

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

Camille Landais

## Online Appendix

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## A Additional Results, Figures and Tables on the Robustness of the RK Design

### A.1 Sensitivity of RKD estimates to bandwidth and polynomial order.

In table A1 panel A, I begin by analyzing the sensitivity of the results to the choice of the polynomial order. I group unemployment spells over all five periods periods, which has the advantage of providing with a larger number of observations at the kink for statistical power. I display the results of the estimation of equation 10 for a linear, a quadratic, and a cubic specification. For all three specifications, the bandwidth is set at 2500. I also report the Aikake Information Criterion (AIC) for all specifications. The estimates for  $\alpha$  are of similar magnitude 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 A1 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 small samples, and therefore is quite demanding in terms of bandwidth size compared to a regression discontinuity design. In practice, I found that the precision and consistency of the estimates would fall quite substantially when reducing bandwidth sizes below 1500.

Table A1: SENSITIVITY ANALYSIS OF THE RKD ESTIMATES, EFFECT OF BENEFIT LEVEL, LOUISIANA SEPT 81- DEC 83

	(1)	(2)	(3)		(4)	(5)	(6)
	<b>A. Sensitivity to Poly Order</b>				<b>B. Sensitivity to Bandwidth</b>		
	Duration of Initial Spell	Duration UI Paid	Duration UI Claimed		Duration of Initial Spell	Duration UI Paid	Duration UI Claimed
	<b>Poly Order=1</b>				<b>Bandwidth=1500</b>		
$\alpha$	.030	.029	.028	$\alpha$	.040	.038	.037
	(.003)	(.003)	(.003)		(.006)	(.006)	(.006)
AIC	159415	159042	158408	AIC	93187	92986	92579
				Opt. poly	1	1	1
	<b>Poly Order=2</b>				<b>Bandwidth=2500</b>		
$\alpha$	.056	.054	.055	$\alpha$	.040	.043	.041
	(.012)	(.012)	(.012)		(.032)	(.031)	(.031)
AIC	159414	159042	158407	AIC	159412	159041	158405
				Opt. poly	3	3	3
	<b>Poly Order=3</b>				<b>Bandwidth=4500</b>		
$\alpha$	.040	.043	.041	$\alpha$	.047	.043	.046
	(.032)	(.031)	(.031)		(.015)	(.015)	(.015)
AIC	159412	159041	158405	AIC	209792.15	209296	208492
				Opt. poly	3	3	3

*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 10. In panel A, the bandwidth level is equal to 2500 for all specifications.  $\alpha$  is the RK estimate of the average treatment effect of benefit level on the outcome. Standard errors for the estimates of  $\alpha$  are in parentheses. AIC is the Aikake Information Criterion.

## A.2 RKD for effect of UI benefits on the hazard rate at different points of the hazard support.

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  $b$ <sup>45</sup>:

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

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  $\alpha_t$  and we have:

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

Estimation of  $\alpha_t$  is done by estimating the numerator of the estimand, with a linear probability model of the following form:

$$Pr[Y = t | Y \geq t, W = w] = \mu_{t,0} + \left[ \sum_{p=1}^{\bar{p}} \gamma_{t,p} (w - k)^p + v_{t,p} (w - k)^p \cdot D \right] \quad \text{where } |w - k| \leq h \quad (11)$$

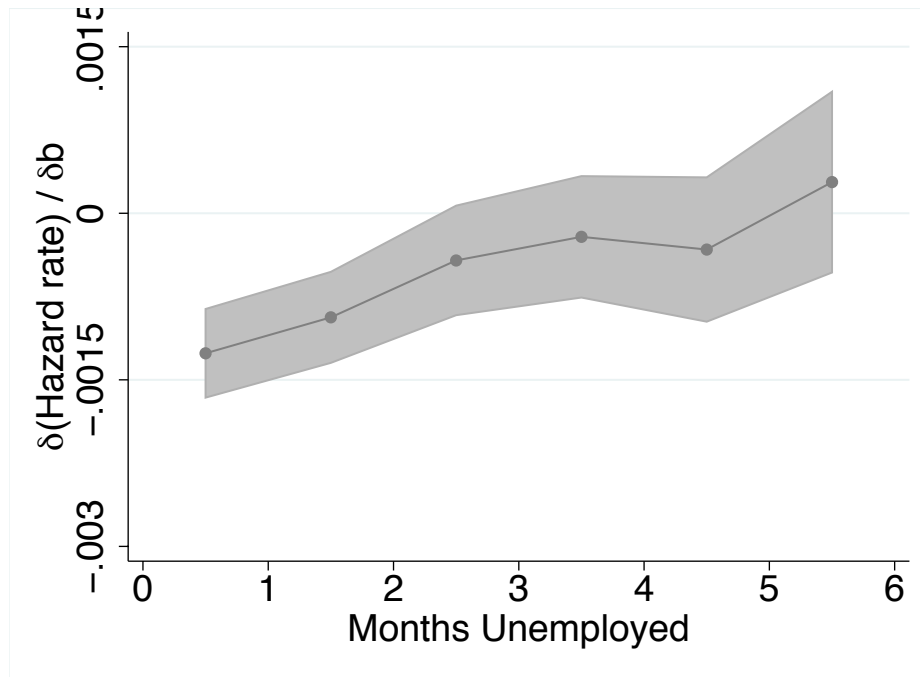
where  $v_{t,1}$  gives once again the numerator of the RK estimand for the effect of benefit level on the hazard rate at week  $t$ .

Figure A1 displays the RKD estimates of  $\alpha_t$  in Louisiana where I define hazard rates as the probability of exiting unemployment each month. The graph shows that having higher benefits has a negative impact on the probability of exiting unemployment, and that this effect is particularly strong at the beginning of a spell.

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  $\theta$  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 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.

<sup>45</sup>The same logic applies to effect of potential duration  $D$ .

Figure A1: RKD ESTIMATES OF THE EFFECT OF BENEFIT LEVEL ON THE HAZARD RATE, LOUISIANA, 1979-1983



Notes: The graph shows RKD estimates of  $\alpha_t = \frac{\partial s_t(Y|W=w)}{\partial b}$ , the effect of benefit level on the hazard rate at time  $t$ . Time periods for the definition of the hazard rate are in months. The grey shaded area represents the 95% confidence interval for the estimates. The graph shows that having higher benefits has a negative impact on the probability of exiting unemployment, and that this effect is particularly strong at the beginning of a spell.

### A.3 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  $y = f(b, w_1, \epsilon)$ , where I want to get an estimate of  $f'_1$ . In this model, we have:  $\frac{dy}{dw_1} = f'_1 \frac{\partial b}{\partial w_1} + f'_2 + f'_3 \frac{\partial \epsilon}{\partial w_1}$ . The RKD assumes that  $f'_2$  and  $f'_3$  are the same on both sides of the kink (smoothness assumptions). Then, it follows that

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

identifies  $f'_1$ , because  $\Delta_{k^+, k^-} f'_2 = 0$  and  $\Delta_{k^+, k^-} f'_3 = 0$ .

If the assumption of smoothness in the functional dependence between the forcing variable and the outcome is violated, meaning that  $\Delta_{k^+, k^-} f'_2 \neq 0$  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  $\Delta_{k^+, k^-} f'_2$  is the same, and for these two groups

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

is different, then  $f'_1$  is identified by  $\alpha_{DD}$ , where:

$$\alpha_{DD} = \frac{\Delta_{A, Bk^+, k^-} \frac{dy}{dw_1}}{\Delta_{A, Bk^+, k^-} \frac{\partial b}{\partial w_1}} \quad (12)$$

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 2). 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

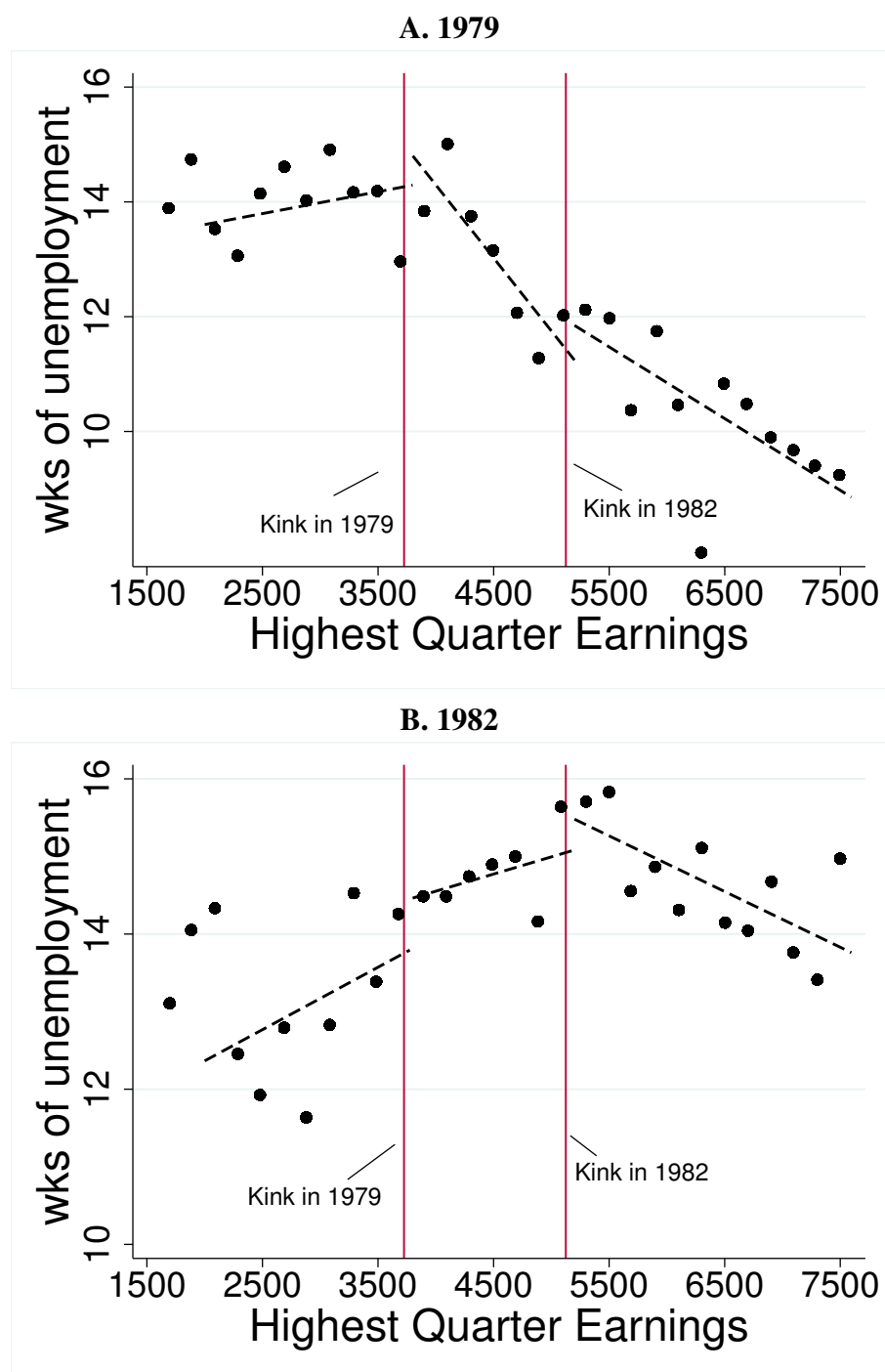
inflation rates during this period. It is important to note here that the maximum benefit amount increased in Louisiana a lot faster than inflation (40% between September 1979 and Sept 1982 and total inflation was less than 20% during that period), so that there is a clear and important change in the schedule in *real* terms <sup>46</sup>. Figure A2 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.

