Unemployment Insurance and the Duration of Employment: Evidence from a Regression Kink Design

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Abstract

This paper studies the existence of a causal link between the availability of unemployment insurance (UI) and the duration of employment spells. After discussing few straightforward reasons why and how UI may affect employment duration, I apply a regression kink design to address this question using linked employer-employee data from the Brazilian labor market. Exploiting kinks in the Brazilian UI schedule, I find a statistically and economically significant effect of benefit level on the duration of employment spells at the lower end of the skill distribution. Surprisingly, the results for these workers indicate that the elasticity of employment duration to benefit level is positive and as large as 0.5. To assess the economic relevance of this result, I extend the reduced welfare formula from Chetty (2008) to deal with this effect on employment duration and show that this elasticity is as relevant for welfare as the elasticity of unemployment duration to benefit level.

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1 Introduction

There is a large body of both theoretical and empirical literature studying a number of issues related to unemployment insurance (UI). Perhaps its most well-established result is that more generous UI creates a moral hazard problem on search effort which increases the duration of unemployment spells. Instead, the question of whether (or how) unemployment insurance affects the dynamic of employment spells has been much less studied. In this paper, by applying a regression kink design (RKD) using Brazilian data, I present evidence that the level of unemployment benefits significantly affects the duration of employment spells at the lower end of the skill distribution, with a positive elasticity of around 0.4. To assess whether the size of this effect is of any relevance for welfare, I provide a welfare formula based on sufficient statistics and show that its impact on welfare has the same magnitude of the distortion caused by the moral hazard on search.

Even though we have little evidence on the issue, there are at least few straight forward reasons for one to suspect that the availability of UI may affect the duration of employment positively or negatively. The question of whether the magnitude of this effect is relevant will be addressed in the data. First, higher unemployment benefit increases the value of unemployment for employed workers. Therefore, it decreases the incentives for employed workers to put effort in keeping their jobs, decreasing the duration of employment. Second, in the vast majority of UI systems, only workers laid-off against their will are eligible to unemployment benefits. Therefore, it decreases the incentives for workers to quit because it means giving up unemployment benefits, especially if the reason for quitting is not engaging in a new job. Differently from the first, this mechanism would increase the duration of employment. Third, most UI systems have a minimum eligibility requirement (MER) in which only workers which are employed for a minimum length of time are eligible to benefits in the case of a lay-off. Such a feature creates incentives for workers to put effort in holding up their jobs until the minimum required period, and thus should increase the duration of the employment. Fourth, in many systems potential duration of benefits is an increasing function, often times discontinuous, of the duration of the employment spell prior to the dismissal. Similarly to MER, this provides an incentive for workers to put effort in holding their jobs for longer periods, increasing the duration of employment.

All these are simple theoretical predictions which can be made without the need to rely on any extreme assumption whatsoever. The real question however is whether one or more of these mechanisms are able to create any economically sizeable effects on the duration of employment spells. Notice that, in principle, such effect could be positive or negative. To answer to this question avoiding the interference of confounding factors, I exploit the assignment rule for benefit level in the Brazilian UI system by implementing a regression kink design. By taking advantage of eight years of linked employer-employee data from the whole Brazilian formal market, I assess the effect of benefit level around three different points of the earnings distribution. Even though the RKD is extremely data demanding, the very sizeable dataset containing more than 50 millions observations per year allows me to have enough precision on the estimates. To the best of my knowledge, this is the first paper to address the question of how UI affects the duration of employment spells with a credible quasi-experimental setup.

The remaining issue though is whether this result is of any relevance for welfare. To address this question, I modify the reduced-form welfare formula provided by Chetty (2008) in a way that it can deal with UI distortions on the duration of employment. I show that the latter affects welfare with the same order of magnitude as the well-known distortion on search, measured by the elasticity of unemployment duration to benefit level. Therefore, this result suggests that the effect of benefit level of the duration of employment spells is as relevant for policy as the moral hazard of search.

The paper is organized as follows. In section 2, I present the model from which the reduced-form welfare formula is derived and discuss its key differences and results with respect to Chetty (2008). In section 3, I describe the institutional background and present the identification strategy. In section 4, I show the results and provide evidence on the validity of the regression kink design. In section 5, I discuss the results and how they link to welfare.

2 Theory

The goal of this model is to derive a reduced form welfare formula which can deal with potential distortions of benefit level on the duration of employment spells. It builds as close as possible to the setup proposed by Chetty (2008). It features incomplete markets where workers are not able to privately insure against unemployment and have a limited ability to borrow against the future. These elements provide the rational for government intervention with unemployment insurance policy. If, otherwise, credit and insurance markets were complete, workers would be able to perfectly insure against unemployment and would face no liquidity constrains. In such world, there would be no reason for the government to intervene. Below, I present the model setup and the agent's problem.

2.1 Model Setup and Agent's Problem

The model runs in discrete time and agents live for T periods {0, 1, ... , T-1}. For a matter of simplicity, I further assume that the agent's discounting rate and interest rates are equal to zero, as in Chetty (2008). In this economy, all agents start the model employed with a wage equal to w and have to pay a tax τ which finances the UI system. They face a lay-off risk which negatively depends on the level of effort e_t that they put in keeping their job. The idea is that workers can make costly decisions which may help them holding their jobs. For instance, workers can decide how punctual they are or how willing they are to do extra hours. It can also be understood under the framework of a standard shirking model: firms use the threatening of firing to motivate workers to exert effort. The more effort the worker puts in his job, the lower the probability of being fired. It is worth noticing, however, that this model is silent with respect to the fact that variations in effort may affect firm productivity. Work effort e_t is costly for the workers and its cost is given by the function $c(e_t)$, which is assumed to be continuous and convex ($c'(e_t) > 0$ and $c''(e_t) > 0$). Furthermore, without loss of generality, e_t is normalized in such a way that it directly represents the probability of a lay-off. The problem of the worker who keeps his job is given by:

$$V_t(A_t) = \max_{A_{t+1} \geq L} v(A_t - A_{t+1} + w_t - \tau) + J^V_{t+1}(A_{t+1}) \tag{1}$$

$$J^V_t(A_t) = \max_{e_t} e_t V_t(A_t) + (1 - e_t)U_t(A_t) - c(e_t) \tag{2}$$

V_t defines the value of the job the worker has at the beginning of the model over time. A_t defines the worker's asset level at period t. Such a level is constrained by a lower bound L, which defines the maximum amount the worker is able to borrow against the future. $v(.)$ defines the utility from consumption of the employed worker. With probability e_t he keeps his job, which yields the value V_t. With probability $(1 - e_t)$ he loses his job and becomes unemployed immediately at period t, which yields the value U_t.[1]

In the case where the worker is laid-off, he receives unemployment benefits equal to $b_t < w_t$, provided that he has worked for at least k periods; otherwise, $b_t = 0$. This characterizes a minimum eligibility requirement (MER) for UI, which is a typical feature of many UI systems.[2] Nevertheless, since k is a parameter which can take any value, the model is also able to suit the case of systems which do not have MER. At this point, the unemployed worker chooses his level of search effort s_t in order to find a new job. As for work effort, s_t is normalized to equal the probability that the worker finds a new job at period t. The cost of search effort is defined by $\psi(s_t)$ which is assumed to be continuous and convex ($\psi'(s_t) > 0$ and $\psi''(s_t) > 0$). Thus, with probability s_t the unemployed worker finds a new job which immediately starts at period t and yields value E_t. With probability $(1 - s_t)$ he fails to find a job at period t and remains unemployed, which yields him the value U_t. His problem is given by:

$$U_t(A_t) = \max_{A_{t+1} \geq L} u(A_t - A_{t+1} + b_t) + J^U_{t+1}(A_{t+1}) \tag{3}$$

$$J^U_t(A_t) = \max_{s_t} s_t E_t(A_t) + (1 - s_t)U_t(A_t) - \psi(s_t) \tag{4}$$

[1] A more intuitive and conventional assumption would be that a lay-off at period t leads to unemployment at period t+1. However, here I shall assume that unemployment comes immediately for a matter of tractability of the model.

[2] More precisely, to the best of my knowledge, I am not aware of any UI system which does not require a minimum number of working months for workers to be granted with UI benefits.

E_t is defined as the value of employment subsequent to unemployment. Following the same spirit of Chetty (2008), I assume this to be an absorbing state. It means that once an unemployed worker finds a new job, he remains employed indefinitely. Furthermore, once reemployed, workers no longer have to contribute for UI since his job now lasts forever.

$$E_t(A_t) = \max_{A_{t+1} \geq L} v(A_t - A_{t+1} + w_t) + E_{t+1}(A_{t+1}) \tag{5}$$

$$\tag{6}$$

The underlying idea of this setup is that the UI system can be properly represented by a initial period where employed workers contribute to the system, and a subsequent period where workers who have lost their jobs are benefited from the insurance. This also seems to be the appropriate order of facts because any UI system requires workers first to work and, only then, they can become eligible for UI. In other words, new entrants in the labor market are not entitled to benefits when they first start looking for a job. Therefore, in this model, for a matter of simplicity, the third state is neutral with respect to the UI system exactly because the initial employment and subsequent unemployment period are enough to capture the relevant features of the system. Making a link with the "real world", once workers are reemployed after enjoying UI benefits, it works as if they were starting their first employment again, for all that matters for UI.

In sum, the model defines an economy with incomplete credit and insurance markets. All workers are employed at $t = 0$ with a net wage of $w_t - \tau$ and face a lay-off risk which negatively depends on their choice level of work effort, period after period. If a worker becomes unemployed, he has to choose a level of search effort in order to find a new job. While unemployed, he is entitled to UI benefits b_t, which last for a maximum of B periods, provided that he has worked for more than k periods (MER), otherwise he receives zero benefits. Once the worker leaves unemployment, he falls into an absorbing state where his new job lasts indefinitely and he has no longer to contribute for the UI system.

2.2 The Reduced-Form Welfare Formula

I leave the solution for the worker's problem in each state of the model to appendix B.1 and B.2, and move to the social planner's problem to derive the welfare formula. The social planner aims to maximize expected utility by choosing the level of unemployment benefits and a tax level τ on employed workers in order to finance the system. In principle, the profile of benefit levels and duration could vary over time, however for a matter of simplicity I focus on "constant benefit, finite duration", as in Chetty(2008).[3] Therefore, I here assume b_t to be constant over time and that benefits last for a maximum of B periods.

[3] Chetty(2008) also remarks that most UI policies indeed provide constant benefits with finite duration. This is also the case for Brazil, which is analyzed in the empirical section.

The general social planner's problem is given below:

$$\max_{b,\tau} J_0^V(b,\tau) = e_0 V_0(b,\tau) + (1-e_0)U_0(b,\tau) - c(e_0) \tag{7}$$

$$s.t. \quad f^{UI} D_B b = D_E \tau \tag{8}$$

The goal of the social planner is to maximize J_0^V which defines the representative worker's expected utility, which is assumed to start the model employed. Since the choice of effort at period 0 can lead to a lay-off at the same period as discussed before, expected utility is the weighted sum of the expected utility of workers who keep their jobs at the initial period, V_0, and of those who enter unemployment already at period 0, U_0; minus the cost of effort. Weights are of course the probability of keeping the job at the initial period, and the probability of being dismissed, respectively.

