Labor Market Outcomes Speak Louder than Age?

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Abstract

Does the National Living Wage in the United Kingdom affects labor market outcomes after turning 25 years of age? The repercussions of minimum wage policies on low-skilled individuals and firms have been subject to debate in Britain, and across the world. Through a sharp regression discontinuity design for low-skilled individuals, the National Living Wage showed no statistically significant local average treatment effects on employment rates and hours worked.

Introduction

The National Living Wage (NLW) was introduced in April 1^{st} of 2016 in the United Kingdom for workers aged 25 and over. Effectively replacing the national minimum wage addressed to individuals older than 22. Minimum wage policies are considered indispensable for reducing income inequality and mitigating poverty. Diametrically oppose, there is aversion to them given possible negative effects on labor market outcomes; especially on low-skilled workers. Consequently, does the NLW have any effect on employment rates and hours worked for low-skilled individuals?

A sharp regression discontinuity design (RDD) was a reasonable approach for answering the question. Naturally, it was imperative to minimize any possible selection bias, and this empirical strategy allowed for randomized variation between treatment and control groups as a consequence of a known assignment rule. According to Hahn, Todd & van der Klaauw, (2001) [1], RDDs enjoy the benefit of requiring bland assumptions compared to other non-experimental methods; yielding highly credible and transparent local average treatment effects. Hence, the objective was to compute an RDD estimation for low-skilled individuals marginally close to turning 25 years of age.

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Previous work from Dickens, Riley & Wilkinson, (2014) [2], evaluating the past minimum wage policy in the UK, found positive effects regarding unemployment after turning 22. In contrast, Neumark & Wascher, (2008) [3] showed negative results for several non-UK countries on employment outcomes after introducing or increasing their respective wage policies. Therefore, given mixed results in the literature across countries, it wasn't unlikely that the effect of the NLW on labor market outcomes had been neutral along the continuum from 24 to 25 years of age.

Data

The Office of National Statistics (ONS) is the body in charge of implementing the Labor Force Survey (LFS) in the UK. This survey contains representative information on employment and hours worked at the individual level. It is part of a series of non-secured micro-datasets. The LFS is available on a quarterly basis, and one-fifth of the sample is replaced every quarter. Therefore, the LFS is available in three different formats: quarterly, two-quarter longitudinal and five-quarter longitudinal.

The chosen datasets to answer the research question were, the Quarterly Labor Force Survey (QLFS) Five-Quarter Longitudinal Datasets; from the third quarter of 2013 to the second quarter of 2018. The five-quarter datasets link data from five consecutive waves across a whole year (for example January 2010 to March 2011 inclusive) and contain data from all five waves. The 87,830 observations merged dataset was handled as pooled cross-sectional data; separately for the periods before and after the NLW was introduced.

This dataset was the only one allowing for the construction of the running variable: age in number of quarters. It had a unique serial number per individual throughout five periods (instead of just two), the quarter surveyed, and the age in each quarter. Thus, allowing for the identification of the "birth quarter" of each individual[1]. Actual dates of birth were not available given the non-secured nature of the data, and therefore, age could not be reduced to a smaller expression than number of quarters. Access to a secured version of the QLFS was not feasible. The conversion of the age variable was essential to expand the sample size around the threshold.

The population of interest were low-skilled individuals, or people without A-levels. That is, individuals with no tertiary/post-secondary education, or at level 3 or below in the National Qualifications Framework (NQF). These are the subjects of interest because they're the most likely to experience direct consequences of minimum wage policies. The

[1] If the age of each individual changed in quarter q_j from q_{j-1}, where $j \in [1, 5]$, then q_j was accurately considered the "birth quarter".

main outcome variables that could affect them are: employment[2] rate per age (per quarter) and weekly hours worked per individual (per quarter). Firms face managerial decisions of whether to let them go, reduce their workload, or retain them at their current position. In fact, firms represented a very important aspect within potential ramifications of minimum wage policies. They were omitted due to the scope of the paper.

