The effects of unemployment insurance benefits on subsequent labor market outcomes: Evidence from an RKD approach

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Abstract

This paper analyzes the effects of unemployment insurance (UI) benefits on subsequent labor market outcomes. Higher benefits may allow a worker to search longer for a better job but, on the other hand, human capital may depreciate during a prolonged unemployment spell. We exploit a kink in the relationship between previous earnings and UI benefits in Finland to identify the causal effect of the benefit level on subsequent outcomes by using a regression kink design. According to our findings, higher UI benefits have a negative effect on employment and earnings in the years following the unemployment spell. Partial unemployment is also effected, with lower UI benefits leading to an increase in the share of days spent on partial unemployment benefits. The benefit level also appears to increase unemployment durations, but the effects are not precisely estimated.

Keywords: Unemployment duration, job match quality, unemployment insurance, regression kink design

JEL codes: J64, J65

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1 Introduction

The level of unemployment insurance (UI) benefits and its consequences for employment outcomes are one of the central and most studied aspects of unemployment insurance systems. Both theoretical and empirical studies have shown that higher unemployment benefits prolong unemployment in most situations (see Tatsiramos and van Ours, 2014 for a recent survey). More generous UI benefits will increase reservation wages and decrease search efforts which both contribute to lower job finding rates. However, it is much less clear what the effects of the benefit level are on other labor market outcomes, such as subsequent employment duration and earnings. Ehrenberg and Oaxaca (1976) analyze the possibility that higher benefits have a positive effect on the wages that unemployed workers are willing to accept. Job seekers can also become more selective in terms of the jobs they will consider with higher benefits enabling them to wait for a better match (Marimon and Zilibotti, 1999; Acemoglu and Shimer, 2000). On the other hand if human capital depreciates during unemployment or if employers discriminate against applicants based on unemployment history, the effects of higher UI benefits on match quality can be negative.

Previous studies that consider the effects of UI benefits on match quality have mostly analyzed the impacts of benefit duration. The results of these studies are mixed, with some findings indicating a positive association between benefit duration and post-unemployment job quality in terms of either higher wages or job stability (e.g. Tatsiramos, 2009; Centeno and Novo, 2009, Guare et al, 2008). Other studies have found negative or no effects of longer benefit durations on match quality (e.g. Degen and Lalive, 2013; Caliendo et al., 2012, Card et al., 2007, van Ours and Vodopivec, 2008; Le Barbanchon, 2012). The evidence on the effects of the benefit level on subsequent labor market outcomes is more scarce and also these studies provide mixed results. Addison and Blackburn (2000) find that higher UI benefits have hardly any effect on subsequent wages in the US labor market, but Centeno (2004) shows that benefits increase the duration of the subsequent employment spell. Ek (2013) finds evidence that higher UI benefits decrease annual earnings and monthly wages in Sweden. The probability of employment and employment durations do not appear to be affected. Altogether these studies provide a very mixed picture of the effects of higher unemployment benefits on subsequent labor market outcomes. From reduced form estimates it is difficult to distinguish between the hypotheses that higher benefits can either lead to job seekers becoming more selective in terms of the jobs they accept or, on the other hand, increased benefits can lead to human capital depreciation and discrimination in hiring due to longer unemployment spells. However, the net effect of opposite effects on labor market outcomes is of considerable interest.

In this study, we provide further evidence on the effects of the UI benefit level on

subsequent labor market outcomes. To identify the causal effect of the UI benefit level, we exploit a kink in the relationship between previous earnings and UI benefits in Finland. The piecewise linear scheme that is used to determine UI benefits allows us to use a regression kink design to identify the effect of the UI benefit level on subsequent outcomes. We consider the effect of the benefit level on unemployment duration, subsequent employment duration as well as post-unemployment earnings. In addition, we analyze the effect on the prevalence of partial unemployment benefits.We address these questions using comprehensive data obtained by combining administrative registers of various authorities. The data covers all individuals who have been unemployed in Finland between 1999 and 2009. For these people we have full details of registered unemployment spells, unemployment benefits received and participation in active labor market programs since 1999. In addition, we observe their complete employment histories before unemployment periods (from the 1960's onwards) as well as all their employment spells following unemployment spells.

According to our findings, higher UI benefits may prolong unemployment durations, but the results are not statistically significant. Unlike Ek (2013) who uses a similar research design, we find that the benefit level has a negative effect on employment three years after the beginning of the unemployment spell. The effects on re-employment earnings are also negative, with higher benefits implying lower earnings in the years following the unemployment spell. This finding is consistent with the results of Ek (2013) for Sweden. We also consider partial unemployment and find that lower UI benefits lead to an increase in the share of days spent on partial unemployment benefits.