The constraint assures that the government budget is balanced. D_E describes the expected duration of the agent's employment at the beginning of the model. Only this duration matters for the government budget's revenue because, as stated before, upon reemployment workers remain employed forever and no longer contribute to the system. D_B defines the agent's expected unemployment duration under UI benefits and f^{UI} is the fraction of workers meeting MER. The former differs from the simple unemployment duration because when the unemployment spell exceeds the maximum duration of benefits (B periods), workers no longer receive benefits. Thus, once the unemployment spell exceeds the maximum duration of benefits, its duration no longer matters for the government budget. Therefore, the left-hand-side of the budget constraint in (8) denotes the expected cost of the policy, while the right-hand-side represents the expected amount received in taxes, which are levied on employed workers.

At this point, it is possible to evaluate how a marginal change in the level of benefits impacts on welfare. In the same spirit of Chetty (2008), I assume that the consumption path during employment is constant since unemployment is unlikely to cause large losses on life cycle earnings. Furthermore, since there is no reason to believe that the liquidity to moral hazard ratio or the probability of finding a job at the initial period of unemployment should vary depending on when individuals have become unemployed, I assume these to be constant over time. Together with the results from the agent's optimal choice of work and search effort, it is possible to derive the final welfare formula (see Appendix B.4 for details):

$$\frac{dW}{db} = f^{UI}\frac{D_B}{D_E}\left\{\frac{1}{1-s_0}(\rho+1) - \left(1 + \epsilon_{f^{UI},b} + \epsilon_{D_B,b} - \epsilon_{D_E,b}\right)\right\} \tag{9}$$

where $f^{UI} = \sum_{i=k}^{T-1}\left[\Pi_{j=0}^{i-1} e_j\right](1-e_i)$ is the share of laid-off workers eligible for UI due to MER and

$\rho = -\frac{\frac{\partial s_i}{\partial A_i}|B}{\frac{\partial s_i}{\partial W_i}|B}$ is the liquidity to moral hazard ratio for each i.

This formula shows the net welfare effect from increasing UI benefits by \$ 1. Welfare effects are a trade-off between the benefits from the liquidity provided to unemployed workers and the costs from higher taxes imposed on employed workers. The benefit from providing liquidity to the unemployed is captured by the liquidity-to-moral hazard ratio ρ. It is also weighted by the fraction of unemployed workers actually eligible for UI, since those not meeting MER are not entitled to benefits. On the cost side $\epsilon_{D_B,b}$ captures the behavioral response from higher benefits on the duration of unemployment under benefits; and $\epsilon_{D_E,b}$ captures the behavioral response from higher benefits on the duration of employment. Furthermore, there is also the behavioral response on the fraction of workers meeting MER, $\epsilon_{f^{UI},b}$. The last three terms captures exactly the distortionary effect of UI on employment and is the key difference from this result to the original formula provided by Chetty (2008).

The formula shows that $\epsilon_{D_E,b}$ affects welfare exactly with the same magnitude of $\epsilon_{D_B,b}$. In the empirical section, I show that $\epsilon_{D_E,b}$ can take values as large as 0.5, which is similar to the size of $\epsilon_{D_B,b}$ found in other studies, roughly ranging from 0.1 to 0.9.

3 Institutional Background and Identification Strategy

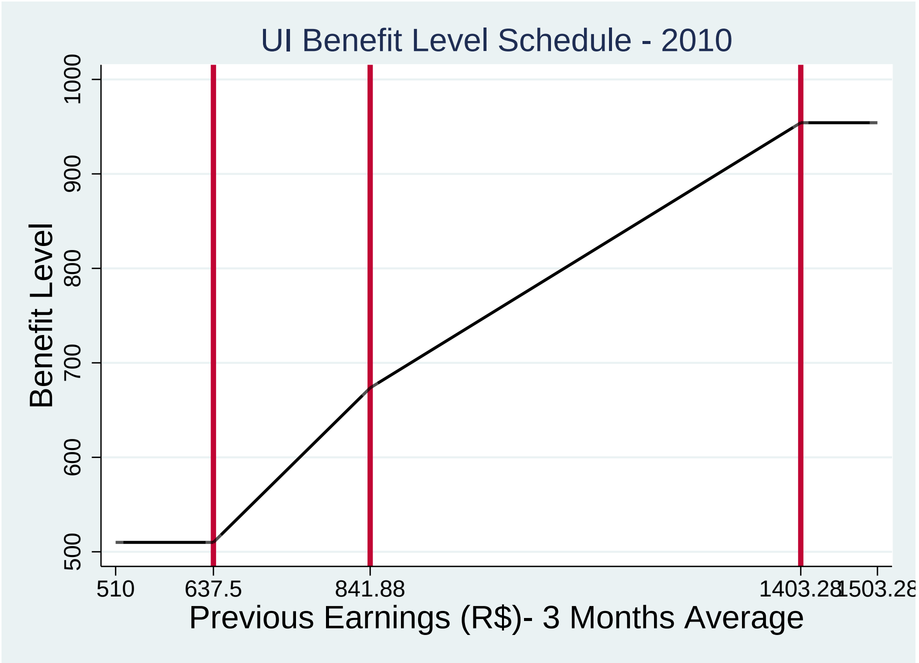
To recover the effect of benefit level on the duration of the employment spell without the interference of confounding factors, I implement a regression kink design to explore kinks on the policy rule which conditions benefit level on previous earnings in Brazil. Throughout this section, I introduce the main characteristics of the UI system in Brazil and the benefit level schedule; explain the identification strategy - *the regression kink design*; and present the data.

3.1 UI Schedule in Brazil

The Brazilian unemployment insurance system is a federal program established in 1986. It offers temporary income for formal sector workers who are dismissed against their will and meet minimum eligibility requirements. These are: (i) have been employed in all the last 6 months prior to the lay-off; (ii) have no other source of income ; (iii) have not been granted with UI benefits for the last 16 months, couting from the date of the last lay-off which enacted benefits. It is important to notice that benefits are granted only for workers dismissed *without a just cause*. This is the most common type of dismissal in Brazil, since employers by law are free to dismiss workers without a just cause in the sense that they need no authorization from any tribunal or government agency to do so. Furthermore, even though dismissing *with a just cause* is less cost for employers, the conditions for this type of dismissal are very tight and it is very hard to collect enough proof to back up cause.[4] Also notice that workers quitting their jobs are not entitled to benefits.

The level of benefits is defined by a rule based on the 3-months average of previous earnings prior to the dismissal. The schedule varies in values on a yearly basis, but its shape remains always the same. I choose to present the schedule with numbers from 2010 for illustrative purpose. The schedules for other years are follow the very same shape but are yearly increased by around 8%. Figure 1 shows the schedule for the year of 2010.

Figure 1: Benefit Level Assignment Rule - Year 2010



Monthly benefits are a function of a reference wage ($r.w.$) which is given by the average monthly earnings in the last three months prior to the dismissal. Benefit level equals 80% of the reference wage if it is lower than R$ 841.88. However, benefits can never be lower than minimum wage, R$ 510 for the year of 2010. This generates the first kink in the assignment rule which can be seen by the red line at the left side of figure 1 (at R$ 637.50). When the reference wage is higher than R$841.88 but not larger than R$1403.28, benefits are given by $[(r.w. - 841.88) * 0.5 + 841.88 * 0.8]$. It defines the second kink present in the assignment rule, at R$841.88, which is indicated by the second red line in figure 1. For reference wages larger than R$1403.28, benefits are always equal to R$954.20. This cap defines the last kink in the assignment rule, which is indicated by the red line at the right side of figure 1. The values present in the schedule are updated every year, which changes the location of the three kinks from year

[4] In general, workers can only be fired on cause only if they: (a) are continuously absent from work (usually more than 30 days) ; (b) commit serious misconduct ; (c) go to work under the effect of alcohol; or (d) commit a large number of small infractions.

to year. These three kinks are the source of exogeneity which will be exploited by the empirical strategy which I implement. The details of the strategy are discussed in the next subsection.

As regards the maximum duration of benefits, it is a function of the number of months worked in the last 36 months prior to the lay-off. Table 1 presents the UI schedule of potential duration:

Table 1: Potential Duration Assignment Rule

Months worked in the last 36 months	Months of Benefit
from 6 to 11	3
from 12 to 23	4
More or equal 24	5

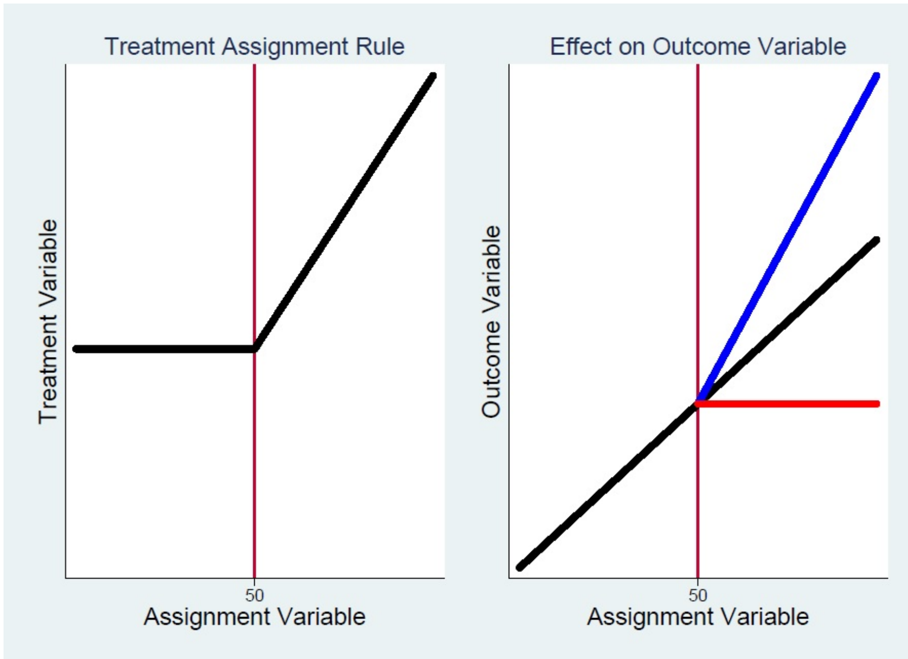
3.2 The Regression Kink Design

The idea of the regression kink design (RKD) is to exploit kinks in the relationship between an assignment variable and a treatment variable, which are the reference wage, based on previous earnings, and the level of unemployment benefits in this application, respectively. Such kinks are present in the relationship explained above and illustrated by figure 1. The intuition of the strategy is that if the treatment variable has a causal effect on a given outcome variable, there should also be a kink in the relationship between the outcome variable and the assignment variable. Therefore, in our context, if we expect that there is a causal relationship between UI benefit level and employment duration, there should also be a kink relationship between employment duration and the reference wage (the assignment variable) at the same kink points marked in red in figure 1.

The idea of this design is similar to a regression discontinuity design (RDD), except that in this case there is not a discontinuity in the level of the assignment rule, but in its slope (or first derivative). The intuition of why it is able to identify the treatment causal effect is exactly that in the vicinity of the kink, subjects have the same pre-treatment characteristics *on the margin* but are however assigned to different levels of treatment *on the margin*.

In figure 2 it is possible to see a graphic example of the RKD. The graph on the left illustrates the kink relationship between the treatment and the assignment variable when it equals 50. It illustrates a hypothetical case in which individuals to the right of the kink receive a linearly increasing level of treatment. The graph on the right side shows the three possible results which can be found by analyzing the relationship between a given outcome variable and the assignment variable. If the treatment yields no effect on the outcome, one should find no kink in the relationship around the kink point, as shown by the black line. In case the treatment has a positive effect on the outcome, one should expect to find a positive change of slope around the kink point, as shown by the blue line. In the case where the treatment has a negative effect on the outcome, there should be a negative change in slope around the kink point, as shown by the red line.