The QLFS was also used by Dickens, Riley & Wilkinson, (2014) [2] as pooled cross-sectional data to analyze the impact of the previous minimum wage on unemployment at the age of 22. Additionally, Lee & Lemieux, (2010) [4] recommend cross-sectional data for this empirical strategy; panel data is not imperative for identification. By design, every individual i was assumed to be different in every quarter q. This was reasonable given the fact that employment status and/or number of hours worked were mutable conditions one quarter to the next. Hence, the data was managed as pooled cross-sectional for the post and pre-treatment periods. Therefore, there is confidence the chosen dataset was suited for the research question.

Model

The model used was a sharp RDD because individuals had a higher probability of receiving the NLW once they turned 25 years[3] of age. This indicates a clear cutoff rule for which the sharp methodology was suitable. The main idea of the model followed from a treatment variable determined by the age in number of quarters for every individual i. The running variable was re-expressed to maximize the sample size around the threshold; which would have otherwise been constrained. The treatment variable is,

$$D_i = 1(Age_i \geq 100) \text{ so } D_i = \begin{cases} D_i = 1 \text{ if } Age_i \geq 100 \\ D_i = 0 \text{ if } Age_i < 100 \end{cases}$$

The objective was to identify the difference between the two groups in a given labor market outcome Y_i, expressed as $E\left[Y_i|D_i = 1\right] - E\left[Y_i|D_i = 0\right]$. This needed to be done in a way that selection bias was avoided. The assumption of discontinuous change in the probability of receiving the NLW was used to study the local causal effect on the outcomes of interest. Therefore, the general form of the estimated model followed a standardized regression discontinuity design,

$$Y_i = \delta_0 + f(Age_i - c) + \rho D_i + \epsilon_i \tag{1}$$

[2] Defined by the International Labor Organization (ILO) and implemented in the QLFS by the ONS. Also, employment rates per age were estimated in the usual way in the script: employed individuals per age (per quarter) over total number of respondents per age (per quarter).

[3] Being 25 years old is equivalent to 100 quarters of life.

The outcome variables Y_i were sensitive to the functional form of the running variable, thus $f(\bullet)$ played an important role in the identification process. Precisely speaking, the causal effect was the difference between $D_i = 1$ compared to $D_i = 0$ at the threshold $c = 100$. This was assumed to be true given individuals that were quarters away from turning 100 were used as counterfactuals for individuals who just crossed the cutoff age. Assuming that individuals didn't decide how old they were, or had an incentive to lie during the survey, then the assignment process into treatment and control groups was considered as good as random[4]. Amplifying the importance of the sample size around c. Hence,

$$\begin{aligned}\rho &= E\left[Y_{1i} - Y_{0i} | Age = c\right] \\ &= E\left[Y_{1i} | Age = c\right] - E\left[Y_{0i} | Age = c\right]\end{aligned}$$

Where ρ in equation (1) is the local average treatment effect (LATE) of the NLW on labor market outcomes for low-skilled individuals. This is accurate because $E\left[Y_{1i} | Age_i, D_i\right]$ and $E\left[Y_{0i} | Age_i, D_i\right]$ are continuous in age around the threshold $c = 100$. In order to produce an unbiased estimator, achieving the largest sample size possible around $c = 100$ was paramount, and somewhat of an innovation to the datatset.

As a complement to equation (1), another simpler models were estimated. It is important to acknowledge that the whole spectrum of data points were informative for the sampled individuals, above and beyond the average group values. So, if there were in fact different group means there should have also been divergence among intercepts in any univariate model of the forcing variable. Thus, comparing groups under any outcome at either period in j looked like,

$$\begin{cases} Y_{t=j} = \beta_{0,t=j} + \beta_1 Age_{D_i=1} \\ Y_{t=j} = \gamma_{0,t=j} + \gamma_1 Age_{D_i=0} \end{cases} \tag{2}$$

Where $\beta_{0,t=j} \neq \gamma_{0,t=j}$ at any $j \in [0, 1]$. We have that $j = 1$ was after the NLW was introduced, and $j = 0$ was the pre-treatment period. The only covariate (Age) in each model holds all individuals belonging to either the treatment ($D_i = 1$) or the control ($D_i = 0$) group. These results are displayed in tables (4) and (5) in the appendix.