The rest of the paper proceeds as follows. In the next section we discuss the Finnish UI system. This is followed by a section describing our identification strategy. Section 4 introduces our data and in section 5 we present our estimation results. The final section concludes.

2 Institutional framework

In Finland earnings-related UI benefits are paid by UI funds. Most UI funds are organized along the industry or occupation lines, and administrated by labor unions. Membership is voluntary, but as many as 85% of all workers are enrolled in UI funds (Uusitalo and Verho, 2010). To receive an unemployment benefit, the worker must first register as an unemployed job seeker at the public employment agency. A worker who has been an insured member of a UI fund for at least 10 months and satisfies the employment condition, that is, has worked for 34 weeks during a review period of 28 months before his or her benefit claim is entitled to 500 days of UI benefits.¹ The waiting period is 7 working days, but it is extended by 90 days (or 30 days if the duration of the job in question was less than 5 days) for those who quit. The benefits are paid 5 days a week, so that the maximum duration of UI benefits is 100 calendar weeks. A worker who leaves unemployment without exhausting his benefits, and then returns to unemployment before satisfying the employment condition again is entitled to his or her unused UI benefits from the previous spell. When the employment condition is satisfied again, a new 100-week period of UI benefits is awarded.

Unemployed persons, who do not fulfil the employment condition, or who have exhausted their UI benefits are eligible for the labor market subsidy paid by the Social Security Institution. In 2006, it amounted to 23.50 EUR a day without child supplements.² This is paid without a limit on duration, but it is means-tested against household income and individuals younger than 26 are subject to stricter eligibility conditions. Those unemployed who do not belong to a UI fund but satisfy the other eligibility conditions described above are eligible for a flat-rate basic allowance which is the same amount as the labor market subsidy but is not means-tested and is paid for a period of 100 weeks. In practise, this benefit type is of minor importance.

The UI benefit consists of a basic component equal to the basic allowance and an earnings-related component that is 45% of the difference between the previous daily wage and the basic daily allowance up to previous monthly wages of 2115 EUR (in 2006). There is no cap on the benefit level but monthly wages exceeding 2115 EUR increase the benefits by only 20% of the exceeding amount. The daily benefit cannot exceed 90% of the underlying daily wage which restricts the benefit amount at low levels of earnings. Figure 1 illustrates the relationship between UI benefits and previous earnings in 2006. The first vertical line corresponds to the basic allowance, and between the first and second vertical lines the afore mentioned rule of max 90% replacement ratio is in effect. The third vertical line corresponds to a monthly wage of 2115 EUR with wages exceeding this level increasing benefits by only 20% of the exceeding amount.

Workers with long employment history can receive a higher benefit, equal to the basic allowance and a higher earnings-related component that is 55% of the difference between the previous daily wage and the basic daily allowance. Above the cut-off at 2115 EUR (in 2006), the monthly wages exceeding the cut-off increase benefits by 32.5% of the exceeding amount. In addition, starting in 2005 workers with some employment history

¹The review period is defined back in time from the end of the last job if that was close to the unemployment entry, otherwise from the start of the unemployment spell. If the entitlement period was renewed last time within the review period, the employment weeks only after that point are accounted for the employment condition. In this case, the effective review period is shorter than two years.

²The daily benefit was raised by 4.45 EUR for one child, by 6.54 EUR for two children and by 8.43 EUR for more than two children.

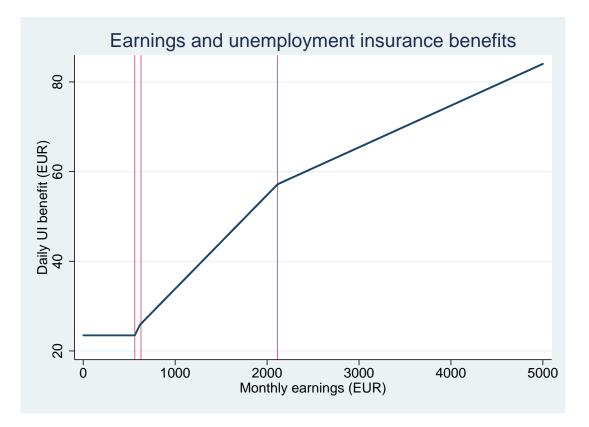


Figure 1: Monthly earnings and daily UI benefit level (EUR)

who receive an employment plan and participate in active labor market programs included in the plan were entitled to higher benefits equal to the basic allowance plus 65% of the wage exceeding the basic allowance up to the cut-off. For wages exceeding the 2115 EUR cut-off, benefits increase by 37.5% of the exceeding amount. We do not consider these groups of workers with differing benefit schedules in our basic analysis. Jos näitä ryhmiä ei tarkastella, turha luetella päivärahan yksityiskohtia - riittää, että mainitaan, että tietyt ryhmät oikeutettuja (eligibiliy-ehdot oleellisia) korkeampiin etuuksiin mutta nämä heivataan pois.