Figure 2: RKD Graphic Example



The key assumption for the RKD is formalized by Card, Lee, Pei & Weber (2015) and requires that the density of the assignment variable is smooth conditional on unobserved characteristics around the kink point present in the policy assignment rule. As in the RDD, one crucial advantage for the credibility of this design is that its key assumption is testable in at least two ways. First, it is possible to test whether the empirical density function of the assignment variable is actually smooth around the kink point. I therefore provide evidence on whether the density of average previous wage is smooth around all the three kink points. Second, the key assumption described above implies that the conditional expectation function of any pre-determined characteristic is also smooth around the kink point. Therefore, I provide evidence on the smoothness of the conditional expectation function of pre-determined variables, such as previous tenure and years of schooling, around all the three kink points. Furthermore, I create a further variable to test the validity of the design. I generate the best linear prediction based on a full set of pre-determined covariates around each kink to test whether it evolves smoothly around each kink. The idea is that if the design is validy, this linear prediction based on pre-determined covariates should not yield any kink around the points. I present this evidence together with tests on the smootness of other covariates.

In order to test and identify the presence of kinks in the data, I apply a local regression in the following parametric form:

$$Y_i = c_0 + [\sum_{p=1}^{P} \gamma_p (w-k)^p + \beta_p (w-k)^p.D] \text{ where } |w-k| \leq h \tag{10}$$

where w is the reference wage, based on previous earnings, in the year (the assignment variable) centered around the kink point k, P is the polynomial order of the regression, h is the bandwidth used, and D is a dummy variable taking value 1 for $(w-k) \geq 0$. The estimate of interest is the slope change in the outcome variable at the kink point, which is identified by β_1. As regards the bandwidth and polynomial order choice, I decided to conduct Monte Carlo simulations with a variety of proposed bandwidth selectors with linear and quadratic polynomials to evaluate the most appropriate choice around each kink, as suggested by Card et al (2015). This procedure is discussed in details in the results section.

3.3 Data

The data I use in this paper comes from the *Relação Anual de Informações Sociais* - RAIS. It is an administrative dataset covering all the employment relationships in the Brazilian formal Labor Market. I have access to this data from the year of 2005 to 2012. It contains detailed information on the characteristics of each labor contract such as start and end date, type of labor contract, type of termination, firm size at two different aggregation levels (branch and holding), municipality and industry; as well as information on workers, such as schooling, gender and wage. Furthermore, it is possible to identify workers and firms through an identification number.

4 The Effect of Benefit Level on Employment Duration

To assess the effect of benefit level on employment duration, I separately explore all the three kinks in the UI schedule pooling data from all years around each threshold. I consider all workers from the private sector which were employed at the first day in which the yearly schedule is introduced. Then, since the schedule is again updated in the subsequent year, the duration of employment is constructed as the spell between the first day in which a yearly UI schedule is in place and the last day of the year. For instance, for the 2010 schedule, I consider all workers employed in the first day in which the schedule is valid, January 1^{st} (2010) in this case, and count for how long they were employed in the year, i.e., until December 31^{st}. In case a worker keeps his job until the last day of the year, I consider the last day of work as December 31^{st}. Notice however that from 2005 to 2009, the yearly schedule was respectively introduced at the first day of May, April, April, March and February, therefore it would be possible to consider the duration until a date further than the 31^{st} December of the previous year in this period. However, I decide always to use the 31^{st} December as the last day of employment in the year because of the structure of dataset, which is based on yearly mandatory information provided by the firms to the government authorities. It avoids computing the duration of spells using data from two different years, which eliminates the risk of any possible endogeneity arising from the selection of firms which report the data for only one of the years.

A drawback from the dataset is that it provides only the worker's average monthly earnings for each year, while the assignment variable for the UI schedule is based on the average monthly earnings only in the three months previous to dismissal. Due to that limitation, I use the average wage in the year as assignment variable for the RKD and need to expect that wages do not change too fast within a given year. In case wage evolution over the year is too step, it is likely that the RKD design would be compromised as the kink would likely be smoothed and it would be hard to identify any kink in the data. Instead, I show that it is indeed possible to identify a kink for employment duration at the precise points presented in the UI schedule.

4.1 Density Smoothness and Data Heaping

To evaluate whether the necessary conditions for the RKD hold, the density function of wages must be smooth and continuous around each of the kink points. However, the raw data contains a number of heaping points which are not precisely in line with the baseline setup of the RKD. These heapings points might be caused by large firms with rigid wage policy and because wages are usually initially set at round numbers. To deal with this, I drop these heaping points of the data. To do so, I count the number of observations at each point of the data at the most disaggregate level (R$0.01), and compute the mean and the variance of the number of observations within a interval range of R$0.25, *for each point in the data*, without considering the point in question for the mean and variance calculation. I drop those points which statistically deviate from the mean at the 95% confidence level (more than 1.965 standard deviations). As indicated by Barreca et al (2014), this procedure allows one to identify the *local average treatment effect* (LATE) on the non-heaped types, even in the case in which sorting is endogenous. Since this procedure drops less than 25% of the data, the LATE recovered is still very meaningful for this population.

After this procedure, I test for the smoothness of the density function of earnings around the kink. To do so, I extend the spirit of the McCrary(2008) density discontinuity test for RDD to check for the presence of a kink in the density of the assignment variable. The idea is to create bins of the assignment variable and count for the number of observations in each bin. Then, I run a regression as in equation (10) on the number of observations allowing for a slope change at each kink in order to test for the smoothness condition. I set the polymial order which has the lowest Akaike criterion. Figure 3-5 display the density of average monthly earnings and the test results for each of the kinks. From visual inspection, the density functions seem to move quite smoothly around all the three kinks and there seems not to be any evidence of slope changes. This impression is supported by the first-derivative test reported in the graphs which does not allow us to reject the null hypothesis of no kink in any of the three cases.

4.2 Graphical Evidence

Kink 1 Figure 6 presents evidence on the kinked relationship between previous wages and the duration of employment at kink 1. The duration of employment spells is relative flat to the left of the kink, while it seems to sharply start to increase around the threshold and yields a clearly increase profile to the right side of the kink point. I interpret this as evidence of a positive kink around this threshold. On the other hand, in appendix Figures A1 and A2 it is possible to observe how covariates evolve around the kink. Overall they seem to evolve quite smoothly, supporting the validity of the design.

Kink 2 and 3 Around the second kink, the presence of a kink in employment duration is less clear, as shown by Figure 7. As regards the covariates, they seem to evolve smoothly as shown by appendix Figures A3 and A4. Around the third kink, the duration of employment seems to evolve quite smoothly around the kink, as displayed in Figure 8. Covariates around this kink seem to evolve smoothly, except for the dummy indicating disabled workers. which apparently displays a sharply negative kink, as shown by appendix Figures A5 and A6.

Nevertheless, I notice that the graphical evaluation in the RKD seems to be a fairly harder enterprise with respect to its parallel in a regression discontinuity design for at least two closely related reasons. First, there is no clear way to display confidence intervals in these graphs. Second, the graphical evidence is fairly sensitive to the scale of the dependent variable. I therefore turn my attention to the choice of bandwidth based on monte carlo simulations and the regression analysis.

4.3 Bandwidth Selector and Polynomial Order

A key issue in the RKD is the choice of the bandwidth and polynomial order, which essentially trade off bias and precision. The only bandwidth selector explictly designed for the RKD is proposed by Cattaneo, Calonico & Titiunik (Forthcoming) - CCT from now on, where they proposed a selector based of optimal mean square error. As in Card & al (2015) - CLPW from now on, I consider this selector with and without its regularization term, which I call "CCT" and "CCT" no regularization[5]. Furthermore, I follow again CLPW and implement the FG bandwidth selector which is based on Fan and Gijbels (1996). To implement the two CCT bandwidths, I use the software developed in CCT (in Press). However, since computation showed to be extremely time consuming due to the size of my dataset, I decided to use an adapted implementation for the CCT bandwidth with and without regularization [6]. Before applying the software from CCT, I collapse the data to the mean on each data point. Once the optimal CCT bandwidth is selected, I estimate the kink with the regression specified in (10) on the *full dataset*. Even though it sharply decreases the number of data points, few simulations

[5]the original selector contains a regularization term to avoid bandwidth which are "too large", as noted in Cattaneo et al (Forthcoming)

[6]The procedure showed to take more than one week to select one single bandwidth when running on the full dataset

showed that the bandwidth choice varies by very small amounts with respect to the choice using the full dataset. As regards polynomial order, I use a linear and quadratic specifications for each bandwidth selector. Therefore, in total I consider six specifications: FG linear, CCT linear, CCT linear without regularization, FG quadratic, CCT quadratic and CCT quadratic without regularization.

Appendix Table A1 shows the estimated slope change using all six bandwidth selectors, in each threshold. Results vary significantly accross specifications, and sometimes even change sign. It leads to the question of which specification do we pick. To evaluate which specification yields the best properties in term of precision and coverage, I conduct a Monte Carlo study around each kink following the procedure suggested by CPLW as close as possible. The idea is to conduct the simulations with a data generation process which closely resemble the actually data around each kink. Therefore, I estimate the conditional expectation funtion around each kink, using separated quintics polynomials to the left and right of the threshold. Then, I use and adjust the linear prediction in such way that the true elasticity of employment duration to benefit is 0.4, which is a plausible value arising from Appendix Table A1. Then, in order to randomly build each dataset for the simulations and perform the regressions using each bandwidth selector, I randomly draw ´x' from the true range of the running variable and the error from the residuals from regression described above. Each simulated dataset is constructed by repeating this procedure for the number of observation around each threshold in such way that each simulation contains the actually size of the data. Each Monte Carlo study is done by running 500 simulations.

On the top of assessing the performance of these six selectors, I decide also to test the performance of using fix bandwidths in a similar range to those picked on average by the selectors described above. Interestingly, some of these specifications perform sometimes better than any of the other selectors, which suggests that using constant bandwidths should also be considered.

Tables 2-4 present the results. The criteria for assessing the best selector for our data around each kink are the root mean square error and the coverage rage at the 95% significance level.

Kink 1 The only estimator which yields a coverage rate higher than 90% is the FG linear, the other two linear specifications are fairly more precise (lower RMSE) but delivers very poor coverage ratios. Therefore, FG linear appears to be a reasonable choice. Amongst the quadratic specifications, CCT without the regularization term seems also to be a reasonable as it delivers only slightly lower coverage but performs slightly better in terms of precision. Therefore, I show both results in the next subsection. Furthermore, simulations suggest that using a linear specification with a fix bandwidth of 10 performs better than any of the six proposed selectors from above, it delivers the lowest RMSE (.29) and the highest coverage (.92). It is also possible to see that a quadratic specification with a fix bandwidth of 25 performs well. For these reasons these results are also presented in the next subsection.

Kink 2 Around this kink, all six selectors performs quite badly, RMSE is always larger than 1.7 times the true slope change, and coverage rates are never higher than 90%. Moreover, none of the fix bandwidth choices seem to deliver better results. These results are not of much suprise since the kink in the assignment rule of benefit is the smallest at this threshold (-0.3 against 0.8 and -0.5 at kink 1 and 3 respectively). It means that in order to identify an elasticity of the same magnitude at kink 1 and 2, estimates have to be almost three times more precise in the second kink, as a result of smaller variation in the treatment. In any case, apparently, the less poor performing choices are the FG linear and quadratic which are the only ones to deliver coverage rate above 50%. Therefore, I report these in the following subsection.