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<sup>46</sup>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 A2: RKD IN DOUBLE-DIFFERENCE USING VARIATIONS IN THE MAXIMUM BENEFIT LEVEL, LOUISIANA, 1979 VS 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 A2: 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
	<b>A. 1979 Kink</b>			<b>B. 1982 Kink</b>		
$\alpha_{DD}$	.064 (.035)	.088 (.035)	.051 (.035)	.065 (.034)	.069 (.034)	.05 (.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.  $\alpha_{DD}$  is the Double-Difference RKD estimate of the average treatment effect of benefit level as described in equation (12). 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  $\alpha_{DD}$  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.

## A.4 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 A3 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 A3: 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
<b>Sep 79-Sep 80</b>			
$\alpha$	-.024 (.046)	-.022 (.045)	-.02 (.045)
Opt. Poly	1	1	1
<b>Sep 80-Sep 81</b>			
$\alpha$	-.025 (.026)	-.019 (.026)	-.019 (.026)
Opt. Poly	1	1	1
<b>Sep 81-Sep 82</b>			
$\alpha$	.026 (.034)	.031 (.033)	.019 (.033)
Opt. Poly	1	1	1
<b>Sep 82-Dec 83</b>			
$\alpha$	.01 (.024)	.009 (.024)	.005 (.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.  $\alpha$  is the RK estimate of the average treatment effect of benefit level on the outcome. Standard errors for the estimates of  $\alpha$  are in parentheses. The displayed estimates are for the optimal polynomial order chosen to minimize the Aikake Information Criterion.

## A.5 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<sup>47</sup> of equation (10) 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<sup>48</sup>. For efficiency, I again group all unemployment spells for all periods together, and center the assignment variable at the kink point applicable given the schedule in place at each particular time. 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<sup>49</sup>. I report in figure A3 the evolution of the R-squared as I change the location of the kink point in specification (10). 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. 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. The kink point that maximizes the R-squared is situated \$200 to the right of the real kink point, but one cannot 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.

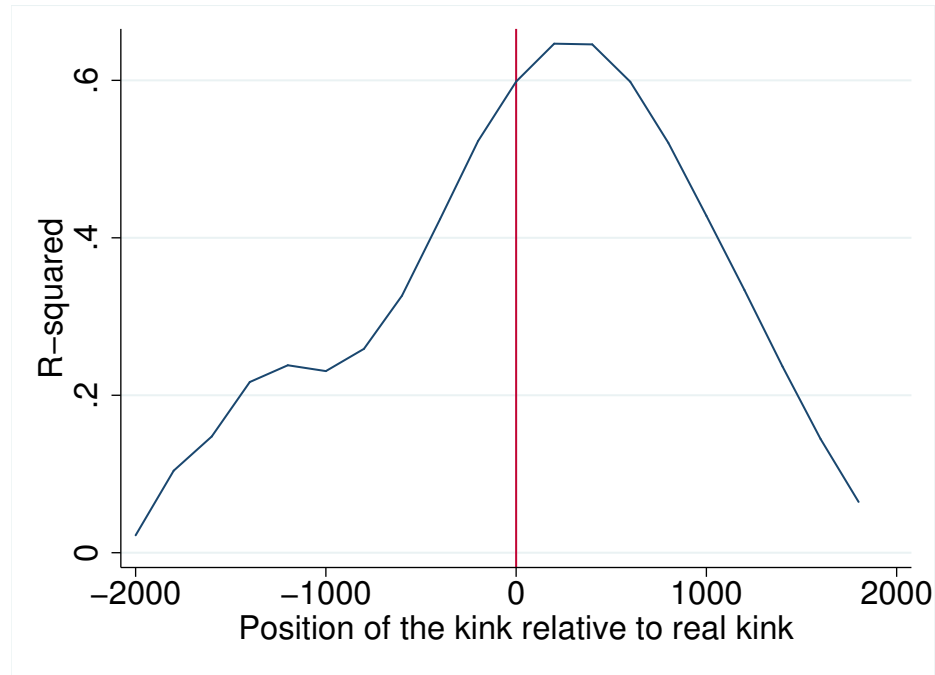
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<sup>47</sup>I again group all unemployment spells for all periods together, and center the assignment variable at the kink point applicable given the schedule in place at each particular time.

<sup>48</sup>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 \[2003\]](#)

<sup>49</sup>This procedure increases the power of the test considerably.

Figure A3: R-SQUARED AS A FUNCTION OF THE LOCATION OF THE KINK POINT IN RKD SPECIFICATION (10), LOUISIANA



*Notes:* The graph shows the value of the R-squared as a function of the location of the kink point in RKD specification (10). 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.

## A.6 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 A4, 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 $\times$ 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  $\epsilon_D \approx -\epsilon_s$ .

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 $\times$ 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 cyclicalities of the partial equilibrium labor supply elasticities in the standard proportional hazard model to analyze the robustness of the results of table A5. Columns (4) and (5) add the interaction of  $\log(\text{UI})$  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 $\times$ quarter cells in our sample).

Table A4: SEMI-PARAMETRIC ESTIMATES OF HAZARD RATES

	(1)	(2)	(3)	(4)	(5)	(6)
	<a href="#">Meyer [1990]</a>					
log(b)	-0.587*** (0.0394)	-0.274*** (0.0365)	-0.320*** (0.0368)	-0.341*** (0.0374)	-0.323*** (0.0370)	
State unemployment rate	-0.0550*** (0.00518)	-0.0552*** (0.00519)	-0.0207 (0.0142)	-0.0226 (0.0143)	-0.0251 (0.0153)	-0.105*** (0.0209)
log(b) × (u > median)				0.0248** (0.00812)		
log(b) × (u > .08)					0.00527 (0.00685)	
log(b) × (u < p25)						-0.363*** (0.0376)
log(b) × (p25 < u < median)						-0.353*** (0.0371)
log(b) × (median < u < p75)						-0.292*** (0.0371)
log(b) × (u > p75)						-0.274*** (0.0378)
Non-param controls for previous wage & experience	NO	YES	YES	YES	YES	YES
Year × 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×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×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×quarter cells in our sample).



## A.7 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<sup>50</sup>. Results are displayed in table [A5](#). In all specifications, I weight the observations<sup>51</sup> by the inverse of the standard error (of the elasticity)<sup>52</sup>

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 cyclicalities 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

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<sup>50</sup>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 [A5](#) 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.

<sup>51</sup>Each observation is a RKD elasticity estimate of unemployment duration with respect to the UI benefit level for a state and sub period.

<sup>52</sup>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 A4, 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.

Table A5: CYCLICAL BEHAVIOR OF THE RKD ESTIMATES OF THE EFFECT OF BENEFIT LEVEL

	(1)	(2)	(3)	(4)	(5)
	Average Treatment Effects				
	$\epsilon_b$	$\epsilon_b$	$\epsilon_b$	$\epsilon_b$	$\epsilon_b$
	Initial Spell	UI Paid	UI Claimed	Initial Spell	
$U$	-0.0195 (0.0262)	-0.0293 (0.0263)	-0.0259 (0.0239)	-0.0289 (0.0303)	-0.00576 (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.

## A.8 Test for the slackness of the liquidity constraint

The result of proposition 1 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.

Formally, if the Euler equation is satisfied, one can express the effect of benefit in period 0 on effort in period 1 using (4):

$$\frac{\partial s_1}{\partial b_0} = \frac{u''(c_0^u)}{\beta(u'(c_1^e) - u'(c_1^u))} \leq 0$$

$\frac{\partial s_1}{\partial b_0}$  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  $\frac{\partial s_1}{\partial b_0}$  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  $\frac{\partial s_1}{\partial b_0} = 0$ .

The implementation of the test relies on estimation of  $\frac{\partial s_{B+1}}{\partial b_B}$ , the effect of receiving extra benefits at time  $B$  on exit rates after benefit exhaustion at time  $B + 1$ . 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<sup>53</sup>, 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 (10) where the outcome is the probability of exiting unemployment between 40 and 60 weeks<sup>54</sup>, 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<sup>55</sup>  $\partial s_{B+1} / \partial B$

<sup>53</sup> 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 as explained in appendix A.2.

<sup>54</sup> Because of the small number of observations, I am forced to choose a rather large interval to increase the precision of the estimates.