Employers can also lay off workers for a fixed period of time. During a temporary layoff, the worker can receive unemployment benefits provided he or she satisfies the general eligibility conditions. We leave these workers out of our analysis. The unemployed who are looking for a full-time job but who take up a part-time job (or a very short full-time job) do not necessarily lose their unemployment benefits entirely but they may keep part of their full-time benefits. In exchange for partial benefits, these workers are expected to continue their search of a full-time job. When the worker is collecting partial UI benefits, his or her entitlement period elapses at a reduced rate proportional to the ratio of the partial benefit to full compensation level. Partially unemployed workers are not part of our analysis.

3 Identification strategy

Unfortunately, there were no policy reforms in the period covered by our data that would provide exogenous variation in UI benefits, which we could exploit for identification. Instead we take advantage of the kink in the benefit rule that determines the benefit level as a function of past wage (i.e the change in the slope at 2115 EUR in Figure 1). The basic idea is that a kink in the relationship between the outcome variable (e.g. unemployment duration) and the past wage at the kink point of the benefit rule is indicative of the causal effect of benefits under the identifying assumption that the direct effect of past wage on the outcome is smooth at that point. This approach is known as the "regression kink design" (RKD) due to Nielsen et. al (2010). It resembles the regression discontinuity design, which identifies the causal effect from a jump in the average outcome associated with a jump in the treatment variable. whereas the RKD identifies the causal effect from a kink in the average outcome associated with a kink in the treatment variable.

To fix ideas, consider the following stylized model

$$Y = \alpha + \tau B + \varepsilon, \tag{1}$$

where Y is an outcome (e.g. unemployment duration or post-unemployment earnings), B = b(W) is the daily UI benefit, which is a deterministic function of the previous daily wage W with a kink at $W = w^*$ (2115 EUR in 2006), and ε is an error term. The parameter of interest is τ , the causal effect of the UI benefit on the outcome Y. Because both Y and W are labor market outcomes and presumably affected by same unobserved characteristics, the unemployed who received different wages on their previous jobs are likely have different expected Y, and therefore $E(\varepsilon|W) \neq 0$. Since is B is a function of W, OLS estimate of τ from (1) would be biased due to the endogeneity of B. To mitigate this problem, we can augment the model by adding a control function g(W):

$$Y = \alpha + \tau B + g(W) + v. \tag{2}$$

However, the effect of B cannot be distinguished from that of g(W) without further assumptions. Nielsen et al. (2010) show that if g(W) and E(v|W=w) are continuous differentiable and neither have a kink at $W = w^*$, then

$$\tau = \frac{\lim_{w \downarrow w^*} dE\left(Y|W=w\right)/dw - \lim_{w \uparrow w^*} dE\left(Y|W=w\right)/dw}{\lim_{w \downarrow w^*} b'(w) - \lim_{w \uparrow w^*} b'(w)}.$$
(3)

The RKD estimand, the right-hand side of (3), equals the ratio of the change in the slope of the conditional expectation of the outcome variable to the change in the slope of the

deterministic benefit rule at the cutoff w^* . Thus, despite the endogeneity of UI benefit, its causal effect is identified without any assumptions about $g(\cdot)$ except the smoothness.

Since the denominator of the RKD estimand is known in our case, we only need an estimate of the numerator. The simple and most common approach in applied work is to estimate a polynomial regression model (or linear model by setting $\beta_2 = \delta_2 = 0$) of the form

$$E(Y|W = w) = \alpha + \delta_0 D + \sum_{p=1}^{P} \left[\beta_p \left(w - w^*\right)^p + \delta_p D \left(w - w^*\right)^p\right],$$
(4)

where $D = 1 (w > w^*)$ is an indicator for observations with the previous wage above the cutoff, by OLS from a subsample of observations in a neighborhood of the cutoff that satisfy the condition $|w - w^*| \le h$. Most empirical applications have focused on either a linear (P = 1) or quadratic (P = 2) specifications. Moreover, the restriction $\delta_0 = 0$ has been often imposed. As δ_1 is the change in the slope of the conditional expectation of Y at w^* , we can obtain an estimate of τ by dividing the OLS estimate of δ_1 with the change in the slope of the benefit rule at w^* . The implementation of this approach requires a choice of the bandwidth h, which is a trade-off between the precision of the estimates and accuracy of the polynomial approximation to the unknown underlying expectation function. In practice, some ad hoc value is typically chosen and the robustness of the results is verified by re-estimating the model with a number of alternative bandwidths.