Kink 3 Around this threshold, most selectors perform relatively poorly in terms of coverage rate. The most reasonable choice seems to be the CCT quadratic as it delivers similar RMSE to others while achieving by far the highest coverage rate. I also report in the next session the quadratic specification with fix bandwidths of 15 and 20 which deliver slight better coverage ratios with similar precision.

4.4 Estimation Results

kink 1 Finally, table 5 present estimation results on all kinks based on the preferred specification/selector derived from the monte carlo simulations. All specifications suggested that the effect of benefit level on employment duration are positive and statiscally significant. The estimated elasticity ranges from 0.41 to 0.97. The two specifications yielding a negative bias from the simulation study (Fix linear b.w. 10 and Fix Quadratic b.w. 25) deliver neverless a positive and statistically significant result. It thus suggests that results are not driven by biased estimators.

kink 2 At the same table it is possible to see the preferred results on kink 2. They are both positive and statistically significant at the 1% level. However, results here should be interpreted with more caution as the simulation study showed that estimation is fairly imprecise around this threshold. Furthermore, the bias associated with the preferred estimator is large and positive, which makes it harder to distinguish whether results arise from a truely kinked relationship or an estimation bias.

kink 3 At this kink, estimates yield different signs and none of them is statistically significant. It could be the result of a truly null effect or a result of the relative poor performance in terms of RMSE assessed by the simulation study. I also notice that standard error from the regressions are fairly high and would not allow to reject the null hypothesis if the true elasticity takes any plausible value below 1.

Table 6 displays the results on covariates around the first and second kink. I ommit results on the third kink for the sake of brevity. Overall estimates do not reject non smoothess for most pre-determined covariates around these kinks. There are however two exceptions for both the first (years of education and gender) and the second kink (predicted employment duration and gender) which raise some concerns because they consistenly point for a slope accross preferred bandwidth selectors. I notice however that these results around kink 1 may not be reason for too much concern. First, the sign of the slope change is not the same accross specifications for gender at the first kink. Second, still in kink 1 the size of the estimated slope seems to be quite small for years of schooling. It suggests R$ 100 higher earnings is associated with less than one extra years of schooling. Third, it has no consistent predictive power on the duration of the employment spell as there is no siginificant slope change consistent accross specifications and there point estimation is very low. Around kink 2 the effect on gender is robust accross specifications but still small. Of more concern is the robust statistically significant sign on the predicted employment duration at kink 2. Notice however that it has the opposite sign to the positive elasticity found around kink 2. Therefore, if covariates do not evolve perfectly smoothly around kink 2, the linear prediction suggested that this imbalance should bias results downwards, while the results on employment duration are actually positive.

Overall, I find the results around the first kink quite robust, indicating that the elasticity of benefit level is positive for the lower end of the skill distribution and range from 0.41 to 0.97. Results on the second kink suggest a positive elasticity ranging from 0.82 to 1.41 but should be interpreted with more caution since the simulation study pointed for a poor performance of estimators around this threshold. At the third kink, results are much less informative as estimations showed to be noisy and estimator performance on simulation studies were relatively poor.

5 Welfare Effects and Conclusion

Now I present a simple exercise on the evaluation of welfare effects based on the estimates of the previous section. Since estimates on the elasticity of UI covered unemployment duration to benefit level are not available for this data, I assume this to equal 1 which is line with the literature. For the liquidity to moral hazard ratio, I recover this estimate from Landais(2014). The goal of the exercise is to show that the size of the effect of UI on the duration of employment is clearly relevant for welfare.

The welfare formula as shown in (9) implies that are still gains from higher benefit level if:

$$\frac{dW}{db} > 0 \iff \frac{1}{1-s_0}(\rho+1) - \left(1 + \epsilon_{f^{UI},b} + \epsilon_{D_B,b} - \epsilon_{D_E,b}\right) > 0 \tag{11}$$

From estimates around kink 1, consider $\epsilon_{D_E,b} = 0.5$. Consider $\epsilon_{D_B,b} = 1$, which is line with the literature, and recover $\phi = 0.88$ from Landais(2014). Also, I estimate $\frac{1}{1-s_0} = \frac{1}{0.97} = 1.04$, where s_0 is the fraction of workers finding a new job within one week of unemployment. To be conservative, assume $\epsilon_{f^{UI},b}$ to equal zero. It implies that the effect of raising UI benefits on welfare by R$1 is given by:

$$\frac{dW}{db} > 0 \iff (0.88 + 1) - (1 + 0 + 1 - 0.5) = 0.38 > 0 \tag{12}$$

If these values recovered from Landais (2014) were the true elasticities at kink 1, the welfare formula suggests that there would still be gains from raising benefit level. If one instead neglects UI effects on the duration of employment, the result would point otherwise:

$$\frac{dW}{db} > 0 \iff (0.88 + 1) - (1 + 0.5 - (\cancelto{0}{0.5})) = -0.12 < 0 \tag{13}$$

In any case, the main message from this simple exercise is that the effect found on the duration of employment is economically significant and clearly relevant for welfare. Recovering previous estimates from the literature on other elasticities, it becomes clear that it has at least the same magnitude of the other elements present in the welfare formula. Therefore, it strongly suggests that policy makers should be aware of such effect and take it into account in order to optimally set the level of unemployment benefits. Pherhaps the most surprising result from this analysis is that unemployment benefit increases the length of employment spells. Introducing this into welfare raises the marginal value for society of providing UI, at least in this partial equibrilum analysis. Whether there are further elements to consider once we accept this effect to be relevant is certainly a question for future research. Such effect could have implications on the optimal job turnover rate and affect worker productivity since it distorts the incentives to keep a job.

Of course, the analysis presented in paper applies to Brazil and represents LATE on workers on the very left of the skill distribution. However, this may not only be the case of a developing country. For instance, Rebollo-Sanz (2012) analyzes data from the Spanish labor market and supports the hypothesis that UI is related to labor turnover in Spain. He also reports spikes in lay-off probabilities once workers qualify for unemployment benefits. To conclude, I believe that the findings here presented suggest that future research should aim at evaluating whether the same effects are sizeable for other groups of workers and in countries with different contexts.

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Figure 3: Density of Wages the Around Kink 1