<sup>55</sup> As explained in appendix A.2, when dealing with hazard rates, identification requires some assumptions regarding the selection process in case some unobserved heterogeneity  $\theta$  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  $\frac{u''(c_B^u)}{u'(c_{B+1}^u) - u'(c_{B+1}^e)}$  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 changes in slope, indicative of the validity of the identifying assumption.

that I then divide by the benefit amount  $b$  to get  $\frac{\partial s_{B+1}}{\partial b_B}$ <sup>56</sup>.

Results are reported in column (1) of table A5. 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. I also provide some quantile regression analysis in appendix A.9 showing that this test does not seem to be contaminated by heterogeneity.

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<sup>56</sup>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 A5.

Table A5: RKD ESTIMATES OF BEHAVIORAL RESPONSES TO UI, TESTS FOR THE SLACKNESS OF THE LIQUIDITY CONSTRAINT, 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]			
$\epsilon_{D_B}$		.730 (.110) [.814]	1.348 (.685) [.388]	
$\epsilon_D$		.291 (.071) [.392]	.330 (.425) [.474]	
$(\frac{1}{B} \frac{\partial s_0}{\partial b} \Big _B - \frac{1}{b} \frac{\partial s_0}{\partial B}) \times 10^3$				-.042 (.01)
<b>Moral Hazard:</b>				.0014
$\Theta_1$				(.0001)
<b>Liquidity to Moral Hazard:</b>				.876
$\rho_1$				(.022)
N	529	6061	2049	9471

Notes: 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 10. Results are obtained from a linear specification. 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). This table shows how to use the RKD to estimate all the statistics needed 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  $b \cdot \frac{\partial s}{\partial b}$ , 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 ( $\epsilon_{D_B}$ ) and of the elasticity of non-employment duration ( $\epsilon_D$ ) 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 and moral hazard effect estimates following the strategy detailed in proposition 1.  $(\frac{1}{B} \frac{\partial s_0}{\partial b} \Big|_B - \frac{1}{b} \frac{\partial s_0}{\partial B})$  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 1, this difference is then used to compute the moral hazard effect  $\Theta_1$  of an increase in benefit level and the ratio of liquidity to moral hazard  $\rho_1$  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.

## A.9 Heterogeneity in the test for slackness of the credit constraint at benefit exhaustion

One potential concern with the test for the slackness of the liquidity constraint presented in section 4 of the paper is that the average effect, which shows that on average the liquidity constraint is not yet binding at benefit exhaustion, is contaminated by heterogeneity. In particular, it may be that some individuals hit the credit constraint, and for them,  $\frac{\partial s_{B+1}}{\partial b_B} = 0$ . To investigate the extent of heterogeneity in the estimate, I estimate quantile treatment effects of the effect of past benefits on  $D_{B+1}$ , the duration of non-employment after 39 weeks (conditional on being unemployed after 39 weeks). In case of a large degree of heterogeneity, (some people being extremely credit constrained, and some other being less credit constrained), we would expect these quantile treatment effects to be very different: because the amount of your credit constraint is directly correlated with your exit rate after exhaustion (the less asset you have, the harder your search effort), the lower quantile of the distribution of  $D_{B+1}$  should react much less (or even not at all) to a change in prior benefits. Results, reported in table A6 show that even though lower quantile of the distribution do react a little less to a change in benefits before 39 weeks, differences across quantiles are small and not statistically significant. This evidence is supportive of the fact that the credit constrained is not firmly binding at benefit exhaustion. Almost everybody maintains some ability to transfer money across periods at time benefits are exhausted (albeit certainly at different costs).

Table A6: HETEROGENEOUS EFFECTS IN THE TEST FOR SLACKNESS OF THE CREDIT CONSTRAINT AT EXHAUSTION

	(1)	(2)	(3)	(4)	(5)
	Quantile Treatment Effects				
	q=.1	q=.25	q=.5	q=.75	q=.9
$\frac{\partial D_{B+1}}{\partial b_B}$	.109 (.068)	.194 (.091)	.545 (.200)	.220 (.170)	.256 (.172)
p-value	.231	.475	.365	.521	.198
Optimal poly.	1	1	1	1	1
$N$	529	529	529	529	529

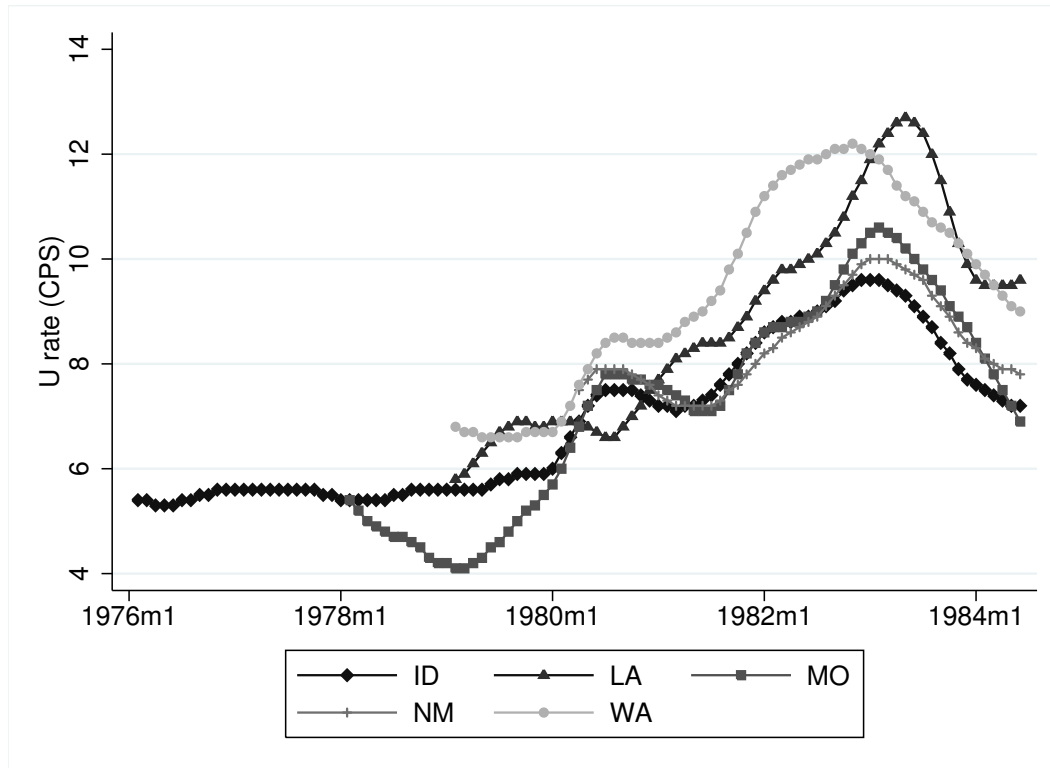
Notes: Bootstrapped standard errors in parentheses.

## **A.10 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  $\frac{\partial s_0}{\partial b} \Big|_B$  (sample 1) to match the distribution of observable characteristics of observations in the sample for the RKD estimates of  $\frac{\partial s_0}{\partial B}$  (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  $\omega = p/(1 - p)$

## B RKD Figures & Results for all 5 states

Figure B1: UNEMPLOYMENT RATES IN CWBH STATES 1976-1984

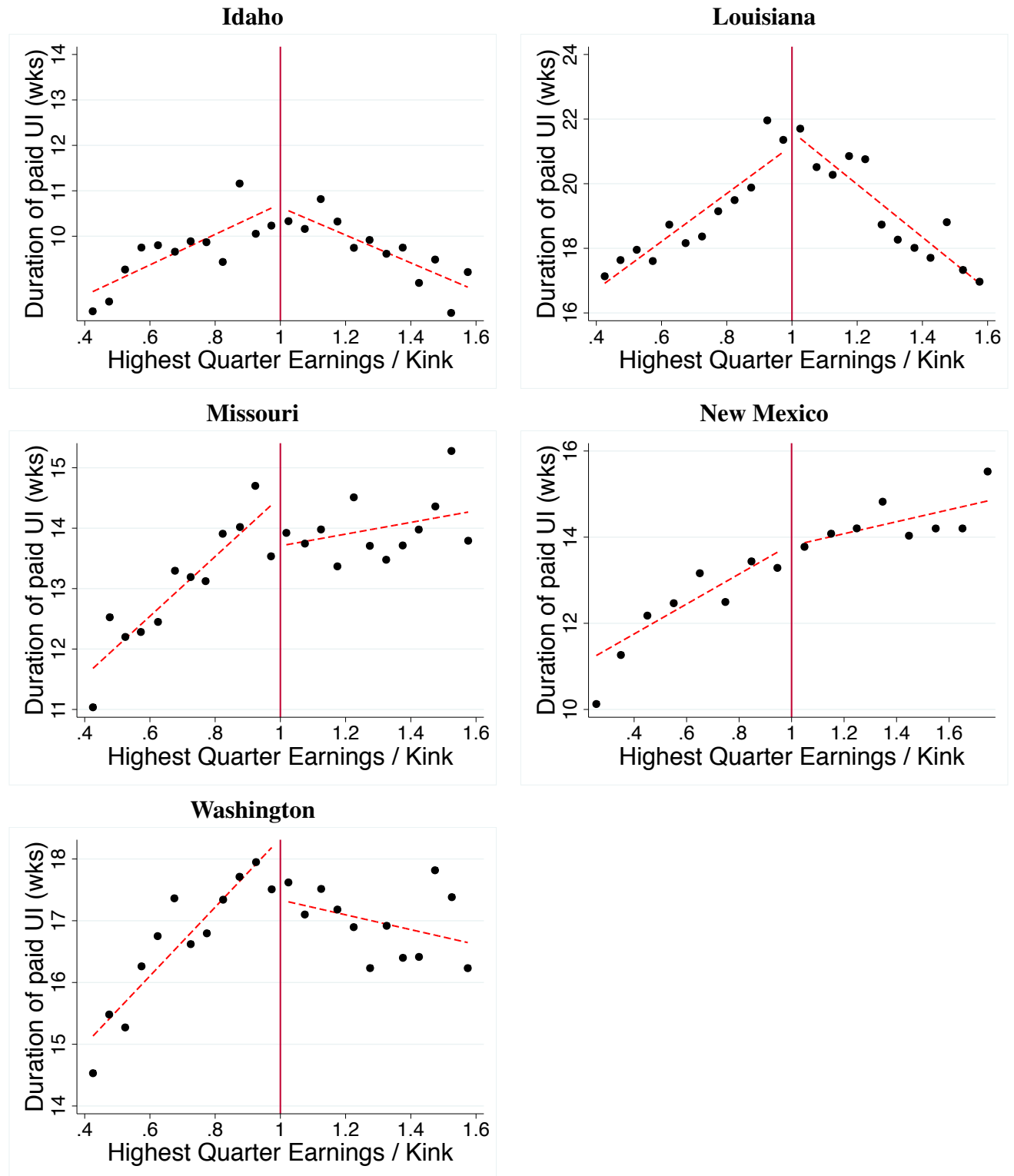


Sources: Current Population Survey

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.