Results

As previously stated, there are two arrays of individuals divided into treatment and control groups. Additionally, there are two time periods to be considered, before and after the NLW was introduced. Now, table 1 shows the difference in means across age groups and

[4]Though Lee & Lemieux, (2010) [4] suggests "such randomized variation is a consequence of agents inability to precisely control the assignment variable near the known cutoff."

time periods for both outcomes of interest; as well as the statistical significance of each difference.

Table 1: Group means per outcome variable

	Employment rate			Hours worked		
	Treatment	Control	$p - value$	Treatment	Control	$p - value$
After NLW	33%	38%	0.000	34	25	0.000
Before NLW	35%	37%	0.000	34	24	0.000
$p - value$	0.000	0.399	—	0.004	0.667	—

NOTE: the $p - values$ refer to the balance test between means, $H_0 : \mu_{it} - \mu_{jt} = 0$.

Considering before and after the NLW was introduced, there seems to be a significant decrease within the treatment group regarding employment rates, but not hours worked. Analogously, there is a significant difference across treatment and control groups in both outcomes and time periods. Can this be granted to a NLW effect on labor market outcomes in the UK? Equation (2) is stated in order to elaborate further on this question.

Table 4 and 5 in the appendix depict equation (2) following a bit more rigorous approach, beyond group means, reinforcing there is in fact different intercepts for both outcomes in treatment and control groups after the NLW was introduced. Nevertheless, the same occurred before the treatment period. This might be happening because the entire sample of low-skilled individuals is being considered, and therefore variation across periods could be hard to identify. There's more to inquire regarding the effect of the treatment D_i and the functional form of the running variable.

The potential identification issues due to model dependence on its functional form can be mitigated by focusing on individuals that are marginally close to the cutoff point. That is, only keeping observations that fall into the interval $\{100 - k \leq Age_i \leq 100 + k\}$ where $k > 0$ determines the size of the bandwidth. Following Imbens & Kalyanaraman, (2012) [5], the value of k is determined separately by an optimal, data dependent choice rule for employment rates and hours worked.

Following the argument made above, tables 6 and 7 in the appendix show naive results for both outcome variables based on equation (1) for employment rates and hours worked. Both equations control for the treatment D_i and different functional forms of the running variable, but relying on OLS estimations. Despite the attempts to fit a model, it appears to be no significant effect of the treatment around the threshold given an optimal bandwidth.

As proposed, equation (1) was ran on multiple functional specifications around the threshold and considering the proposed bandwidth for each outcome using a proper RDD[5] specification. This allowed for different kernels that were substantially more robust around c

[5]The RDD analysis was performed in the statistical software R using the *rdd* package. The script and the dataset can be found in the replication files.

than the hand-made estimations on tables 6 and 7. Following Hall's (2015) [6] empirical strategy, rectangular, cubic and triangular kernels were computed for validation. The triangular kernel produces the IK local linear LATE. These estimations were replicated before and after the NLW was introduced.

As expected, table 2 shows how the running variable had no effect on employment rates per age and hours worked for low-skilled individuals before the NLW was introduced. As for the research question, table 3 confirms the null, or the absence of a statistically significant effect of the treatment D_i on employment rates and hours worked for low-skilled individuals after the policy came into effect; across different specifications.

Table 2: RDD estimates on low-skilled individuals: pre-treatment

	Employment rate			Hours worked		
	Local linear	Cubic	IK local linear	Local linear	Cubic	IK local linear
LATE	0.07	0.07	0.07	3.11	-3.56	-2.38
	(0.10)	(0.10)	(0.10)	(4.04)	(4.62)	(4.42)
Observations	87	87	87	313	313	313
Bandwidth	2.71	2.71	2.71	9.36	9.36	9.36
Kernel	Rectangular	Tricube	Triangular	Rectangular	Tricube	Triangular

NOTE: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 3: RDD estimates on low-skilled individuals: post-treatment

	Employment rate			Hours worked		
	Local linear	Cubic	IK local linear	Local linear	Cubic	IK local linear
LATE	0.03	0.03	0.03	-2.06	-1.03	-1.35
	(0.09)	(0.09)	(0.09)	(2.28)	(2.56)	(2.44)
Observations	164	164	164	506	648	506
Bandwidth	2.71	2.71	2.71	9.36	9.36	9.36
Kernel	Rectangular	Tricube	Triangular	Rectangular	Tricube	Triangular

NOTE: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

It is worth noting that the results from table 6 and 7 in the appendix, in the second column (different slope), match the estimates from table 3 in both outcomes. The employment rate matches in all three LATE specifications, and hours worked only matches in the rectangular kernel. This is in tandem with suggestions from Lee & Lemieux, (2010) [4] and Hall (2015) [6] about choosing a rectangular kernel as a "good alternative", and a triangular kernel as the "correct" kernel for an RDD. Graphical depictions for both outcomes can be seen in figures 3 and 4 in the appendix.