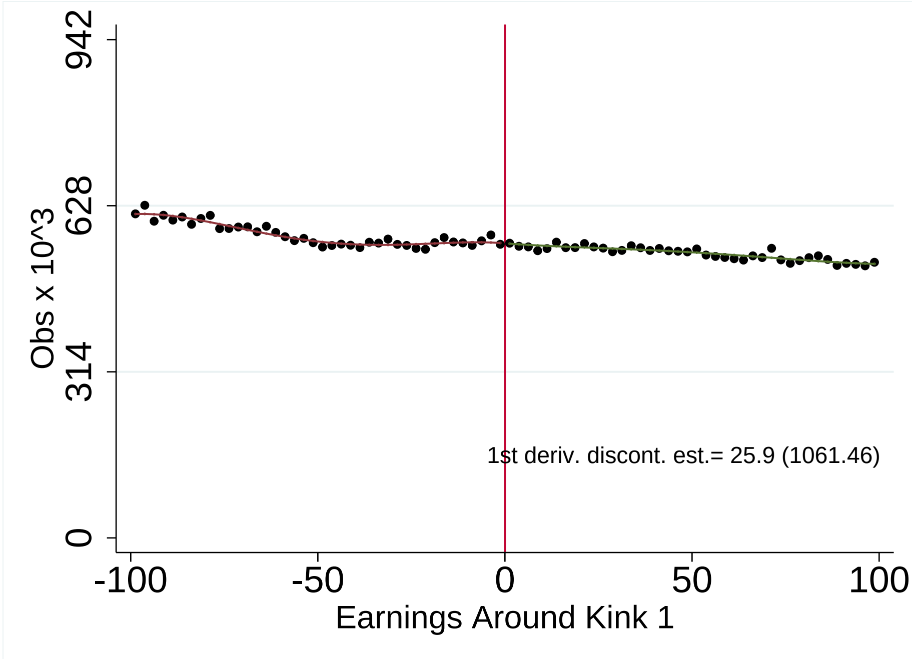

Figure 4: Density of Wages the Around Kink 2

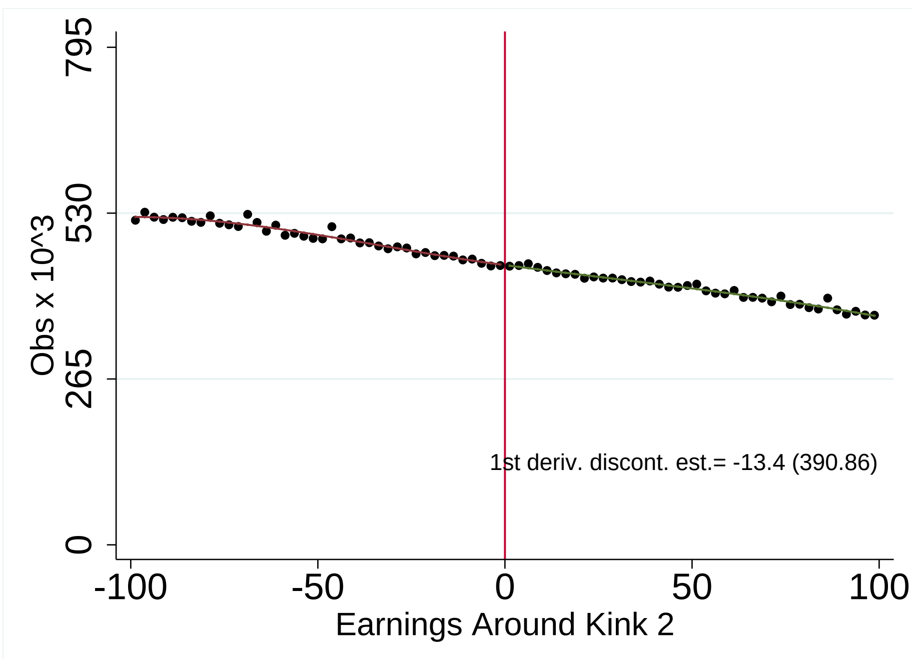

Figure 5: Density of Wages the Around Kink 3

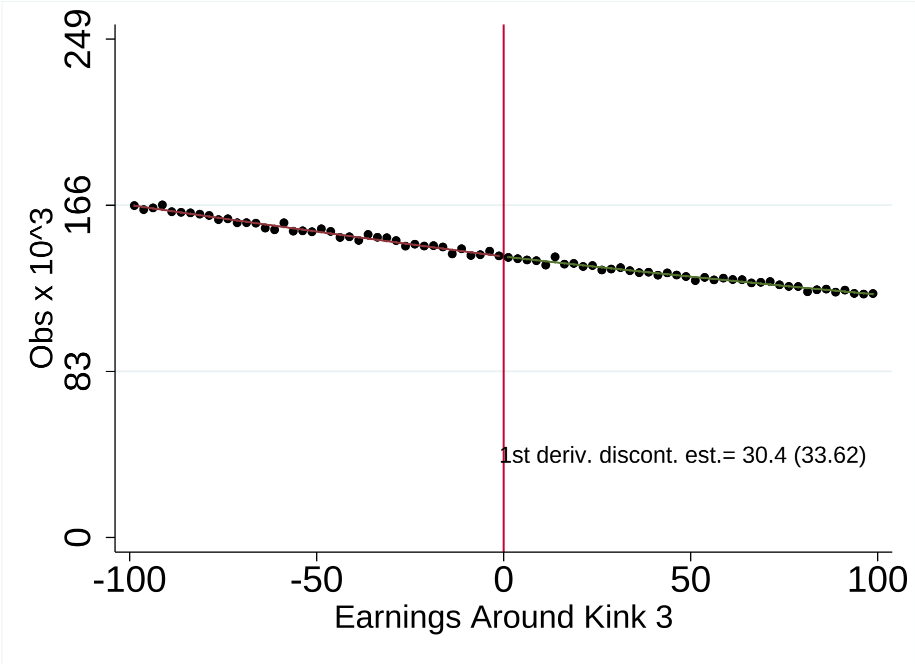

Figure 6: Employment Duration Around Kink 1

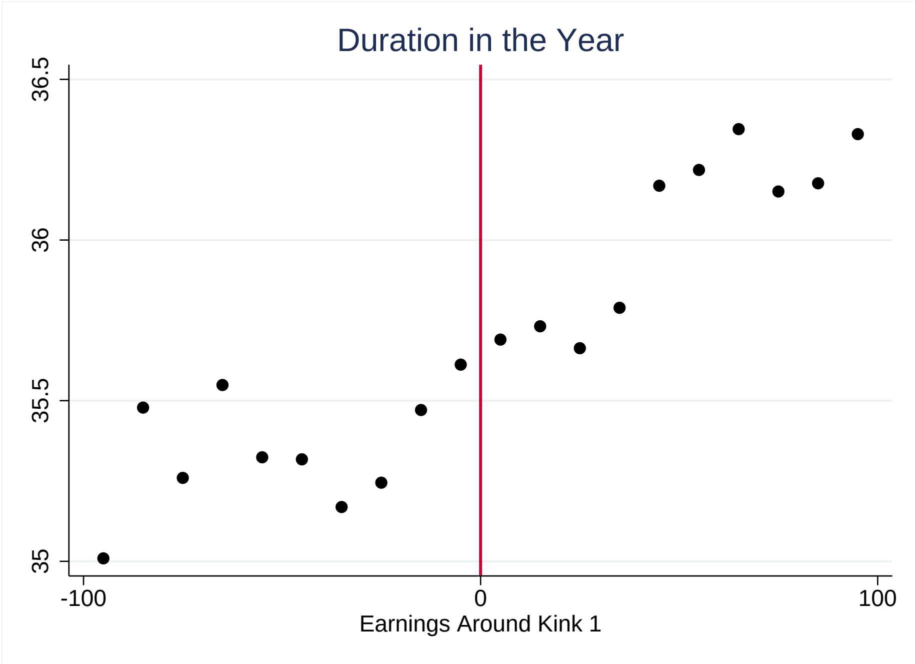

Figure 7: Density of Wages the Around Kink 2

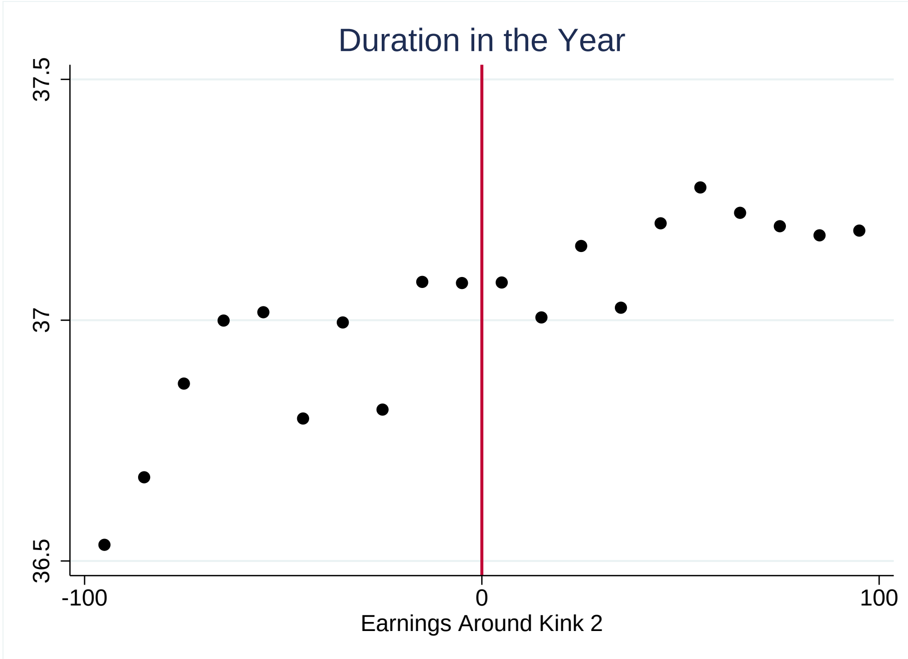

Figure 8: Density of Wages the Around Kink 3

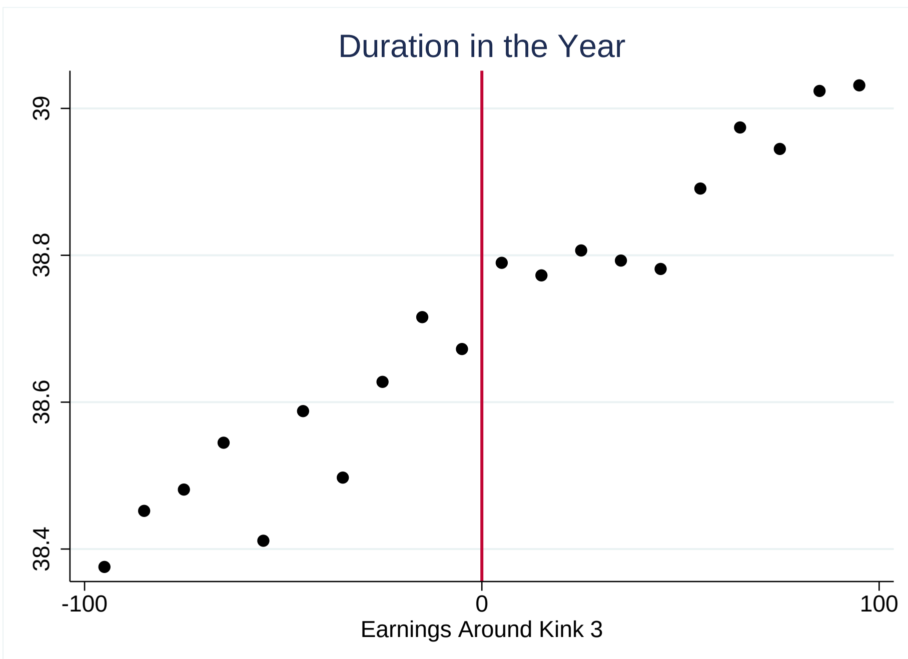

Table 2: Monte Carlo Simulations - Employment Duration - *First Kink*

Bandwidth Selector	Mean b.w.	RMSE/true value	C.I. Coverage rate	Bias/true value
CCT linear, no regul.	18.7	0.41	0.38	-0.32
CCT linear	12.7	0.37	0.53	-0.28
FG linear	5.8	0.69	0.91	0.28
CCT quadratic, no regul.	18.7	0.67	0.84	0.29
CCT quadratic	15.9	0.76	0.87	0.43
FG quadratic	14.9	0.76	0.88	0.46
Fix b.w. - linear	5	0.81	0.92	0.35
Fix b.w. - linear	10	0.29	0.92	-0.12
Fix b.w. - linear	15	0.42	0.19	-0.39
Fix b.w. - linear	20	0.54	0.00	-0.54
Fix b.w. - linear	25	0.58	0.00	-0.57
Fix b.w. - linear	30	0.54	0.00	-0.53
Fix b.w. - linear	35	0.44	0.00	-0.44
Fix b.w. - linear	40	0.30	0.00	-0.30
Fix b.w. - quadratic	5	3.09	0.94	0.98
Fix b.w. - quadratic	10	1.30	0.87	0.78
Fix b.w. - quadratic	15	0.73	0.87	0.44
Fix b.w. - quadratic	20	0.40	0.92	0.14
Fix b.w. - quadratic	25	0.33	0.87	-0.19
Fix b.w. - quadratic	30	0.55	0.26	-0.51
Fix b.w. - quadratic	35	0.81	0.00	-0.79
Fix b.w. - quadratic	40	1.05	0.00	-1.04

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Table 3: Monte Carlo Simulations - Employment Duration - *Second Kink*

Bandwidth Selector	Mean b.w.	RMSE/true value	C.I. Coverage rate	Bias/true value
CCT linear, no regul.	19.5	1.72	0.01	1.63
CCT linear	13.2	1.76	0.08	1.66
FG linear	6.0	2.22	0.86	1.37
CCT quadratic, no regul.	33.8	2.10	0.29	1.81
CCT quadratic	21.1	1.97	0.49	1.59
FG quadratic	15.1	2.27	0.80	1.52
Fix b.w. - linear	5	2.45	0.92	1.21
Fix b.w. - linear	10	1.82	0.42	1.63
Fix b.w. - linear	15	1.68	0.03	1.62
Fix b.w. - linear	20	1.63	0.00	1.61
Fix b.w. - linear	25	1.50	0.00	1.49
Fix b.w. - linear	30	1.31	0.00	1.31
Fix b.w. - linear	35	1.09	0.00	1.08
Fix b.w. - linear	40	0.84	0.00	0.84
Fix b.w. - quadratic	5	8.15	0.94	-0.60
Fix b.w. - quadratic	10	3.18	0.94	1.09
Fix b.w. - quadratic	15	2.28	0.82	1.57
Fix b.w. - quadratic	20	2.02	0.61	1.62
Fix b.w. - quadratic	25	2.07	0.27	1.91
Fix b.w. - quadratic	30	2.26	0.03	2.19
Fix b.w. - quadratic	35	2.45	0.00	2.41
Fix b.w. - quadratic	40	2.60	0.00	2.58

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Table 4: Monte Carlo Simulations - Employment Duration - *Third Kink*

Bandwidth Selector	Mean b.w.	RMSE/true value	C.I. Coverage rate	Bias/true value
CCT linear, no regul.	17.3	0.54	0.09	0.51
CCT linear	14.1	0.54	0.15	0.51
FG linear	17.7	0.52	0.23	0.46
CCT quadratic, no regul.	28.4	0.68	0.49	0.52
CCT quadratic	20.2	0.58	0.78	0.36
FG quadratic	31.1	0.75	0.37	0.65
Fix b.w. - linear	5	0.90	0.94	0.26
Fix b.w. - linear	10	0.52	0.72	0.43
Fix b.w. - linear	15	0.54	0.11	0.51
Fix b.w. - linear	20	0.54	0.00	0.53
Fix b.w. - linear	25	0.51	0.00	0.51
Fix b.w. - linear	30	0.45	0.00	0.44
Fix b.w. - linear	35	0.35	0.00	0.35
Fix b.w. - linear	40	0.25	0.00	0.24
Fix b.w. - quadratic	5	3.51	0.93	-0.40
Fix b.w. - quadratic	10	1.16	0.93	0.07
Fix b.w. - quadratic	15	0.69	0.94	0.25
Fix b.w. - quadratic	20	0.56	0.82	0.39
Fix b.w. - quadratic	25	0.61	0.56	0.54
Fix b.w. - quadratic	30	0.73	0.11	0.70
Fix b.w. - quadratic	35	0.85	0.00	0.83
Fix b.w. - quadratic	40	0.96	0.00	0.95

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Table 5: Preferred Bandwidth Selectors

Elasticity of Employment Duration to Benefit Level			
Preferred Bandwidth	b.w.	Estimated Elasticity	Std. Error
First Kink			
FG Linear	10.7	0.41**	(0.177)
CCT Quadratic no regul	26.6	0.97***	(0.165)
Fix b.w. - Linear	10	0.5***	(0.170)
Fix b.w. - Quadratic	25	0.67***	(0.190)
Second Kink			
FG Linear	13.8	1.41***	(0.297)
FG Quadratic	51.3	0.82***	(0.186)
Third Kink			
CCT Quadratic	30.0	-0.61	(0.392)
Fix b.w. - Quadratic	15	0.94	(1.089)
Fix b.w. - Quadratic	20	-0.07	(0.710)