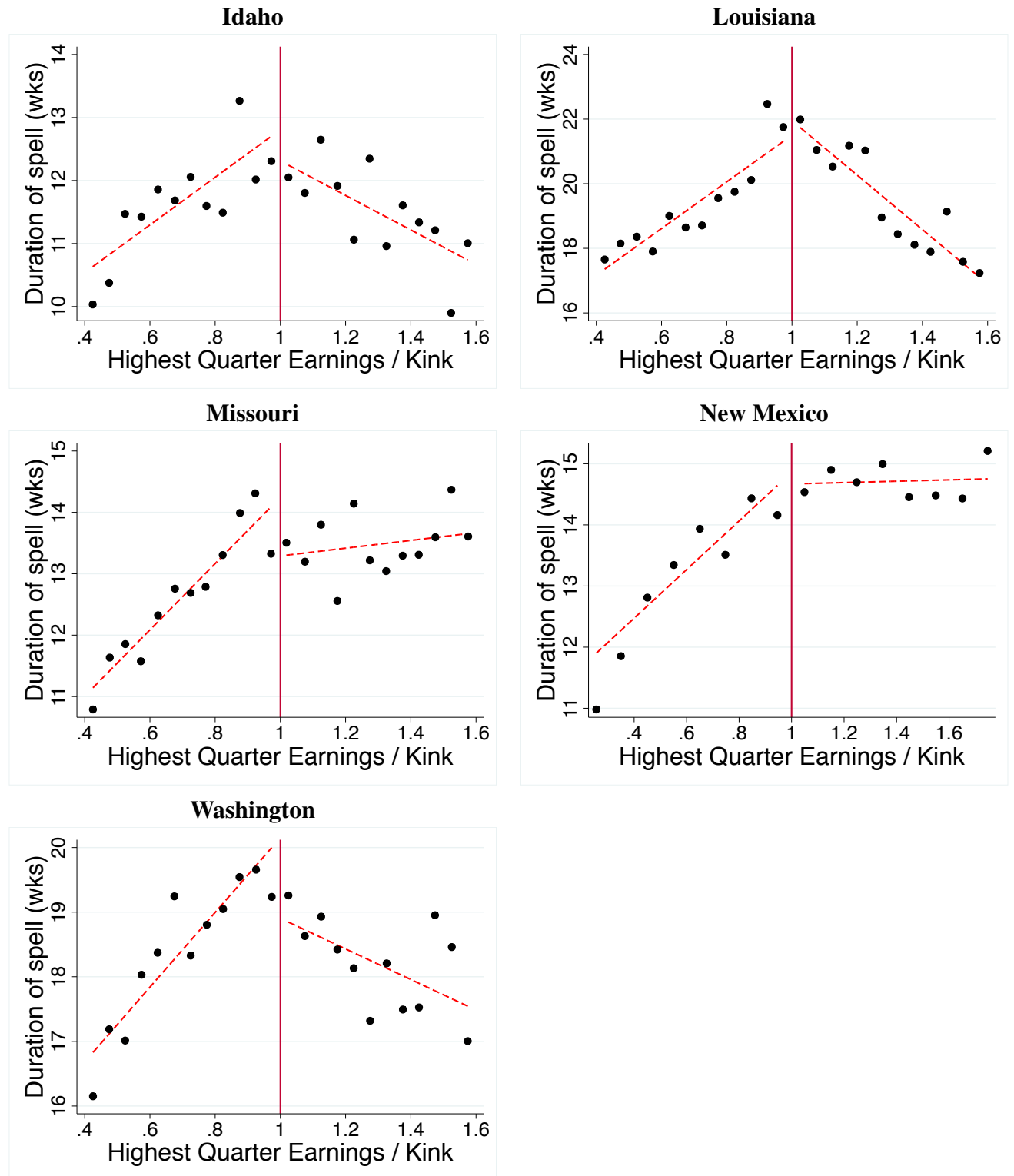


Figure B2: RKD EVIDENCE OF THE EFFECT OF BENEFIT LEVEL: DURATION UI PAID VS HIGHEST QUARTER EARNINGS FOR ALL 5 STATES



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 10 are displayed in table 2. The red lines display predicted values of the regressions in the linear case allowing for a discontinuous shift at the kink.

Figure B3: RKD EVIDENCE OF THE EFFECT OF BENEFIT LEVEL: DURATION OF INITIAL UNEMPLOYMENT SPELL VS HIGHEST QUARTER EARNINGS FOR ALL 5 STATES

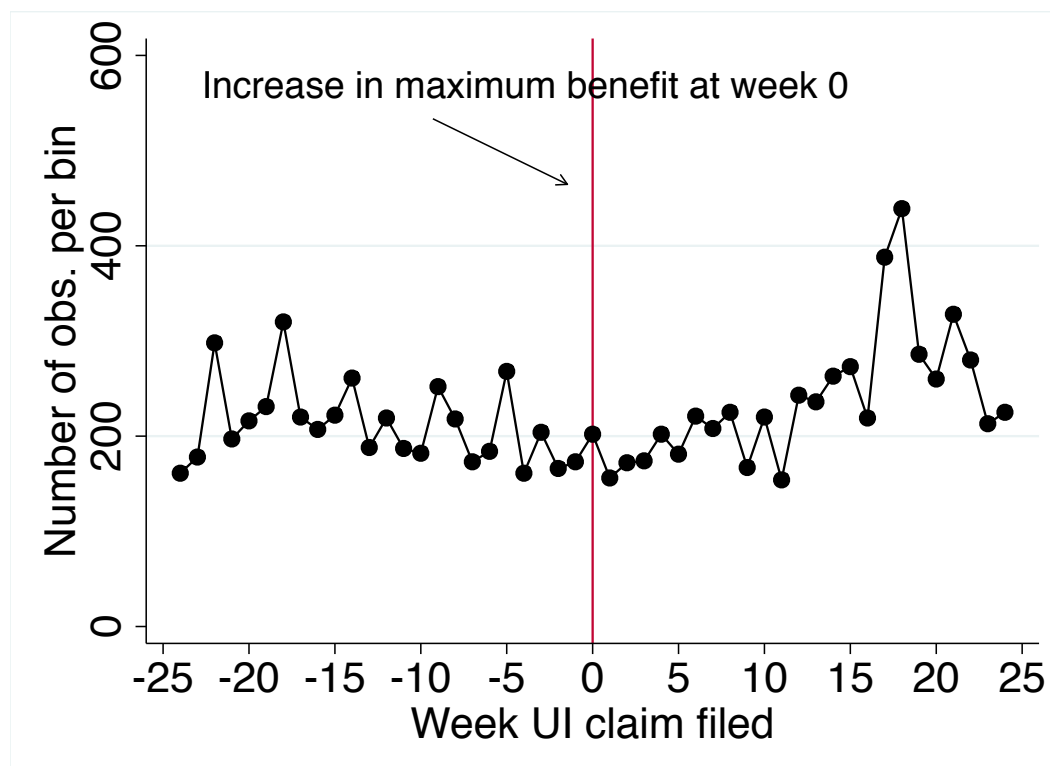


Notes: The graph shows for the first sub-period of analysis in each state the mean values of the duration of initial spell in each bin of \$250 of highest quarter of earnings, which is the assignment variable in the RK design for the estimation of the effect of benefit level. The assignment variable 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 10 are displayed in table 2. The red lines display predicted values of the regressions in the linear case allowing for a discontinuous shift at the kink.

### **Strategic timing of UI claims**

If individuals can perfectly anticipate when the maximum benefit amount is increased, this may lead to strategic behaviors in terms of the timing of UI claims. To investigate the extent of strategic manipulation of the timing of claims, I look at the distribution of claims by dates (in weeks) centered at the time when the maximum benefit is increased (week 0). I pool all maximum benefit increases together to maximize power. The sample is restricted to individuals who have highest quarter earnings above the kink of the initial schedule (prior to the benefit increase) so that all individuals in the sample would benefit from the increase in the maximum benefit if they claimed after week 0. In the presence of strategic manipulation, we would expect the presence of bunching just after week 0, and a hole in the distribution just before week 0. In practice, no evidence of manipulation can be detected in the distribution of claiming dates, as can be seen from Figure B4 which shows the distribution of claiming dates centered at the time the maximum benefit amount is increased for Louisiana. This evidence greatly alleviates the concern that strategic timing of claims may affect our empirical setting.

Figure B4: DISTRIBUTION OF CLAIMING DATES, CENTERED AT THE TIME THE MAXIMUM BENEFIT AMOUNT IS INCREASED, LOUISIANA



*Notes:* The figure investigates the extent of strategic manipulation of the timing of claims that may arise if individuals can perfectly anticipate when the maximum benefit amount is increased. The figure displays the distribution of claims by dates (in weeks) centered at the time when the maximum benefit is increased (week 0). I pool all maximum benefit increases together to maximize power. The sample is restricted to individuals who have highest quarter earnings above the kink of the initial schedule (prior to the benefit increase) so that all individuals in the sample would benefit from the increase in the maximum benefit if they claimed after week 0. In the presence of strategic manipulation, we would expect the presence of bunching just after week 0, and a hole in the distribution just before week 0. In practice, no evidence of manipulation can be detected in the distribution of claiming dates. This evidence greatly alleviates the concern that strategic timing of claims may affect our empirical setting.