Although the model outlined above is rather general, Card et al. (2012) show that the RKD estimand, the right-hand side of (3), can be interpreted as the average treatment effect in an even more general, nonseparable model

$$Y = y(B, W, \varepsilon), \tag{5}$$

which allows for unrestricted heterogeneity in the effect of B. They show that for this model the RKD estimand identifies

$$E\left(\frac{\partial y(b^*, w^*, \varepsilon)}{\partial b} \middle| B = b^*, W = w^*\right),\tag{6}$$

where $b^* = b (w^*)$ and the expectation is taken with respect to the conditional distribution of ε given $B = b^*$ and $W = w^*$. This parameter is known as "the treatment on the treated" (Florens et al. 2008) or "local average response" (Altonji and Matzkin 2005), and it equals the average effect of a marginal increase in b at the point (b^*, w^*) holding fixed the conditional distribution of unobservable characteristic.

Card et al. (2012) discuss nonparametric inference using local linear and local quadratic regression models. In the quadratic case, the estimation of the conditional expectation of

the outcome variable amounts to solving $(\alpha^-, \beta_1^-, \beta_2^-)$ and $(\alpha^+, \beta_1^+, \beta_2^+)$ by minimizing the objective functions

$$\sum_{i \in \Omega^{-}} \left(Y_i - \alpha^{-} - \beta_1^{-} \left(w_i - w^* \right) - \beta_2^{-} \left(w_i - w^* \right)^2 \right)^2 K\left(\frac{w_i - w^*}{h} \right)$$

and

$$\sum_{i \in \Omega^+} \left(Y_i - \alpha^+ - \beta_1^+ \left(w_i - w^* \right) - \beta_2^+ \left(w_i - w^* \right)^2 \right)^2 K\left(\frac{w_i - w^*}{h} \right)$$

where $K(\cdot)$ is a kernel function, h is the bandwidth, Ω^- and Ω^+ are the set of observations below and above the wage cutoff w^* respectively. An estimate for the average local treatment in (6) is obtained by dividing the estimate of $\beta_1^+ - \beta_1^-$, the numerator of the RKD estimand, with the change in the slope of the benefit rule at w^* .

Card et al. (2012) provide the conditions under which the local linear and quadratic estimators are consistent and asymptotically normal They do not provide a means to choose an optimal bandwidth but use a rule-of-thumb bandwidth based on Fan and Gijbels (1996) in their empirical application. Calonico et al. (2014) argue that the commonly used bandwidth selectors, which aim to balance the squared-bias and variance of the estimator, tend to yield bandwidths that are too large to ensure the validity of the underlying distributional approximations. As a result, the RKD estimates may be subject to a nonnegligible bias and the resulting confidence intervals can be severely biased. They propose an alternative, more robust method. In their approach, the RKD point estimate is corrected by an estimated bias term, and the standard error estimates are adjusted for the additional variability that results from the estimation of the bias-correction term. This procedure produces the bias-corrected RKD point estimate and the confidence intervals that are more robust to the bandwidth choice than the conventional methods. Calonico et al. (2014) also introduce a new method to choose the optimal bandwidth.

In their follow-up paper Card et al. (2015) compare conventional nonparametric RKD estimates and their bias-corrected alternatives obtained using different polynomial orders and bandwidth selectors and using both real-world data and simulated data. They argue that in some cases (including their analysis of the effects of UI benefits on unemployment duration using Austrian data) the uncorrected linear RKD model can produce more useful estimates than the bias correction procedure of Calonico et al. (2014). This is because the overall variance of the bias-corrected estimator can be much higher if the bias term were imprecisely estimated. Overall the RKD estimates seem to be rather sensitive with respect to polynomial order and bandwidth choices, which is unfortunate as there is no generally accepted procedure to choose these parameters. While Calonico et al. (2014) advocate the use of the bias-corrected estimates from the quadratic model using their

selector for the optimal bandwith, Card et al. (2015) favor the uncorrected estimates from the linear model with the rule-of-thumb bandwidth of Fan and Gijbels (1996).For this reason, we estimate various model specifications with alternative bandwidths. In our nonparametric analysis, we apply the methods (the optimal bandwidth choice and robust RKD inference with the bias correction) developed by Calonico et al. (2014). We also report results from augmented model specifications that include various sets of control variables.

The key identifying assumption is that conditional on ε , the density of the past wage is smooth at the wage cutoff w^* . This smooth density condition implies that also the densities of predetermined covariates should be smooth in a neighborhood of the wage cutoff. To test the validity of the RKD we detect bunching of observations at the wage cutoff and analyze the densities of predetermined covariates around the wage cutoff.

