duration of benefits B normalized by the benefit amount b is therefore the same as a marginal change in b_B [62]. In this context, following the same logic as previously, we have that :

$$\frac{dW_0}{dB} = b.\frac{dW_0}{db_B} = b.\Big(-(1-s_0)\psi''(s_0)\Big[\big(\frac{\partial s_0}{\partial a_B} - \frac{\partial s_0}{\partial w_B}\big) + \frac{d\tau}{db}\big(\frac{\partial s_0}{\partial w_B}\cdot(1/(S(B)-s_0)-1)\big)\Big]\Big)$$

Differentiating the budget constraint of the government, we get that:

$$\frac{d\tau}{db_B} = \frac{1}{b}\cdot\frac{d\tau}{dB} = \frac{D_B}{B\cdot(T-D)}(\varepsilon_{D_B,B} + \varepsilon_{D,B}\frac{D}{T-D}) \tag{19}$$

where $\varepsilon_{D_B,B} = \frac{B}{D_B}\frac{dD_B}{dB}$ is the elasticity of the duration of paid unemployment with respect to the potential duration of UI benefits and $\varepsilon_{D,B} = \frac{B}{D}\frac{dD}{dB}$ is the elasticity of the duration of total unemployment with respect to the potential duration of UI benefits. Note of course that because $D_B = \sum_{t=0}^{B-1} S(t)$, we have that $\frac{\partial D_B}{\partial B} = \sum_{t=0}^{B-1}\frac{\partial S(t)}{\partial B} + S(B)$, which means that the effect of a change in potential duration on the actual average duration of UI benefits is the sum of the mechanical effect of truncating the distribution of spells at a later point in time $S(B)$ and a behavioral response. This point is central to the argument in Schmieder et al. [2012].

Using (19) and

$$1+\rho_2 = (\frac{1}{S(B)-s_0} - 1)\frac{D_B}{B\cdot(T-D)}(\varepsilon_{D_B,B} + \varepsilon_{D,B}\frac{D}{T-D}) \tag{20}$$

where $\rho_2 = -\frac{\frac{\partial s_0}{\partial a_B}}{\frac{\partial s_0}{\partial w_B}}$ is the liquidity to moral hazard ratio in the effect of an increase of potential duration. When the lefthand side of 20 is superior to the righthand side, it is socially desirable to increase the potential duration of benefits, at the given level of benefit level b.

Proof of corollary 1:

Consider the choice between two policies, a benefit extension and an increase in generosity that would relax the budget constraint of an equivalent amount so that $\frac{d\tau}{dB} = \frac{d\tau}{db}$. Given an equivalent relaxation of the budget constraint, the social planner will find it more desirable to increase the potential duration of benefit B if for $\frac{d\tau}{dB} = \frac{d\tau}{db}$ we have $\frac{dW_0}{dB} \geq \frac{dW_0}{db}$. The result of proposition 1 follows immediately from 2 and 1.

Proof of proposition 2:

[62] This is the case if B can potentially be increased by a fraction of period (a week in our case) and that if the potential duration B is not an integer number of periods, then, we can change b_t within a period such that the benefits in a given period is the fraction of the period that is covered time the benefit amount b.

Effect of increase in benefit level on exit rate at time 0 if potential duration=B:

$$\left.\frac{\partial s_0}{\partial b}\right|_B = \sum_{i=0}^{B-1}\frac{\partial s_0}{\partial b_i} = -\frac{u'(c_0^u)}{\psi''(s_0)} - \sum_{i=1}^{B-1}\frac{\beta^i S(i)u'(c_i^u)}{\psi''(s_0)}$$

Using Euler equation when borrowing constraint does not bind, we have that:

$$\left.\frac{\partial s_0}{\partial b}\right|_B = -\left\{\frac{Bu'(c_0^u)}{\psi''(s_0)} - \sum_{t=1}^{B-1}\frac{F_1(t)u'(c_0^e)}{\psi''(s_0)}\right\} \tag{21}$$

Effect of an increase in potential duration scaled by the benefit level b, using Euler equation when borrowing constraint is not binding:

$$\frac{1}{b}\frac{\partial s_0}{\partial B} = \frac{\partial s_0}{\partial b_B} = -\left\{\frac{u'(c_0^u)}{\psi''(s_0)} - F_1(B)\frac{u'(c_0^e)}{\psi''(s_0)}\right\} \tag{22}$$

Using 21 and 22, we have that:

$$\frac{1}{B}\left.\frac{\partial s_0}{\partial b}\right|_B - \frac{1}{b}\frac{\partial s_0}{\partial B} = \left(S(B) - \frac{D_B+s_0}{B}\right)\left\{\frac{u'(c_0^e)}{(1-s_0)\psi''(s_0)}\right\} \tag{23}$$

The moral hazard effect of increasing benefit level b for B periods is given by (17) so that:

$$\frac{1}{B}\left.\frac{\partial s_0}{\partial b}\right|_B - \frac{1}{b}\frac{\partial s_0}{\partial B} = \Phi_1\Theta_1 \tag{24}$$

where $\Phi_1 = \frac{S(B)-\frac{D_B+s_0}{B}}{D_B-s_0(B-1)}$