Table B2: RKD ESTIMATES, EFFECT OF BENEFIT LEVEL, IDAHO, 1976 - 1983

	(1) Duration of Initial Spell	(2) Duration UI Claimed	(3) Duration UI Paid
<b>Period 1: jan1976 to jul1978</b>			
$\alpha$	.037 (.009)	.037 (.008)	.043 (.009)
$\varepsilon_b$	.337 (.086)	.386 (.086)	.334 (.072)
p-value	.022	.007	.003
$N$	7487	7487	7487
<b>Period 2: jul1978 to jul1980</b>			
$\alpha$	.087 (.009)	.079 (.008)	.09 (.009)
$\varepsilon_b$	.756 (.079)	.815 (.084)	.698 (.07)
p-value	.035	.02	.099
$N$	8143	8143	8143
<b>Period 3: jul1980 to jul1981</b>			
$\alpha$	.065 (.016)	.038 (.014)	.057 (.016)
$\varepsilon_b$	.58 (.144)	.392 (.141)	.445 (.125)
p-value	.602	.277	.38
$N$	3596	3596	3596
<b>Period 4: jul1981 to jun1982</b>			
$\alpha$	.006 (.02)	.005 (.016)	-.002 (.018)
$\varepsilon_b$	.053 (.143)	.048 (.144)	-.015 (.122)
p-value	.443	.57	.273
$N$	3968	3968	3968
<b>Period 5: jun1982 to dec1983</b>			
$\alpha$	.047 (.022)	.048 (.02)	.045 (.022)
$\varepsilon_b$	.381 (.182)	.466 (.195)	.319 (.16)
p-value	.121	.275	.062
$N$	2245	2245	2245

Notes: Duration outcomes are expressed in weeks.  $\alpha$  is the RK estimate of the average treatment effect of benefit level on the outcome. Standard errors for the estimates of  $\alpha$  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 10. The optimal polynomial order is chosen based on the minimization of the Aikake Information Criterion. Periods correspond to stable UI benefit schedules.

Table B3: RKD ESTIMATES, EFFECT OF BENEFIT LEVEL, MISSOURI JAN 1978 - DEC 1983

	(1) Duration of Initial Spell	(2) Duration UI Claimed	(3) Duration UI Paid
<b>Period 1: jan1978 to dec1979</b>			
$\alpha$	.02 (.009)	.02 (.01)	.031 (.01)
$\varepsilon_b$	.164 (.075)	.165 (.08)	.196 (.064)
p-value	.131	.479	.259
$N$	6071	6071	6071
<b>Period 2: dec1979 to dec1980</b>			
$\alpha$	.031 (.012)	.026 (.013)	.044 (.013)
$\varepsilon_b$	.226 (.089)	.179 (.087)	.24 (.073)
p-value	.49	.346	.077
$N$	5500	5500	5500
<b>Period 3: jan1981 to jan1982</b>			
$\alpha$	.01 (.012)	.005 (.012)	.02 (.013)
$\varepsilon_b$	.084 (.102)	.043 (.102)	.13 (.084)
p-value	.877	.843	.942
$N$	3625	3625	3625
<b>Period 4: jan1982 to aug1982</b>			
$\alpha$	.033 (.016)	.034 (.017)	.049 (.018)
$\varepsilon_b$	.232 (.117)	.239 (.119)	.277 (.102)
p-value	.174	.091	.006
$N$	2550	2550	2550
<b>Period 5: aug1982 to dec1983</b>			
$\alpha$	.052 (.011)	.043 (.012)	.061 (.012)
$\varepsilon_b$	.376 (.082)	.317 (.085)	.364 (.07)
p-value	.489	.529	.597
$N$	5036	5036	5036

Notes: Duration outcomes are expressed in weeks.  $\alpha$  is the RK estimate of the average treatment effect of benefit level on the outcome. Standard errors for the estimates of  $\alpha$  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 10. The optimal polynomial order is chosen based on the minimization of the Aikake Information Criterion. Periods correspond to stable UI benefit schedules.

Table B4: RKD ESTIMATES, EFFECT OF BENEFIT LEVEL, NEW MEXICO 1980 - 1983

	(1) Duration of Initial Spell	(2) Duration UI Claimed	(3) Duration UI Paid
<b>Period 1: apr1980 to jan1981</b>			
$\alpha$	.051 (.019)	.046 (.019)	.055 (.018)
$\varepsilon_b$	.353 (.129)	.332 (.135)	.34 (.114)
p-value	.20 2851	.24 2851	.18 2851
<b>Period 2: jan1981 to jan1982</b>			
$\alpha$	.033 (.012)	.026 (.013)	.031 (.012)
$\varepsilon_b$	.316 (.118)	.272 (.129)	.262 (.105)
p-value	.3 4906	.29 4906	.37 4906
<b>Period 3: jan1982 to jan1983</b>			
$\alpha$	.041 (.016)	.023 (.017)	.037 (.016)
$\varepsilon_b$	.342 (.137)	.202 (.147)	.273 (.122)
p-value	.9 3905	.783 3905	.647 3905
<b>Period 4: jan1983 to dec1983</b>			
$\alpha$	.04 (.015)	.03 (.015)	.04 (.015)
$\varepsilon_b$	.382 (.14)	.297 (.149)	.335 (.123)
p-value	.391 4209	.389 4209	.375 4209

Notes: Duration outcomes are expressed in weeks.  $\alpha$  is the RK estimate of the average treatment effect of benefit level on the outcome. Standard errors for the estimates of  $\alpha$  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 10. The optimal polynomial order is chosen based on the minimization of the Aikake Information Criterion. Periods correspond to stable UI benefit schedules.

Table B5: BASELINE RKD ESTIMATES, EFFECT OF BENEFIT LEVEL ON UNEMPLOYMENT AND NON-EMPLOYMENT DURATION, WASHINGTON 1979 - 1983

	Duration Initial Spell	Duration UI Claimed	Duration UI Paid	Non- Employment Duration
<b>Period 1: July 1979- July 1980</b>				
$\alpha$	.085 (.018)	.078 (.017)	.087 (.018)	.088 (.022)
$\varepsilon_b$	.68 (.147)	.69 (.152)	.657 (.136)	.419 (.104)
Opt. Poly	1	1	1	1
p-value	.162	.197	.198	.327
N	3485	3485	3485	3485
<b>Period 2: July 1980- July 1982</b>				
$\alpha$	.07 (.017)	.059 (.016)	.077 (.017)	.056 (.02)
$\varepsilon_b$	.583 (.138)	.546 (.146)	.591 (.128)	.278 (.097)
Opt. Poly	1	1	1	1
p-value	.987	.991	.985	.968
N	3601	3601	3601	3601
<b>Period 3: July 1982- Dec 1983</b>				
$\alpha$	.054 (.021)	.035 (.02)	.055 (.021)	.059 (.022)
$\varepsilon_b$	.37 (.146)	.263 (.153)	.351 (.137)	.281 (.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. Washington is the only state for which we observe reemployment dates from wage records in the CWBH data. I therefore constructed a variable for the total duration of non-employment in Washington, and display in column (4) the estimates of the effect of benefit level on this duration outcome as well.  $\alpha$  is the RK estimate of the average treatment effect of the UI benefit level on the outcome. Standard errors for the estimates of  $\alpha$  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 10. The optimal polynomial order is chosen based on the minimization of the Aikake Information Criterion. Periods correspond to stable UI benefit schedules.



## C Proofs and Results

### C.1 Understanding the comparison with a simple dynamic labor supply model with no state dependance:

Here, I briefly present a very simple two-period model with no state dependance, to understand how one can relate a dynamic search model to this general class of models. I also show how the Frisch elasticity literature uses variations along the wage profile over time to identify distortionary effects and liquidity effects separately, and how this relates to the technique employed in this paper to identify moral hazard effects and liquidity effects. Imagine a simple two-period model where utility in each period is given by  $U_t = u(c_t) - \psi(s_t)$  where  $s_t$  is some effort level that brings a monetary reward (wage)  $r_t$ .  $\psi(\cdot)$  is increasing and convex. Agents start with some asset level  $A_0$ . The individual's program is therefore:  $\max_{c_0, c_1, s_0, s_1} U_0 + U_1$  s.t.  $r_0 s_0 + r_1 s_1 + A_0 \geq c_0 + c_1$  The first order conditions give us:

$$\begin{cases} \psi'(s_0) = \lambda r_0 \\ \psi'(s_1) = \lambda r_1 \\ u'(c_0) = \lambda \\ u'(c_1) = \lambda \end{cases}$$

where  $\lambda$  is the Lagrange multiplier, or in other words, the marginal utility of wealth. Combining these first order conditions we get the Euler equation giving the optimal inter temporal allocation:

$$\frac{u'(c_0)}{u'(c_1)} = 1$$

And the static intratemporal optimal allocation rule:

$$\psi'(s_0) = r_0 u'(c_0)$$

From this, we immediately see that the response to a change in the return to effort at time 0 is the sum of a liquidity effect and of a distortionary effect:

$$\frac{\partial s_0}{\partial r_0} = \frac{-\lambda - r_0 \frac{\partial \lambda}{\partial r_0}}{\psi''(s_0)} = \frac{-u'(c_0)}{\psi''(s_0)} - \frac{r_0 u''(c_0)}{\psi''(s_0)}$$

This decomposition is exactly the same as the one in [Chetty \[2008\]](#), and is at the centre of the dynamic labor supply literature: The first-term is the Frisch effect, keeping marginal utility of consumption constant. The second one is a liquidity effect because we alter the marginal utility of consumption:  $-\frac{r_0 u''(c_0)}{\psi''(s_0)} = \frac{\partial s_0}{\partial A_0}$ . Here of course, the return to effort is continuous ( $r$ ), but it is easy to see from a simple Taylor expansion that it is equivalent to the liquidity effect ( $-\frac{u'(c_e) - u'(c_u)}{\psi''(s_0)} = \frac{\partial s_0}{\partial A_0}$ ) that we have in [Chetty \[2008\]](#) in the case of the return to job search effort.