4 Data and descriptive statistics

Our data was obtained by combining various administrative registers. The primary source of information is the administrative register on job seekers, maintained by the Ministry of Employment and the Economy (TEM). The register covers all registered applicants at the public employment agency. Because without registration as an unemployed job seeker one cannot qualify for unemployment benefits, all unemployment benefit recipients - and many unemployed non-recipients and employed job seekers - should be included. The register contains information on unemployment spells, training courses and subsidized employment programs, as well as demographic characteristics, such as age, gender, education, occupation and living region. However, the register does not contain any information on receipt of unemployment benefits, nor on regular job spells. Therefore we supplemented the data by merging benefit informations from the registers of the Insurance Supervisory Authority (FIVA) and the Social Security Institution (KELA) and employment and earnings information from the registers of the Finnish Centre for Pension (ETK).

While UI benefits are paid by individual UI funds, each fund must report on a quarterly basis the benefits it paid out to the FIVA. From its registers we obtained information on UI fund membership and received UI benefits (including also earnings-related labor market training subsidies). Along with daily benefits the data also contains information on the number of unused UI weeks at the end of each quarter, which allows us to compute the length of the UI entitlement period at the beginning of the unemployment spell. From the registers of KELA, which pays all flat-rate unemployment and social security benefits, we obtained data on basic allowances and labor market subsidies.Finally, for all people who have been unemployed, we merged employment and earnings records from the beginning of their working career from the registers of the ETK. ETK is a statutory co-operation body of all providers of earnings-related pensions in Finland. It keeps comprehensive records on job spells and earnings for the entire Finnish population, which will be used to determine pension benefits.

We define the spell of unemployment as the time the worker is registered as an unemployed job seeker and collecting unemployment benefits. More precisely, we combine sequential spells of benefit receipt whose distance is no longer than 4 weeks by treating such benefit periods as part of the same unemployment spell but ignoring the days between the benefit periods in our unemployment duration measure. The time spent in training courses is counted as part of the unemployment spell. The resulting unemployment spell may thus include periods on different types of benefits. For example, a worker may first receive UI benefits, then labor market training subsidy for the duration of a training course, and finally end up to labor market subsidy after exhausting UI benefits.

The unemployment spell may end with a transition to regular work, subsidized work or non-participation. All subsidized employment programs are observed in the TEM data. That data also includes information on exits to regular jobs that applicants found themselves or through the referrals of the employment agency. But the information on job findings may not be very reliable and the exit destination is often missing for those who found a new job without the help of the unemployment agency. For these reasons, the exits to regular work are detected by comparing the ending days of the unemployment spells and the starting days of the employment spells observed in the ETK data.

We focus on unemployed workers who are eligible for the full 100 weeks of earningsrelated UI benefits at the beginning of their unemployment spell. We exclude unemployed workers who are eligible for the higher earnings-related benefit based on long employment history or due to participating in active labor market policies based on employment plans. We also exclude individuals whose UI benefits have been reduced due to other benefits and those who have been laid off temporarily.³ Our main analysis covers unemployment spells that begin in years 2003-2007. The beginning of the period is restricted by the fact that there were changes in the benefit schedule before this. We do not consider unemployment spells that begin after 2007 in order to have a long enough follow-up period for postunemployment outcomes. Our current data ends in December 2009.

Figure 2 displays how the UI benefit rule shows up in the data. There are hardly any observations outside the true benefit schedule which allows us to use a sharp regression kink design.

In Table 1 we report descriptive statistics for the whole estimation sample described

³Benefits such as home care allowance when taking care of children as well as partial disability pension can lower the UI benefit an unemployed worker is entitled to.

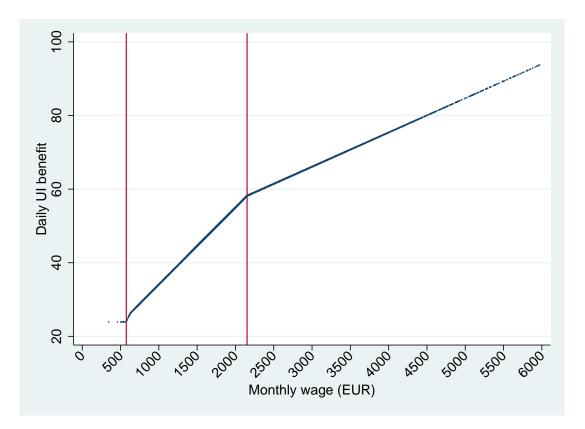


Figure 2: Monthly wage and daily UI benefit level in the data in 2007

above as well as the sample around the kink point. The main differences in individual characteristics between the full sample and the sample around the kink point stem from the location of the kink point slightly higher than the mean in the wage distribution. The sample around the kink point has a slightly lower share of women and is slightly higher education. Our main outcome for unemployment duration is days on UI benefits. We also examine the share of UI benefit days that is spent on partial benefits as well as post unemployment employment and earnings.