-

Table 6: Smooth of Covariates with Preferred Bandwidth Selectors

Preferred Bandwidth	FG Linear		CCT Quadratic no reg	
First Kink	Estimated Marginal Effect	Std. Error	Estimated Marginal Effect	Std. Error
Predicted Duration	0.02***	(0.005)	0	(0.006)
Previous Tenure	-0.31***	(0.111)	0.14	(0.155)
Years of Educ.	0.0055***	(0.002)	0.0084***	(0.003)
Gender	-0.0005***	(0.000)	0.001*	(0.001)
Firm Size 1	0.21	(1.014)	3.74*	(2.243)
Firm Size 2	-138.96	(126)	-224.53	(204)
White Worker	0	(0.000)	0	(0.000)
Weekly Workload	0	(0.001)	0	(0.004)
Worker is Disable	0	(0.000)	0	(0.000)

Preferred Bandwidth	FG Linear		FG Quadratic	
Second Kink	Estimated Marginal Effect	Std. Error	Estimated Marginal Effect	Std. Error
Predicted Duration	-0.03***	(0.004)	-0.04***	(0.005)
Previous Tenure	0.08	(0.153)	0.01	(0.091)
Years of Educ.	-0.0007	(0.001)	-0.0005	(0.002)
Gender	0.0005*	(0.000)	0.0009***	(0.000)
Firm Size 1	0.02	(0.426)	0.61	(0.969)
Firm Size 2	55.03	(49)	84.21	(77)
White Worker	0	(0.000)	0	(0.000)
Weekly Workload	-0.01	(0.004)	-0.01**	(0.002)
Worker is Disable	0**	(0.000)	0	(0.000)

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A Appendix

A.1 Tables

Table A1: All Bandwidth Selectors

Elasticity of Employment Duration to Benefit Level			
Bandwidth Selector	b.w.	Estimated Elasticity	Std. Error
First Kink			
FG linear	10.7	0.41**	(0.177)
CCT linear, no regularization	21.9	-0.04	(0.065)
CCT linear	18.8	-0.02	(0.085)
FG quadratic	33.8	-0.29**	(0.143)
CCT quadratic, no regularization	26.6	0.97***	(0.165)
CCT quadratic	23.2	0.98***	(0.217)
Second Kink			
FG linear	13.8	1.41***	(0.297)
CCT linear, no regularization	38.3	0.5***	(0.084)
CCT linear	26.4	0.11	(0.123)
FG quadratic	51.3	0.82***	(0.186)
CCT quadratic, no regularization	57.3	1.4***	(0.189)
CCT quadratic	39.2	0.85***	(0.254)
Third Kink			
FG linear	40.6	0.22***	(0.065)
CCT linear, no regularization	87.1	0	(0.024)
CCT linear	29.4	0.04	(0.103)
FG quadratic	176.3	0.23***	(0.076)
CCT quadratic, no regularization	71.0	0.42***	(0.113)
CCT quadratic	30.0	-0.61	(0.392)