The important insight from extending this simple example to a multi period case is that, in the absence of state-dependance as is the case here, effort at time  $t$  is always a function of wage at time

$t$  and all other wages affect current effort only through  $\lambda$ , because of the optimal inter temporal allocation rule. So that we have  $s_t = s_t(r_t, \lambda_t)$  where  $\lambda_t = \lambda_t(r_0, \dots, r_N, A_0)$ .

From this, there are two possible routes to identify the Frisch effect of a change in the wage rate. The first route, as in [MaCurdy \[1981\]](#) is to impose some structure on the problem by specifying the utility function so as to obtain a nice log-linear form for the Frisch effort function of individual  $i$ :  $\ln(s_t^i) = \beta \ln r_t^i + \alpha \ln \lambda_t^i$  and under some assumptions, the marginal utility of consumption can be written as an individual fixed effect and a time effect  $\ln \lambda_t^i = \gamma_i + e_t$ . Then, the model can be identified in first-difference using panel data and variations along the wage profile:  $\Delta \ln(s_t^i) = \beta \Delta \ln r_t^i + \Delta e_t$ . The difficulty is to find credibly exogenous variations in the wage profile.

The second route is to use more credibly exogenous variations, and use reduced form estimates of the effect of a change in the wage at different point in times. This is the route chosen in this paper. The idea is that we have:

$$\begin{cases} \frac{\partial s_0}{\partial r_0} = \frac{-\lambda - r_0 \frac{\partial \lambda}{\partial r_0}}{\Psi''(s_0)} \\ \frac{\partial s_0}{\partial r_1} = \frac{-r_0 \frac{\partial \lambda}{\partial r_1}}{\Psi''(s_0)} \end{cases}$$

And we also know that  $\frac{\partial \lambda}{\partial r_1} = \frac{\partial \lambda}{\partial r_0}$ . The difference in the reduced form estimates of the effect of a change in wages at time 0 and 1 can identify the Frisch effect  $\frac{-\lambda}{\Psi''(s_0)}$  keeping marginal utility of wealth constant. This technique has the advantage that the identifying variations are more transparent, but relies on the exact same idea of using variations along the wage profile over time. In this paper, the only complication comes from the presence of state dependence, as explained in section 1.

## C.2 Multi-period model:

Here, I present the multi-period model extension of the simple model presented in section 1 of the paper and derive the main results. 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<sup>57</sup>. 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<sup>58</sup>, and when an unemployed finds a job, it lasts forever. When unemployed, an agent starts her unemployment spell with asset level  $A_0$  and receives unemployment insurance benefits  $b_t$  each period. As a baseline, I consider that the initial asset level  $A_0$  is exogenous and do not allow for heterogeneity. Both assumptions can be relaxed, as I show in extensions of the model below. To finance the unemployment benefits, the government levies a lump sum tax  $\tau$  on

<sup>57</sup>This captures the presence of search frictions in the labor market.

<sup>58</sup>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. \[2007\]](#) 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.

each employed worker.

The planner sets taxes  $\tau$  and benefits  $b$  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 defined by a constant level  $b$  for a fixed period  $B$ <sup>59</sup>. Therefore choosing the optimal benefit schedule amounts to choosing potential duration  $B$  and benefit level  $b$ .

**Timing of the model:** Individuals 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 is 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  $\psi(\cdot)$  is increasing and convex.

For simplicity, and following [Chetty \[2008\]](#) who shows that in simulations  $U$  is always concave, we assume  $U$  is always concave.

**Definition and notations:** 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:

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

We also define a series of search and duration measures in the following way:

- $f_k(t) = \prod_{i=k}^{t-1} (1 - s_i) s_t$  is the probability that the unemployment spell lasts exactly  $t$  periods conditional on being still unemployed at the beginning of period  $k$ .
- $S_k(t) = \prod_{i=k}^t (1 - s_i)$  is the survival rate at time  $t$  conditional on being still unemployed at period  $k$ .
- $F_k(t) = \sum_{s=k}^t f(s) = 1 - S_k(t)$  is the probability that the length of a spell is inferior or equal to  $t$  conditional on being still unemployed at period  $k$ .

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<sup>59</sup>A large theoretical literature has derived the full optimal time-path of UI benefits. See for instance [Hopenhayn and Nicolini \[1997\]](#), or ?.

- $D_k^T = \sum_{i=0}^T S_k(i)$  is the average duration of a spell truncated at  $T$  periods conditional on being still unemployed after  $k$  periods.

**Optimal search effort** at time  $t$  is given by the following first-order condition:

$$\Psi'(s_t) = V(A_t) - U(A_t) \quad (13)$$

**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:

$$\forall t \quad u'(c_0^e) = \beta^t u'(c_t^e) \quad (14)$$

$$\begin{aligned} \forall t \quad u'(c_0^u) &= \sum_{j=1}^t \left( \prod_{i=1}^{j-1} (1 - s_i) s_j \right) \beta^j u'(c_j^e) + \beta^t \prod_{i=1}^t (1 - s_i) u'(c_t^u) \\ &= F_1(t) u'(c_0^e) + \beta^t S_1(t) u'(c_t^u) \end{aligned} \quad (15)$$

**Moral hazard and liquidity effects:**

Using the first order condition for search effort given in equation 13 we get the effect of benefit level at time  $t$  on optimal search:

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

and more generally the effect of benefit level at time  $t + j$  on optimal search at time  $t$ :

$$\frac{\partial s_t}{\partial b_{t+j}} = - \frac{\beta^j \prod_{i=1}^j (1 - s_{t+i}) u'(c_{t+j}^u)}{\Psi''(s_t)} = - \frac{S_{t+1}(t+j) \beta^j u'(c_{t+j}^u)}{\Psi''(s_t)} \quad (16)$$

From 13, we also have that:

$$\begin{aligned} \frac{\partial s_t}{\partial A_t} &= \frac{u'(c_t^e) - u'(c_t^u)}{\Psi''(s_t)} \\ \frac{\partial s_t}{\partial w_t} &= \frac{u'(c_t^e)}{\Psi''(s_t)} \end{aligned}$$

so that:

$$\frac{\partial s_t}{\partial b_t} = \underbrace{\frac{\partial s_t}{\partial A_t}}_{\text{liquidity effect}} - \underbrace{\frac{\partial s_t}{\partial w_t}}_{\text{moral hazard effect}} \quad (17)$$

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

The first term is a liquidity effect that is proportional to the difference in marginal utility of consumption while employed and unemployed. 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

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:

$$\frac{\partial s_0}{\partial b} \Big|_B = \overbrace{\frac{\partial s_0}{\partial A} \Big|_B}^{\text{liquidity effect}} - \underbrace{\frac{\partial s_0}{\partial w} \Big|_B}_{\text{moral hazard effect}} \quad (18)$$

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

### C.3 Proof of proposition 1:

I now show how  $\frac{\partial s_0}{\partial w} \Big|_B$ , the moral hazard 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 be identified using variations in search effort at time 0 in response to a change in benefit level  $\frac{\partial s_0}{\partial b} \Big|_B$  and variations in search effort at time 0 in response to a change in benefit duration  $\frac{\partial s_0}{\partial B}$ .

This proof is a simple generalization in a multi-period model of the proof given in the two-period model in the main text of this paper.

Using the first order condition for search effort given in equation 13 we get the effect of a change in wage at time  $t$  on optimal search at time 0:

$$\frac{\partial s_0}{\partial w_t} = \frac{\frac{\partial V(A_0)}{\partial w_t} - \frac{\partial U(A_0)}{\partial w_t}}{\Psi''(s_0)}$$

After some algebra, we have that:

$$\begin{aligned} \frac{\partial V(A_0)}{\partial w_t} &= \beta^t u'(c_t^e) \\ \frac{\partial U(A_0)}{\partial w_t} &= F_1(t) \beta^t u'(c_t^e) \end{aligned}$$

so that, using the Euler equations, we have that:

$$\frac{\partial s_0}{\partial w_t} = \frac{(1 - F_1(t))\beta' u'(c_t^e)}{\Psi''(s_0)} = \frac{S_1(t)u'(c_0^e)}{\Psi''(s_0)} = S_1(t) \frac{\partial s_0}{\partial w_0} \quad (19)$$

Equation 19 generalizes equation 5 from the two period model, and gives the relationship between the effect on effort at time 0 of a change in wage at time  $t$  and the effect on effort at time 0 of a change in wage at time 0. This relationship stems from the presence of state dependance. In the absence of state dependance, as is usually the case in the standard dynamic labor supply literature,  $S_1(t) = 0$  and therefore there is no moral hazard effect of changing benefits in time  $t$  on current effort at time 0: all the effect of changing the wage rate at time  $t$  on effort at time 0 happens through the liquidity effect (the change in the marginal utility of wealth). The intuition is that  $S_1(t) = 0$  means that no matter what my effort at time 0 is, I will be employed at time  $t$  with certainty, therefore changing the wage rate at time  $t$  has no forward-looking effect on my effort at time 0. The higher the probability that I remain unemployed at time  $t$ , the larger the forward looking effect of changing the wage rate at time  $t$  on my effort at time 0.