5 Results

5.1 Validity of identifying assumptions

A crucial assumption in regression kink design is that there is no manipulation of the assignment variable at the kink point. Figure 3 shows the number of unemployment spells by bins of log wage relative to the cutoff. The choice of bin size (0.013) is based on the test of excess smoothing as suggested by Lee and Lemieux (2010) in the regression discontinuity design context. The graph shows no signs of discontinuity in the number of spells and the assignment variable at the cutoff. A formal McCrary test as usually

	Full sample		Around kink	
	Mean	SD	Mean	SD
UIB days paid	216.74	198.97	192.32	190.51
Share of partial unemployment in UIB days	0.05	0.21	0.04	0.17
Monthly wage used to determine UIB	1814	888	2311	246
Daily UI benefit	58.29	13.23	71.32	5.84
Share of UIB spells ending in employment	0.69	0.46	0.77	0.42
Cumulative days employed in next 3 years	335	267	370	254
Cumulative earnings in next 3 years	$26\ 283$	$35 \ 421$	$34\ 121$	31 302
Age	41.21	11.06	40.96	10.73
Share of women	0.67	0.47	0.46	0.50
Share of tertiary educated	0.12	0.33	0.23	0.42
Number of children (basis of benefit payments, max. 3)	0.74	1.00	0.73	0.99
Observations	$250 \ 881$		76 450	

Table 1: Descriptive statistics for full sample and sample around the kink point (bandwidth of $+/0.16 \log EUR$ in daily wage)

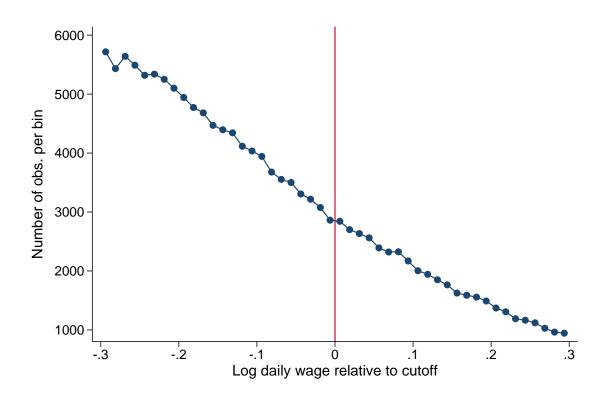
conducted in the regression discontinuity design literature also shows no lack of continuity at the kink⁴. Card et al. (2012) also extend the idea of the McCrary test to the RKD by testing the assumption of the continuity of the derivative of the p.d.f. The number of observations in each bin is regressed on polynomials of previous earnings (centered at the cut-off) and the interaction term as was done above for the outcomes. We do a similar exercise and the coefficient of the interaction term for the first order polynomial is insignificant which indicates that the smoothness assumption is not violated.

The regression kink design also requires that the relationship between the covariates and the outcome variable is smooth around the cut-off point. In order to examine whether this holds in our set up, we provide estimates of the change of slope at the cut-off point when using the covariates as outcomes in a specification similar to that described above. We also plot mean values of the covariates in each bin of the assignment variable. Figure 4 indicates that the covariates evolve smoothly around the cutoff point. The share of women shows a slight significant estimate at the kink, but no such effect is found when a quadratic specification is allowed. The share of women can be expected to be somewhat non-linear across the wage distribution.

5.2 Estimation

We first examine the effect of the level of UI benefits on the number of days spent on UI benefits. Figure 5 displays the relationship between previous wage and days on UIB. The previous wage is determined during the employment condition weeks and is the actual wage used as the basis of the benefit payments. The figure also shows a linear fit and 95% confidence intervals for a bandwidth of 0.16 log EUR on both sides of the