-

A.2 Figures

Figure A1: Smoothness of Covariates A - Kink 1

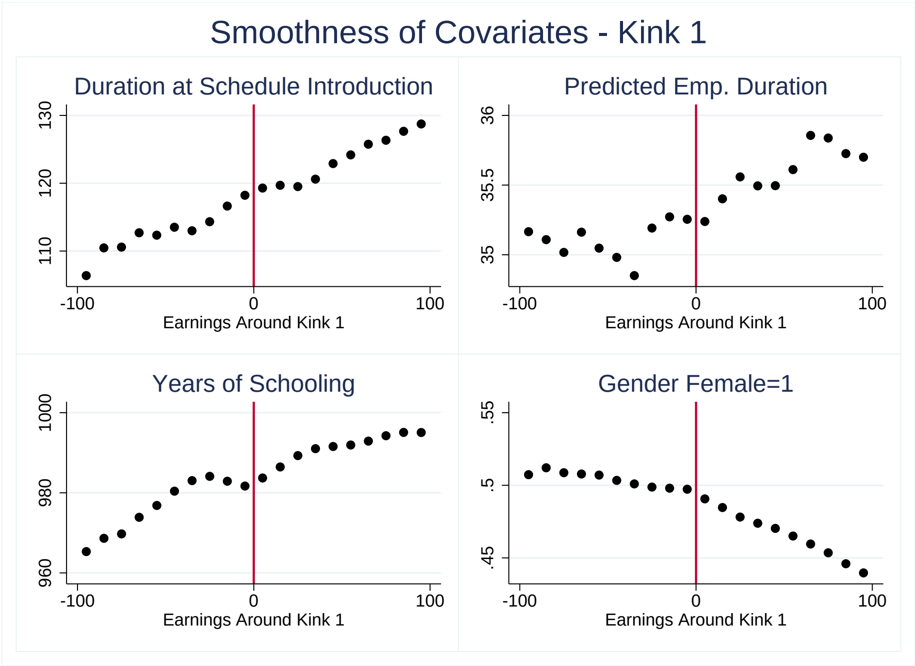


Figure A2: Smoothness of Covariates B - Kink 1

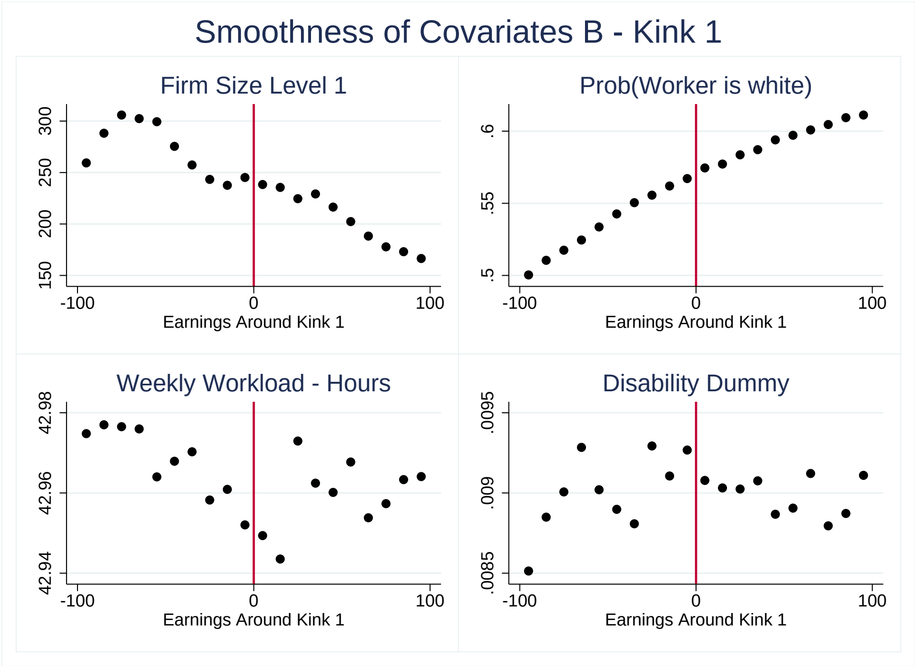


Figure A3: Smoothness of Covariates A - Kink 2

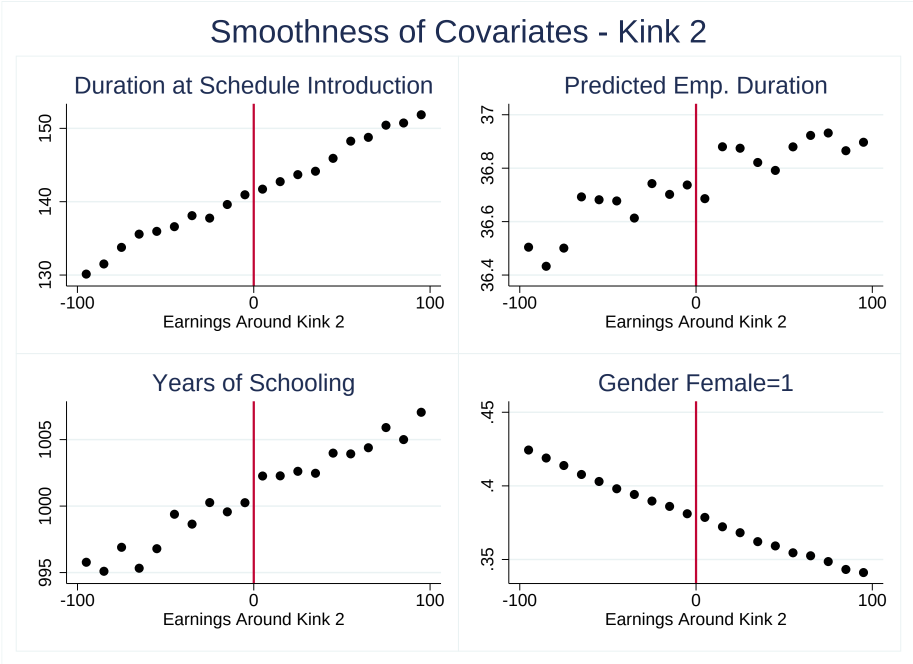


Figure A4: Smoothness of Covariates B - Kink 2

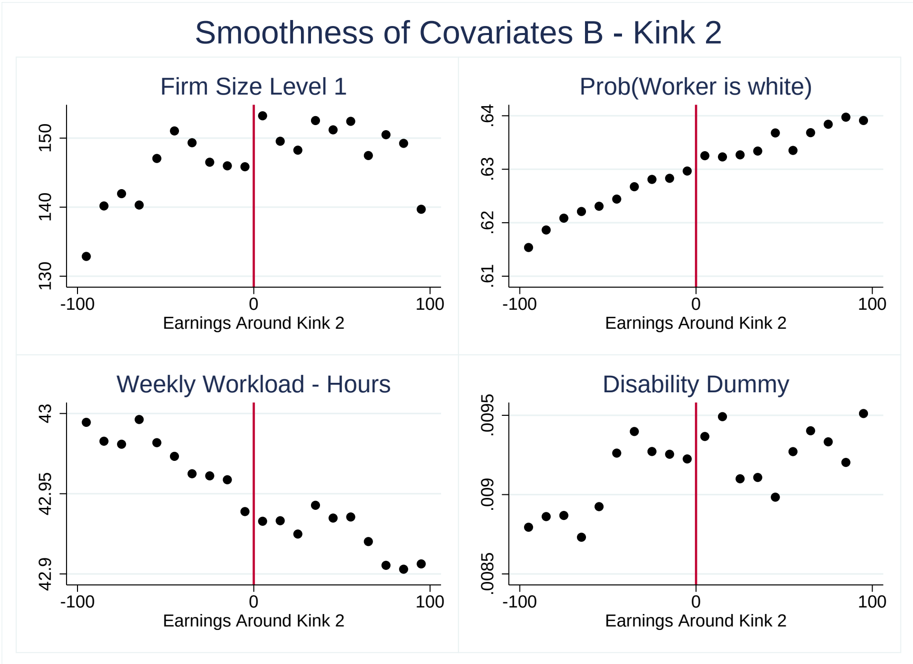


Figure A5: Smoothness of Covariates A - Kink 3

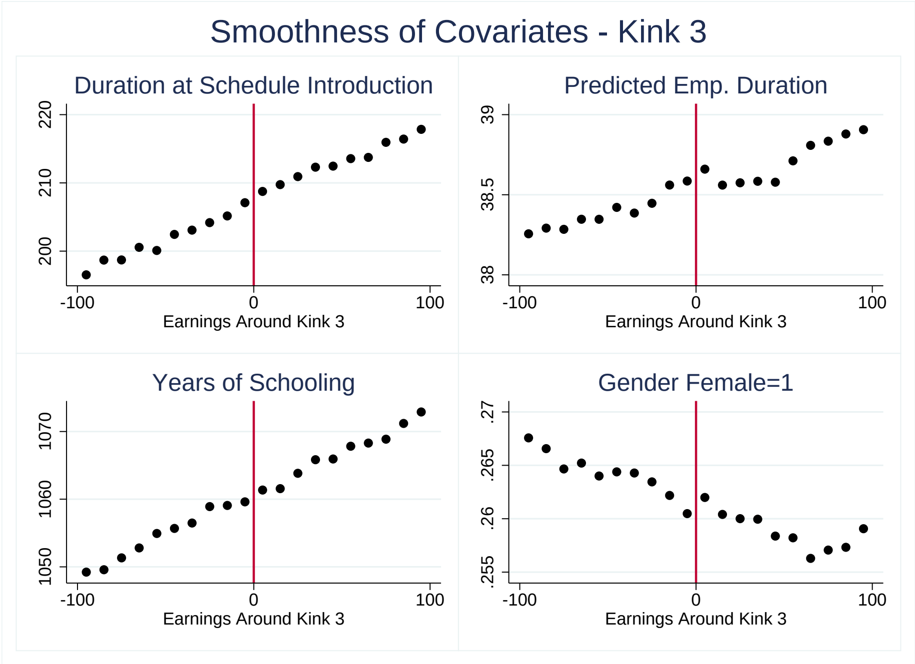
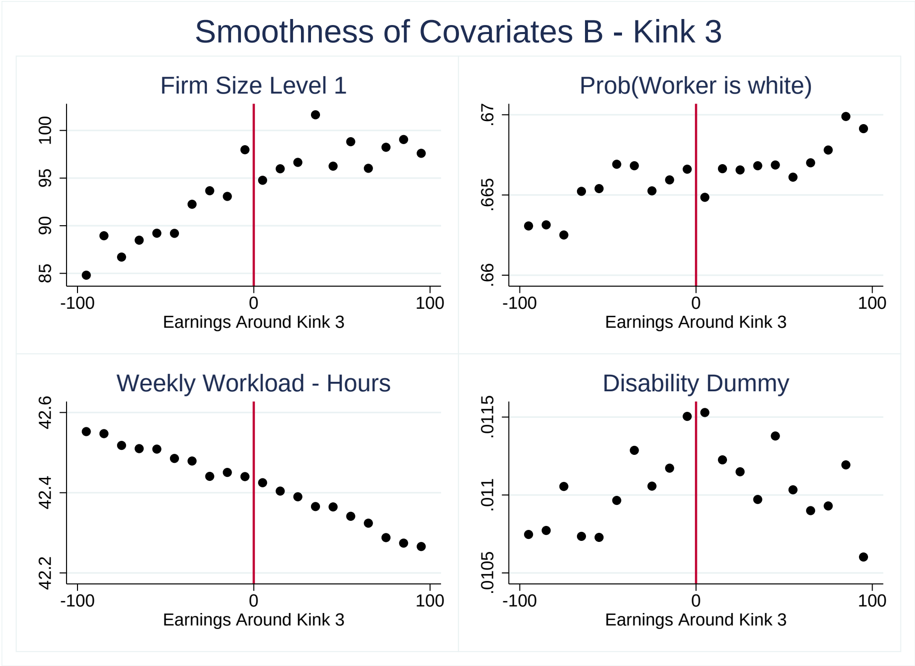


Figure A6: Smoothness of Covariates B - Kink 3



B Appendix

B.1 Benefit Level and the Choice of Search Effort by the Unemployed

I first characterize the agent's optimal choice of search effort and then analyze how this choice reacts to variations in the level of unemployment benefits. The analysis regards the case of unemployed workers who have to choose a level of search intensity for a given level of benefits as stated in equation (4). First-order conditions are given by: [7]

$$\psi'(s_t) = E_t(A_t) - U_t(A_t) \tag{14}$$

The optimal level of search intensity is simply the one where the marginal cost of search (left-hand-side of the equation) equals the net gain from finding a new job (right-hand-side of the equation). Such gains are given by the difference between the value of a new job $E_t(A_t)$ and the value of unemployment $U_t(A_t)$. The larger the value of finding a new job *vis-a-vis* the value of remaining unemployed, the greater the incentive to search.

At this point, it is possible to approach the question of how a small change in the level of benefits affects the incentives to search. From the previous first-order condition and by applying the envelope theorem we have: [8]

$$\frac{\partial s_t}{\partial b_t} = \frac{-u'(c_t^u)}{\psi''(s_t)} < 0 \tag{15}$$

It shows that an \$1 increase in UI benefits decreases search intensity by an amount which depends on the marginal utility of consumption of the unemployed worker adjusted by how the marginal cost of search is increasing at a given point. For instance, it means that if an unemployed worker is already enjoying a high level of consumption, his marginal utility of consumption is low and, thus, a small increase in benefits will not affect by much his level of search intensity.

As in Chetty (2008), it is possible to show that an increase in the level of benefits affects search through two distinct channels: a liquidity and a moral hazard effect. With this purpose, we notice that:

[7] Here we adopt the so-called "first-order approach" and assume $U_t(A_t)$ to be concave as in Chetty(2008), which shows that for plausible parameters non-concavity never arises.

[8] The envelope theorem states that for small changes of parameter values in an optimization problem, the relevant effects on the function of interest are the direct effects. It means that indirect effects should be ignored. In our case, b_t is the changing parameters of the optimization problem. The envelope condition allows us to ignore the effects of b_t on both $E_t(A_t)$ and $U_t(A_t)$. In other words, $\frac{\partial E_t(A_t)}{\partial b_t} = 0$ and $\frac{\partial U_t(A_t)}{\partial b_t} = 0$.

$$\frac{\partial s_t}{\partial A_t} = \frac{v'(c_t^e) - u'(c_t^u)}{\psi''(s_t)} \leq 0 \tag{16}$$

$$\frac{\partial s_t}{\partial w_t} = \frac{v'(c_t^e)}{\psi''(s_t)} \geq 0 \tag{17}$$

Equation (7) shows that the larger the gap between the marginal utilities of consumption when employed ($v'(c_t^e)$) and unemployed ($u'(c_t^u)$), the larger the effect of an increase in the agent's asset level on search intensity. This means that when unemployed workers are significantly liquidity constrained, and so the gap in consumption between unemployment and employment is sizeable, providing an extra small amount of liquidity to this agent will lower his search intensity significantly. Equation (8), instead, shows that an increase in the pay-off of finding a new job (higher w_t) positively affects search intensity. The magnitude of this effect depends on the marginal utility of consumption when employed adjusted by the slope of the marginal cost of search at a given point. The intuition is that if consumption when employed is already large, so marginal utility is low, an small increase of w_t does not change substantially the reward of finding a job and, thus, the change in search intensity is small.

By combining the results of (7) and (8) with (6), we can decompose the marginal distortion of unemployment benefits on search in two distinct elements: liquidity and moral hazard effect:

$$\frac{\partial s_t}{\partial b_t} = \frac{\partial s_t}{\partial A_t} - \frac{\partial s_t}{\partial w_t} < 0 \tag{18}$$

This is the core result provided by Chetty (2008). It highlights that the effect of UI benefits on search intensity is a mix between a moral hazard component ($\frac{\partial s_t}{\partial w_t}$) and a liquidity effect ($\frac{\partial s_t}{\partial A_t}$). The moral hazard regards the that fact unemployment benefits distort the pay-off from leaving unemployment because as soon as the worker finds a new job, his benefits are ceased. Therefore, it directly decreases the net benefits of search which are given by $(w_t - b_t)$ and characterizes a substitution effect.[9] The liquidity effect, on the other hand, has to do with the ability the agent has to smooth consumption across states. It means that when workers are liquidity constrained, they search more intensely than they would if credit markets were complete. Once you provide these workers with UI benefits, they decrease their search intensity because now they are less liquidity constrained and thus can better smooth consumption across states.

For example, suppose an unemployed worker has zero liquid assets, no access to credit markets and is not entitled to UI benefits in this model. This worker searches very intensely for a new job because he

[9]Technically, it also embodies a wealth effect as a variation in the net value of finding a job also affects life time wealth. However, in the context of unemployment benefits such effect is arguably very low since the total amount of benefits are only a very small fraction of lifetime earnings.

cannot borrow against the future and, thus, he experiences a very low (zero) level of consumption while unemployed. If he is granted with a lump sum cash grant, he will decrease search effort not because the net benefit of finding a job changes (as is the case for UI benefits), but simply because he is less liquidity constrained and can now better smooth consumption across states. Therefore, a hypothetical cash grant unveils the liquidity effects on search. Such effect is embodied in the total distortion caused by UI benefits because it also provides more liquidity to workers.

The other part of the distortion relates to the fact that when such a worker is granted with UI, the net benefit of finding a new job decreases. This happens because, differently from the cash grant, benefits cease as soon as he comes back to employment, representing a decrease in the reward of finding a new job.

Equation (18), however, shows how the effect of an *one period* increase in UI benefits on search can be decomposed into a liquidity and a moral hazard effect. The expression bellow shows how the decomposition applies for a B-periods increase in the level of UI benefits, as shown in Appendix B.3:

$$\frac{\partial s_t}{\partial b} = \frac{\partial s_t}{\partial a}|_B - \frac{\partial s_t}{\partial w}|_B \tag{19}$$

where $\frac{\partial s_t}{\partial b}$ denotes the effect on search at the initial period when the level of UI benefits increase for all the B periods. $\frac{\partial s_t}{\partial a}|B = \sum_{i=t}^{t+B-1} \frac{\partial s_t}{\partial a_i}$ and $\frac{\partial s_t}{\partial w}|B = \sum_{i=t}^{t+B-1} \frac{\partial s_t}{\partial w_i}$ describe, respectively, the liquidity and moral hazard effect on search in the first B periods of unemployment.

B.2 Benefit Level and the Choice of Work Effort by the Employed

Here I approach the problem of how variations in benefit levels affect the the choice of effort by the employed. This analysis is analytically symmetric to the one found in the previous subsection. Equation (2) states the problem faced by the employed worker. From there it is possible to derive the following first-order condition:[10]

$$c'(e_t) = V_t(A_t) - U_t(A_t) \tag{20}$$

It shows that employed workers decide their level of effort by adjusting the marginal cost of effort to keep his job (left-hand-side of the equation) to the net gain of keeping their jobs, which is given by the difference between the value of employment and unemployment.

[10] As for the problem of the unemployed worker, I take the "first-order" approach and assume $V_t(A_t)$ to be concave.