Using equation 19, we can now rewrite the moral hazard effect of an increase in benefit level  $b$  for  $B$  periods that we call  $\Theta_1$ :

$$\Theta_1 = \frac{\partial s_0}{\partial w} \Big|_B = \sum_{t=0}^{B-1} \frac{\partial s_0}{\partial w_t} = \frac{\partial s_0}{\partial w_0} \cdot \sum_{t=0}^{B-1} S_1(t) \quad (20)$$

Using equation 16 and the Euler equations, the effect of an increase in benefit level at time  $t$  on exit rate at time 0 can be written:

$$\begin{aligned} \frac{\partial s_0}{\partial b_t} &= - \frac{S_1(t)\beta' u'(c_t^u)}{\Psi''(s_0)} \\ &= \frac{F_1(t)u'(c_0^e) - u'(c_0^u)}{\Psi''(s_0)} \\ &= \frac{(1 - S_1(t))u'(c_0^e) - u'(c_0^u)}{\Psi''(s_0)} \\ &= \frac{\partial s_0}{\partial A_0} - S_1(t) \frac{\partial s_0}{\partial w_0} \end{aligned} \quad (21)$$

Equation 21 generalizes equation 6 from the two period model. Equation 21 stems from the presence of state dependance and has the same intuition as equation 19 above. In the absence of state dependance, as is usually the case in the standard dynamic labor supply literature,  $S_1(t) = 0$  all the effect of changing the wage rate at time  $t$  on effort at time 0 happens through the liquidity effect (the change in the marginal utility of wealth). But with state dependance, changing benefits at time  $t$  has a negative forward-looking moral hazard effect on effort at time 0 on top of the mere liquidity effect. The higher the probability  $S_1(t)$  that I remain unemployed at time  $t$ , the larger the forward looking effect of of increasing benefits at time  $t$  on my effort at time 0.

Using equation 21, we can write the effect of an increase of benefit level  $b$  for  $B$  periods as:

$$\begin{aligned}
\left. \frac{\partial s_0}{\partial b} \right|_B &= \sum_{t=0}^{B-1} \frac{\partial s_0}{\partial b_t} \\
&= B \cdot \frac{\partial s_0}{\partial A_0} - \frac{\partial s_0}{\partial w_0} \cdot \sum_{t=0}^{B-1} S_1(t)
\end{aligned} \tag{22}$$

Using equation 21, we can also write the effect of an increase in benefit duration  $B$  periods keeping constant benefit level  $b$ :

$$\begin{aligned}
\frac{\partial s_0}{\partial B} &\approx b \cdot \frac{\partial s_0}{\partial b_B} \\
&= b \cdot \left\{ \frac{\partial s_0}{\partial A_0} - \frac{\partial s_0}{\partial w_0} \cdot S_1(B) \right\}
\end{aligned} \tag{23}$$

From 22 and 23, it follows that:

$$\begin{aligned}
\left. \frac{1}{B} \frac{\partial s_0}{\partial b} \right|_B - \frac{1}{b} \frac{\partial s_0}{\partial B} &= - \left( \sum_{t=0}^{B-1} \frac{S_1(t)}{B} - S_1(B) \right) \frac{\partial s_0}{\partial w_0} \\
&= - \left( \overline{S_1^B} - S_1(B) \right) \frac{\partial s_0}{\partial w_0}
\end{aligned} \tag{24}$$

where  $\overline{S_1^B}$  is the average survival rate between time 1 and time  $B - 1$  conditional on being unemployed at time 1. Proposition 1 follows from using 20 and 24:

$$\left. \frac{1}{B} \frac{\partial s_0}{\partial b} \right|_B - \frac{1}{b} \frac{\partial s_0}{\partial B} = - \frac{\overline{S_1^B} - S_1(B)}{D_1^B} \cdot \Theta_1 \tag{25}$$

## C.4 Optimal benefit level $b$ :

**Planner's problem:** the government cannot observe effort and cannot contract directly on  $s_t$ , any increase in  $b_t$  leads to a decline in search effort. The planner sets taxes  $\tau$  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 defined by a constant level  $b$  for a fixed period  $B$ <sup>60</sup>. Therefore choosing the optimal benefit schedule amounts to choosing potential duration  $B$  and benefit level  $b$ .

The social planner chooses the UI benefit level to maximize expected utility subject to a balanced-budget constraint and given a potential duration of benefits  $B$ :

<sup>60</sup>A large theoretical literature has derived the full optimal time-path of UI benefits. See for instance [Hopenhayn and Nicolini \[1997\]](#), or ?.

$$\max_{b, \tau} W_0 = (1 - s_0)U(A_0) + s_0V(A_0) - \Psi(s_0)$$

$$\text{subject to } D_B \cdot b = (T - D)\tau$$

The first order condition is given by:

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

From 13, we have that:

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

So that:

$$\frac{dW_0}{db} = -(1 - s_0)\Psi''(s_0) \frac{\partial s_0}{\partial b} \Big|_B - \frac{d\tau}{db} \left( (1 - s_0) \frac{\partial U_0}{\partial w} \Big|_B + s_0 \frac{\partial V_0}{\partial w} \Big|_B \right) \quad (26)$$

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

$$\begin{aligned} \frac{\partial V_0}{\partial w} \Big|_B &= \sum_{t=0}^{B-1} \beta^t u'(c_t^e) \\ &= B u'(c_0^e) \quad \text{if the credit constraint does not bind at time } B \end{aligned} \quad (27)$$

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

$$\begin{aligned} \frac{\partial U_0}{\partial w} \Big|_B &= \sum_{t=1}^{B-1} F_1(t) \beta^t u'(c_t^e) \\ &= \sum_{t=1}^{B-1} F_1(t) u'(c_0^e) \quad \text{if the credit constraint does not bind at time } B \end{aligned} \quad (28)$$

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

$$\begin{aligned} (1 - s_0) \frac{\partial U_0}{\partial w} \Big|_B &= \sum_{t=1}^{B-1} (1 - s_0) F_1(t) u'(c_0^e) \\ &= \sum_{t=1}^{B-1} F_0(t) u'(c_0^e) \\ &= (B - D_B - s_0) u'(c_0^e) \end{aligned} \quad (29)$$

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  $B$ :

$$\begin{aligned}\left.\frac{\partial s_0}{\partial w}\right|_B &= \frac{1}{\Psi''(s_0)} \left[ \left.\frac{\partial V_0}{\partial w}\right|_B - \left.\frac{\partial U_0}{\partial w}\right|_B \right] \\ &= \frac{(D_B - s_0(B-1))u'(c_0^e)}{(1-s_0) \cdot \Psi''(s_0)}\end{aligned}\quad (30)$$

Using (18), (27), (29) and (30), we can rewrite (26) such that:

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

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:

$$1 + \rho_1 = \left( \frac{B}{D_B - s_0(B-1)} - 1 \right) \frac{D_B}{T-D} (1 + \varepsilon_{D_B} + \varepsilon_D \frac{D}{T-D}) \quad (31)$$

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 31 is superior to the righthand side, it is socially desirable to increase the benefit level  $b$ , at the given level of potential duration  $B$ .

## C.5 Optimal 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  $b_B$ <sup>61</sup>. In this context, following the same logic as previously, we have that :

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

<sup>61</sup>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  $b$ .

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

$$\frac{d\tau}{db_B} = \frac{1}{b} \cdot \frac{d\tau}{dB} = \frac{D_B}{B \cdot (T-D)} (\epsilon_{D_B,B} + \epsilon_{D,B} \frac{D}{T-D}) \quad (32)$$

where  $\epsilon_{D_B,B} = \frac{B}{D_B} \frac{dD_B}{dB}$  is the elasticity of the duration of paid unemployment with respect to the potential duration of UI benefits and  $\epsilon_{D,B} = \frac{B}{D} \frac{dD}{dB}$  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 (32) and

$$1 + \rho_2 = \left( \frac{1}{S(B) - s_0} - 1 \right) \frac{D_B}{B \cdot (T-D)} (\epsilon_{D_B,B} + \epsilon_{D,B} \frac{D}{T-D}) \quad (33)$$

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 33 is superior to the righthand side, it is socially desirable to increase the potential duration of benefits, at the given level of benefit level  $b$ .

## C.6 Stochastic wage offers:

The result of proposition 1 can be extended to the presence of stochastic wage offers, whereby an agent's hazard rate out of unemployment would depend both on her search effort and her reservation wage. Suppose that in period  $t$  with probability  $s_t$  (controlled by search intensity) the agent is offered a wage  $w \sim \hat{w} + F(w)$  and assume i.i.d. wage draws across periods. In such a framework, the agent follows a reservation-wage policy: in each period, there is a cutoff  $R_t$  such that the agent accepts a job only if the wage  $w > R_t$  ([McCall \[1970\]](#)). I show here that the result of proposition 1 remains unchanged in this context. The intuition for the result is that the agent is setting her reservation wage profile optimally, so that the envelope theorem applies and there is no first-order effect of a change in reservation-wage policy on the agent's expected utility.

For simplicity we focus on the two-period case. Expected utility at the start of period 0 is then:

$$\begin{aligned} \mathcal{U} = & s_0 P[w \geq R_0] u(c_0^e) + (1 - s_0 P[w \geq R_0]) u(c_0^u) - \psi(s_0) + \\ & \beta \left( s_0 P[w \geq R_0] u(c_1^e) + (1 - s_0 P[w \geq R_0]) \left( s_1 P[w \geq R_1] u(c_1^e) + (1 - s_1 P[w \geq R_1]) u(c_1^u) - \psi(s_1) \right) \right) \end{aligned} \quad (34)$$

where  $P[w \geq R_t]$  is the probability that the wage offered in period  $t$  is larger than the reservation wage in period  $t$ .