⁴Point estimate of log difference in height 0.0069, standard error 0.021





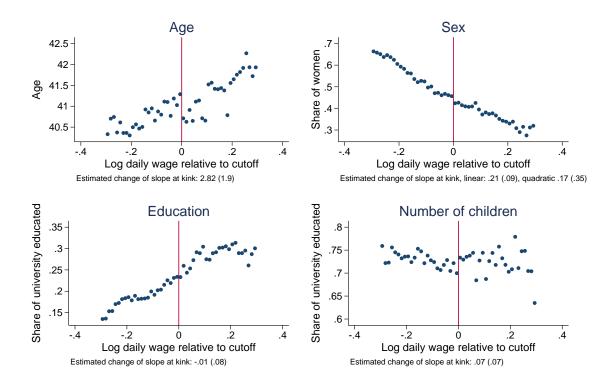


Figure 4: Linearity of covariates

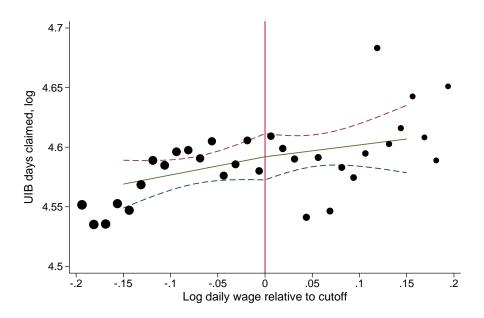


Figure 5: Pre-unemployment daily wage and UIB days

cutoff⁵. Figure 5 shows hardly any kink in the relationship between the previous wage and days on UI benefits. It is therefore to be expected that our further analysis does not show a strong effect of the UI benefit level on the time spent on UI benefits. However, when we look at days spent on partial unemployment benefits, figure 6 implies that UI benefits have a significant effect on the share of partial unemployment days in the unemployment spell. It would appear that lower UI benefits induce an increase in the prevalence of partial unemployment. Also subsequent employment and earnings appear to be affected, with figures 7 and 8 showing a clear kink in the relationship between the pre-unemployment wage and cumulative days in employment in the three years after the start of the unemployment spell as well as smaller but noticeable kink in the relationship between the previous wage and subsequent earnings. We next analyze these findings in more detail.

Table 2 presents results for the elasticity of our different outcomes relative to the benefit level. The first panel shows results with days of UI benefits paid as the dependent variable. The first column corresponds to a local linear model estimated using the rule of thumb bandwidth of Fan and Gijbels (1996). The point estimate is positive but imprecisely estimated and as our graphical anlaysis implied, there is no significant effect of the UI benefit level on days spent on UI benefits. Columns 2 and 3 show the estimates for a similar estimation but with added controls. The estimates do not change much as a result. Columns 4 and 5 show estimates using the bias corrected method of Calonico et al. (2014). The linear specification in column 4 yields similar results than the conven-

⁵This is approximately the "rule of thumb" bandwidth of Fan and Gijbels (1996).

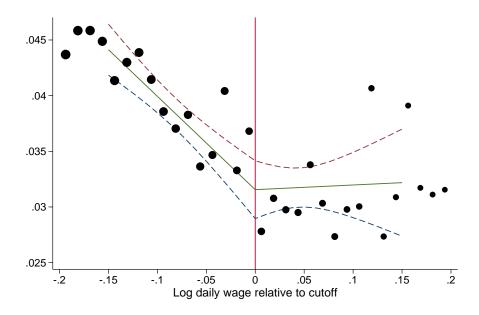


Figure 6: Pre-unemployment daily wage and partial unemployment

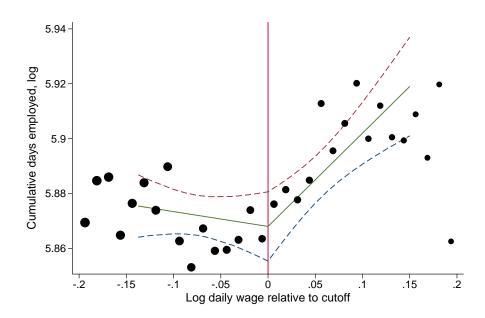


Figure 7: Pre-unemployment daily wage and subsequent employment

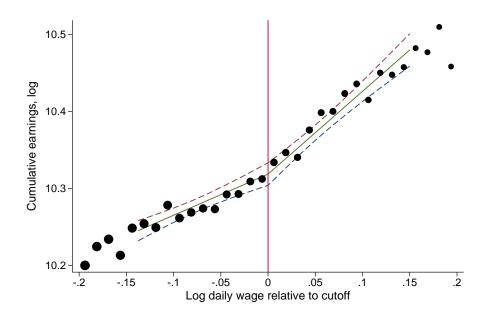


Figure 8: Pre-unemployment daily wage and subsequent employment

tional estimation but the quadratic specification that CCT recommend implies a positive and significant elasticity of UIB days with respect to the UI benefit level. The share of UI benefit days spent in partial unemployment appears to decrease with higher UI benefits, wioth the point estimate significant in all specifications and slightly higher for the quadratic specification than the others. This would imply that lower benefits induce job seekers to take e.g. part time and temporary jobs.

The lower two panels in Table 2 show results for post-unemployment outcomes. The results indicate that higher unemployment benefits decrease cumulative days in employment during the three years after the start of the unemployment spell and also decrease cumulative earnings during this period. The point estimates are significant and similar on magnitude for different specifications with the estimates from the quadratic specifications slightly higher again.