From the first-order condition above, it is possible to assess how work effort reacts to a small variation in the level of benefits:

$$\frac{\partial e_t}{\partial b_t} = \frac{-u'(c_t^u)}{c''(e_t)} < 0 \tag{21}$$

If the agent's level of consumption when unemployed is expected to be low, so that marginal utility is high, the distortion caused by a small variation in potential benefits will be large. Analogously to the case analyzed in the previous subsection, it is possible to decompose this distortion into a liquidity and a moral hazard problem. The derivatives below show how the level of work effort reacts to a small change in asset levels and wages, respectively:

$$\frac{\partial e_t}{\partial A_t} = \frac{v'(c_t^v) - u'(c_t^u)}{c''(e_t)} \leq 0 \tag{22}$$

$$\frac{\partial e_t}{\partial w_t} = \frac{v'(c_t^v)}{c''(e_t)} \geq 0 \tag{23}$$

By combining equation (12) and (13) with (11), we can decompose the effect of UI benefits on work effort as:

$$\frac{\partial e_t}{\partial b_t} = \frac{\partial e_t}{\partial A_t} - \frac{\partial e_t}{\partial w_t} < 0 \tag{24}$$

Similarly to the case of the unemployed, this equation shows that effects of benefits on work effort depends on two distinct factors: a liquidity ($\frac{\partial e_t}{\partial A_t}$) and a moral hazard ($\frac{\partial e_t}{\partial w_t}$) component. The moral hazard effect concerns the fact that UI benefits imply a decrease of the net loss caused by a lay-off. In other words, unemployment is less unattractive relatively to being employed. The liquidity effect, however, has to do with the fact that UI raises asset level and may help the worker to smooth consumption between employment and unemployment.

Once again, the decomposition above applies for a *one period* increase in benefit level. Below is the decomposition for a B periods increase in the level of benefits:

$$\frac{\partial e_t}{\partial b}|_B = \frac{\partial e_t}{\partial a}|_B - \frac{\partial e_t}{\partial w}|_B \tag{25}$$

where $\frac{\partial e_t}{\partial a}|B = \sum_{i=t}^{t+B-1} \frac{\partial e_t}{\partial a_i}$ and $\frac{\partial e_t}{\partial w}|B = \sum_{i=t}^{t+B-1} \frac{\partial e_t}{\partial w_i}$.

B.3 Liquidity and Moral Hazard in the T Periods Model

Let $x \in \{a, b, w\}$, $s \in \{0, 1, ..., T-1\}$, $\frac{\partial e_0}{\partial x}|s = \sum_{t=0}^{T-1} \frac{\partial e_0}{\partial x_t}$ and $\frac{\partial s_0}{\partial x}|s = \sum_{t=0}^{T-1} \frac{\partial s_0}{\partial x_t}$.
Exploiting the FOCs with envelope conditions, we have:

$$\frac{\partial e_0}{\partial x}|s = \frac{1}{c''(e_0)} \left\{ \frac{\partial V_0}{\partial x}|s - \frac{\partial U_0}{\partial x}|s \right\} \tag{26}$$

$$\frac{\partial s_0}{\partial x}|s = \frac{1}{\psi''(s_0)} \left\{ \frac{\partial E_0}{\partial x}|s - \frac{\partial U_0}{\partial x}|s \right\} \tag{27}$$

Notice that:

$$\frac{\partial E_0}{\partial a}|_B = \frac{\partial E_0}{\partial w}|_B$$

$$\frac{\partial U_0}{\partial a}|_B = \frac{\partial U_0}{\partial w}|_B + \frac{\partial U_0}{\partial b}|_B$$

$$\frac{\partial V_0}{\partial a}|_B = \frac{\partial V_0}{\partial w}|_B + \frac{\partial V_0}{\partial b}|_B$$

Combining these conditions, it follows that:

$$\frac{\partial e_0}{\partial b}|_B = \frac{\partial e_0}{\partial a}|_B - \frac{\partial e_0}{\partial w}|_B \tag{28}$$

$$\frac{\partial s_0}{\partial b}|_B = \frac{\partial s_0}{\partial a}|_B - \frac{\partial s_0}{\partial w}|_B \tag{29}$$

B.4 The Welfare Formula in the T Periods Model

$$\max_{b,\tau} J_0^V(b, \tau) = (1 - e_0)U_0(b, \tau) + e_0 V_0(b, \tau) - c(e_0) \tag{30}$$

$$s.t. D_B b = D_E \tau \tag{31}$$

Deriving with respect to the level of benefits:

$$\frac{dJ_0}{db} = (1 - e_0)\underbrace{\frac{\partial U_0}{\partial b}}_{0} + e_0 \frac{\partial V_0}{\partial b} - \frac{d\tau}{db}\left[(1 - e_0)\frac{\partial U_0}{\partial w} + e_0 \frac{\partial V_0}{\partial w}\right] \tag{32}$$

Notice that $\frac{\partial U_0}{\partial b} = 0$ because workers laid-off in the first period are not eligible for UI. Let $E_{0,T-1}v'(c_t^V)$ denote the unconditional average marginal utility while employed and D_E the expected duration of (first) employment. Then:

$$E_{0,T-1}v'(c_t^V) = \frac{1}{D_E}\left[(1-e_0)\frac{\partial U_0}{\partial w} + e_0\frac{\partial V_0}{\partial w}\right] \tag{33}$$

Also:

$$e_0\frac{\partial V_0}{\partial b} = \sum_{i=k}^{T-1}\left[\Pi_{j=0}^{i-1}e_j\right](1-e_i)\frac{\partial U_i}{\partial B_i} \tag{34}$$

Where $\frac{\partial U_i}{\partial B_i}$ is the effect of raising UI benefits for workers entering unemployment at period i. Then, it implies:

$$\frac{dJ_0}{db} = \sum_{i=k}^{T-1}\left[\Pi_{j=0}^{i-1}e_j\right](1-e_i)\frac{\partial U_i}{\partial B_i} - \frac{d\tau}{db}(D_E)E_{0,T-1}v'(c_t^V) \tag{35}$$

Higher benefits increase the value of employment at $t=0$ by raising the value of subsequent unemployment after minimum eligibility requirement, at period k.

Normalize welfare by the gain from raising wages by \$ 1:

$$\frac{dJ_0}{dw} = (1-e_0)\frac{\partial U_0}{\partial w} + e_0\frac{\partial V_0}{\partial w} = (D_E)E_{0,T-1}v'(c_t^V) \tag{36}$$

Therefore:

$$\frac{dW}{db} = \frac{\frac{dJ_0}{db}}{\frac{dJ_0}{dw}} = \frac{\sum_{i=k}^{T-1}\left[\Pi_{j=0}^{i-1}e_j\right](1-e_i)\frac{\partial U_i}{\partial B_i}}{(D_E)E_{0,T-1}v'(c_t^V)} - \frac{d\tau}{db} \tag{37}$$

For workers becoming unemployed at period i, it is true that:

$$\frac{\partial s_i}{\partial B_i} = \frac{1}{\psi''(s_i)}\left\{\cancelto{0}{\frac{\partial E_i}{\partial B_i}} - \frac{\partial U_i}{\partial B_i}\right\} \tag{38}$$

$$\implies \frac{\partial U_i}{\partial B_i} = -\psi''(s_i)\frac{\partial s_i}{\partial B_i} \tag{39}$$

Then, it follows that:

$$\frac{dW}{db} = \frac{\sum_{i=k}^{T-1} \left[\Pi_{j=0}^{i-1} e_j\right] (1-e_i) \left(-\psi''(s_i)\frac{\partial s_i}{\partial B_i}\right)}{(D_E) E_{0,T-1} v'(c_t^V)} - \frac{d\tau}{db} \tag{40}$$

Now since:

$$\frac{\partial s_i}{\partial B_i} = \frac{\partial s_i}{\partial A_i}|B - \frac{\partial s_i}{\partial W_i}|B \tag{41}$$

We have:

$$\frac{dW}{db} = \frac{\sum_{i=k}^{T-1} \left[\Pi_{j=0}^{i-1} e_j\right] (1-e_i) \left[-\psi''(s_i)\frac{\partial s_i}{\partial W_i}|B \left(\frac{\frac{\partial s_i}{\partial A_i}|B}{\frac{\partial s_i}{\partial W_i}|B} - 1\right)\right]}{(D_E) E_{0,T-1} v'(c_t^V)} - \frac{d\tau}{db} \tag{42}$$

Let $E_{i,i+B-1}v'(c_t^E)$ be the average marginal utility over the first B periods while employed conditional on becoming unemployed at $t = i$, and notice that:

$$E_{i,i+B-1}v'(c_t^E) = \frac{1}{B - D_B}\left(s_i \frac{\partial E_i}{\partial W_i}|_B + (1-s_i)\frac{\partial U_i}{\partial W_i}|_B\right) \tag{43}$$

From (26) and (27), after some manipulation, it follows that:

$$\frac{\partial s_i}{\partial W_i}|B = \frac{1}{\psi''(s_i)}\frac{1}{1-s_i}\left\{\frac{\partial E_i}{\partial W_i}|_B - \left(s_i \frac{\partial E_i}{\partial W_i}|_B + (1-s_i)\frac{\partial U_i}{\partial W_i}|_B\right)\right\} \tag{44}$$

$$= \frac{1}{\psi''(s_i)}\frac{1}{1-s_i}\left\{Bv'(c_i^E) - (B-D_B)E_{i,i+B-1}v'(c_t^E)\right\} \tag{45}$$

$$\tag{46}$$

These results in $\frac{dW}{db}$ imply:

$$\frac{dW}{db} = \frac{\sum_{i=k}^{T-1} \left[\Pi_{j=0}^{i-1} e_j\right] (1-e_i) \left[\frac{1}{1-s_i}\left\{Bv'(c_i^E) - (B-D_B)E_{i,i+B-1}v'(c_t^E)\right\}(-\rho_i - 1)\right]}{(D_E) E_{0,T-1} v'(c_t^V)} - \frac{d\tau}{db} \tag{47}$$

where $\rho_i = -\frac{\frac{\partial s_i}{\partial A_i}|B}{\frac{\partial s_i}{\partial w_i}|B}$ is the liquidity to moral hazard ratio at period i.

Notice that from the government budget constraint:

$$\frac{d\tau}{db} = f^{UI}\frac{D_B}{D_E}\left\{1 + \epsilon_{f^{UI},b} + \epsilon_{D_B,b} - \epsilon_{D_E,b}\right\} \tag{48}$$

As in Chetty (2008), assume that the consumption path during employment is constant since unemployment is unlikely to cause large losses on life cycle earnings. This means that $E_{i,i+B-1}v'(c_t^E) = E_{0,T-1}v'(c_t^V) = v'(c_i^E), \forall i$. Using this assumption and the budget constrain, it implies that:

$$\frac{dW}{db} = \frac{D_B}{D_E}\left\{\sum_{i=k}^{T-1}\left[\Pi_{j=0}^{i-1}e_j\right](1-e_i)\frac{(\rho_i+1)}{1-s_i} - f^{UI}\left[1 + \epsilon_{f^{UI},b} + \epsilon_{D_B,b} - \epsilon_{D_E,b}\right]\right\} \tag{49}$$

The term $\sum_{i=k}^{T-1}\left[\Pi_{j=0}^{i-1}e_j\right](1-e_i)\frac{(\rho_i+1)}{1-s_i}$ is the weighted average of the liquidity-to-moral hazard ratio of a worker becoming unemployed at period $i > k$, divided by the probability that he does not find a job at the first period of the spell. If we assume that both the liquidity-to-moral ratio and s_i at the first period of the spell do not vary with respect to the period in which workers become unemployed, as is implicity in Chetty (2008), it is true that $\rho_i = \rho$ and $s_i = s_0$. Then it follows our final welfare formula:

$$\frac{dW}{db} = f^{UI}\frac{D_B}{D_E}\left\{\frac{1}{1-s_0}(\rho+1) - \left(1 + \epsilon_{f^{UI},b} + \epsilon_{D_B,b} - \epsilon_{D_E,b}\right)\right\} \tag{50}$$

where $f^{UI} = \sum_{i=k}^{T-1}\left[\Pi_{j=0}^{i-1}e_j\right](1-e_i)$ is the share of laid-off workers eligible for UI due to MER.