First-order conditions of the agent's problem with respect to  $s_0$

$$\begin{aligned} \psi'(s_0) = & P[w \geq R_0]u(c_0^e) + \beta P[w \geq R_0]u(c_1^e) - P[w \geq R_0]u(c_0^u) \\ & - P[w \geq R_0] \left( s_1 P[w \geq R_1]u(c_1^e) + (1 - s_1 P[w \geq R_1])u(c_1^u) - \psi(s_1) \right) \end{aligned} \quad (35)$$

First-order conditions of the agent's problem with respect to  $R_0$

$$\begin{aligned} 0 = & \frac{\partial P[w \geq R_0]}{\partial R_0} u(c_0^e) + \beta \frac{\partial P[w \geq R_0]}{\partial R_0} u(c_1^e) - \frac{\partial P[w \geq R_0]}{\partial R_0} u(c_0^u) \\ & - \frac{\partial P[w \geq R_0]}{\partial R_0} \left( s_1 P[w \geq R_1]u(c_1^e) + (1 - s_1 P[w \geq R_1])u(c_1^u) - \psi(s_1) \right) \end{aligned} \quad (36)$$

First-order conditions of the agent's problem with respect to  $R_1$

$$s_1 \frac{\partial P[w \geq R_1]}{\partial R_1} u(c_1^e) - s_1 \frac{\partial P[w \geq R_1]}{\partial R_1} u(c_1^u) = \psi'(s_1) \quad (37)$$

Euler equations:

$$\begin{aligned} u'(c_0^e) &= \beta u'(c_1^e) \\ u'(c_0^u) &= \beta (s_1 P[w \geq R_1]u'(c_1^e) + (1 - s_1 P[w \geq R_1])u'(c_1^u)) \end{aligned}$$

Using the envelope theorem:

$$\frac{\partial s_0}{\partial b_0} = - \frac{P[w \geq R_0]u'(c_0^u)}{\psi''(s_0)}$$

And using the Euler equations and the envelope theorem:

$$\frac{\partial s_0}{\partial b_1} = \frac{\partial s_0}{\partial b_0} - \frac{s_1 P[w \geq R_1]P[w \geq R_0]u'(c_0^e)}{\psi''(s_0)}$$

Because  $\frac{\partial s_0}{\partial w_0} = - \frac{P[w \geq R_0]u'(c_0^e)}{\psi''(s_0)}$  we have that

$$\frac{\partial s_0}{\partial b_0} - \frac{\partial s_0}{\partial b_1} = -h_1 \frac{\partial s_0}{\partial w_0}$$

where  $h_1 = s_1 P[w \geq R_1]$  is the hazard rate out of unemployment in period 1, and  $P[w \geq R_1]$  is the probability that the wage offered in period 1 is larger than the reservation wage in period 1  $R_1$ .

The only difficulty lies in defining the empirical counterparts for the implementation of the formula, as changes in empirically observed job finding hazards cannot be directly used to infer the relevant changes in search intensity because part of the change in job finding hazards comes from changes in the reservation wage. There are two options for empirical implementation. The

first one relies on the estimation of reservation wage variations to changes in UI benefits and therefore requires credible data on reservation wages. The idea is that the job finding hazard  $h_t$  can be decomposed into its search effort component  $s_t$  and its reservation-wage policy component  $P[w \geq R_t] = 1 - F(R_t)$  where  $F$  is the c.d.f. of the job offer distribution. We have for instance in the two-period case:

$$\frac{d \log s_0}{db_0} - \frac{d \log s_0}{db_1} = \left[ \frac{d \log h_0}{db_0} - \frac{d \log h_0}{db_1} \right] - \frac{f(R_0)}{1 - F(R_0)} \cdot \left[ \frac{\partial R_0}{\partial b_0} - \frac{\partial R_0}{\partial b_1} \right]$$

To back out the difference in the effect of benefits at time 0 and at time 1 on search effort, one needs to estimate the difference in the effect of benefits at time 0 and at time 1 on the hazard rate  $(\frac{d \log h_0}{db_0} - \frac{d \log h_0}{db_1})$  as well as the difference in the effect of benefits at time 0 and at time 1 on the reservation wage  $(\frac{\partial R_0}{\partial b_0} - \frac{\partial R_0}{\partial b_1})$ . There is unfortunately little empirical evidence on the behaviour of reservation wages. The best empirical evidence comes from [Krueger and Mueller \[2014\]](#), who, using high frequency survey data on reservation wage matched with administrative UI data in New Jersey, show that reservation wage profiles do not respond to UI benefits  $(\frac{\partial R_0}{\partial b} \approx 0)$ . The second option consists as in [Chetty \[2008\]](#) in using variations in mean accepted wages upon reemployment in response to variations in UI benefits. Again, recent evidence indicates that UI benefit levels have little effect on wages and other measures of the accepted job's quality ([Ours and Vodopivec \[2006\]](#)). In light of the empirical evidence, the empirical implementation of formula 1 using changes in hazard rates  $h_0$  to directly infer changes in search effort  $s_0$  seems to remain a valid approximation in the presence of stochastic wage offers.

## D 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<sup>62</sup>.

### D.1 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 B5.

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<sup>62</sup>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  $D_{max} \cdot \frac{\tau_1}{\tau_2} > 4$  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 B5: 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

## D.2 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.

### D.3 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 after 02dec1979.

#### **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.

### D.4 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 after 02dec1979.

\$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.

## D.5 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 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<sup>63</sup>. However, no additional benefit period was paid while a Federal program was in effect.

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<sup>63</sup>The additional benefits correspond to an *ad hoc* program which is triggered on only if the Governor determines it necessary.



## **D.6 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.

## **D.7 Graphical illustration of the kinks in the schedule of UI benefit level and of UI potential duration**

The schedule of UI benefits exhibits kinks for both potential duration and benefit level. But in some cases these two schedules are related, and therefore the location of the kinks may also overlap as

one can see from the formula for the schedule of potential duration

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

To analyze independently the effects of duration and of the benefit amount in the regression kink design, it is therefore useful to break down the sample in different subgroups. Figure D1 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  $bpw = D_{max} \cdot \frac{b_{max}}{\tau_2}$ .

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

The schedules of  $b$  and  $D$  for this subgroup is displayed on the left of panel B in figure D1.

For claimants who are below the maximum weekly benefit amount,  $b < b_{max}$ , there is a kink in the relationship between potential duration and the ratio of base period earnings to the highest-earning quarter at  $\frac{bpw}{hqw} = D_{max} \cdot \frac{\tau_1}{\tau_2}$ .

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

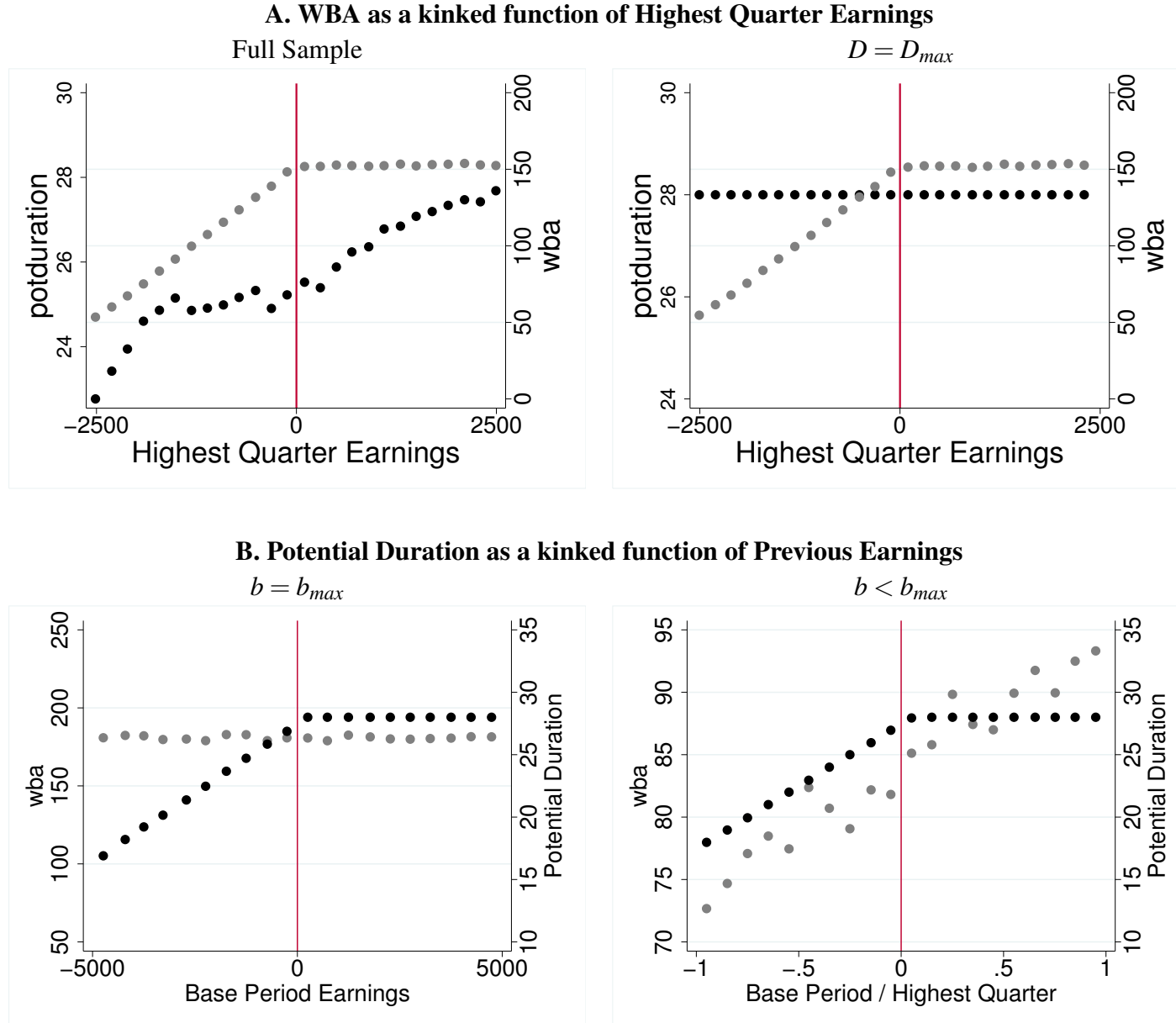
These claimants are displayed on the right of panel B in figure D1.

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

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

, 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. The schedule for these claimants is displayed on the left of panel A in figure D1. 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.

Figure D1: UI BENEFIT SCHEDULE: WEEKLY BENEFIT AMOUNT (GREY) & POTENTIAL DURATION (BLACK), LOUISIANA



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).