In order to examine the robustness of our results we next present results for estimation of the elasticity of our different outcomes with respect to the UI benefit level for a range of bandwidths. The results in figures 9 are for a linear specification with the point estimate for the optimal bandwidth depicted by the blue dashed line. The FG and CCT bandwidths discussed above are depicted as vertical red lines. As expected the point estimates are noisier at smaller bandwidths. The estimates for UIB days are not significant at any bandwidth and for partial unemployment the estimates are only precise for quite a narrow range of bandwidths. The estimates for post-unemployment outcomes are more stable with the elasticities of both employment and earnings negative and significant across a reasonably wide range of bandwidths.

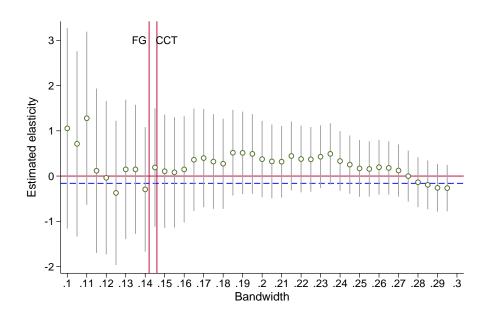


Figure 9: Elasticity of UIB days with respect to the benefit level, estimates at different bandwidths (bandwidth in log EUR)

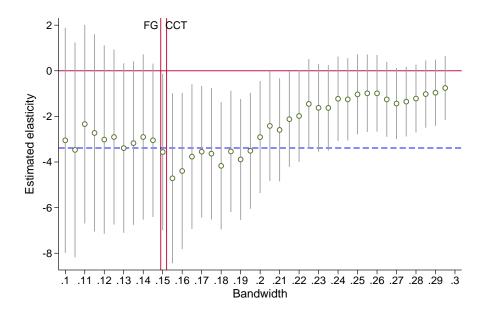


Figure 10: Elasticity of UIB days with respect to the benefit level, estimates at different bandwidths (bandwidth in log EUR)

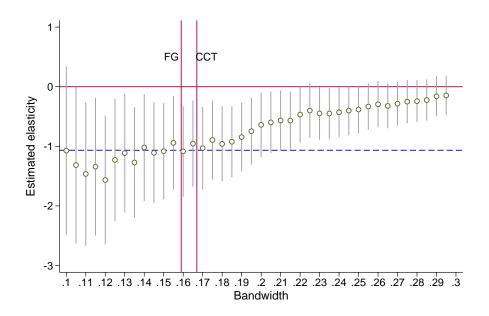


Figure 11: Elasticity of UIB days with respect to the benefit level, estimates at different bandwidths (bandwidth in log EUR)

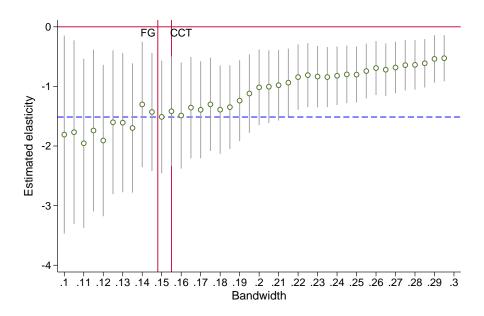


Figure 12: Elasticity of UIB days with respect to the benefit level, estimates at different bandwidths (bandwidth in log EUR)

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Table 2: RKD estimates

6 Conclusions

Research on the effects of the UI benefit level on labor market outcomes other than unemployment duration is scarce and the results are mixed. In this study we have provided further evidence on the effects of the UI benefit level on subsequent labor market outcomes. To identify the causal effect of the UI benefit level, we exploited a kink in the relationship between previous earnings and UI benefits in Finland. The piecewise linear scheme that is used to determine UI benefits enabled us to use a regression kink design to identify the effect of the UI benefit level on subsequent outcomes. We analyzed the effect of the benefit level on UIB days, the share of partial unemployment in the unemployment spell, suebsequent employment as well as post-unemployment earnings. Our results indicated that higher UI benefits may prolong unemployment durations, but the results were not statistically significant. Unlike Ek (2013) who uses a similar research design, we found that the benefit level has a negative effect on employment three years after the beginning of the unemployment spell. The effects on re-employment earnings were also negative, with higher benefits implying lower earnings in the years following the unemployment spell. This finding is consistent with the results of Ek (2013) for Sweden. In addition, we found that lower UI benefits lead to an increase in the share of days spent on partial unemployment benefits implying that lower benefits may encourage job seekers to accept part time or temporary work.

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