These results are robust to different tests such as: bandwidth sensitivity, placebo thresholds and balance checks for covariates. In the appendix, figures 5-8 depict the robustness checks for these tests. Table 8 in the appendix show the test results of the chosen covariates as placebo outcomes. Figure 9 shows there is in fact sorting around the threshold for the running variable in both outcomes. The McCrary test rejected the null hypothesis, in both periods, of no discontinuity around the threshold for the running variable; except when testing the whole panel.

Conclusion

The NLW had a null effect on employment rates and hours worked for low-skilled individuals around the threshold. It appears that labor market outcomes speak louder than age when it comes to the minimum wage in the UK. The RDD in equation (1) estimate the average effect of the NLW for the sub-population around 25 years of age; expressed in number of quarters. The null effect could be a repercussion of the average firm anticipating when exactly their workers turn 25, and thus planning accordingly into the future. This results could have important implications for policy making, but prudence is advised given more complete versions of the LFS are available, and more importantly, not all robustness checks were met.

There is sorting around the threshold in the post-treatment period and that is not encouraging. It is possible this is due to some individuals under 25 already earning more than the NLW, or people lying about their ages. Although it seems rather implausible for individuals wanting to exercise control over their ages in order to get some benefit during the survey, it needs to be addressed in further research. A fuzzy RDD strategy was not strictly necessary in this case given: (i) wages were not an outcome variable for this paper, and (ii) it represented 0.08% of sampled individuals. Additionally, Dickens, Riley & Wilkinson, (2014) [2] also implemented a sharp methodological strategy despite having marginal non-compliance.

There is still much research to undertake about the impacts of minimum wage policies on labor market outcomes. The NLW could still be further evaluated by taking into consideration a larger sample of the LFS[6] and by adding information about firms. It would be very valuable to understand the type of firms that make the decisions of keeping or letting workers go. A better understanding of sectors and firms could lead to a better mechanism of designing minimum wage policies. Then it might be feasible to assist those who need a more leveled playing field, while keeping the economy unconstrained. Policymakers would do well to keep this in mind.

[6] Adding dates of birth would be very beneficial to the precision of the estimates.

References

[1] Hahn, Jinyong., Todd, Petra & Van der Klaauw, Wilbert., Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design. *Econometrica, Vol. 69, No. 1: pp 201-209*, (2001).

[2] Dickens, Richard., Riley, Rebecca & Wilkinson, David., The UK minimum wage at 22 years of age: a regression discontinuity approach. *Journal of the Royal Statistical Society, 177: Part 1, pp 95-114*, (2014).

[3] Neumark, David & Wascher, William L., Minimum Wages. *MIT Press*, (2008).

[4] Lee, David S & Lemieux, Thomas., Regression Discontinuity Designs in Economics. *Journal of Economic Literature, 48: pp 281-355*, (2010).

[5] Imbens, Guido & Kalyanaraman, Karthik., Optimal Bandwidth Choice for the Regression Discontinuity Estimator. *Review of Economic Studies, Vol. 79, No. 3: pp 933-959*, (2012).

[6] Hall, Andrew B., What Happens When Extremists Win Primaries? *American Political Science Review, Vol. 109, No. 1*, (2015).

Appendix

Table 4: Equation (2) for employment rates

	Treatment after (2)	Control after (2)	Treatment before (2)	Control before (2)
Constant	0.57^{***}	0.68^{***}	0.56^{***}	0.72^{***}
	(0.00)	(0.01)	(0.00)	(0.01)
Age	-0.00^{***}	0.01^{***}	-0.00^{***}	0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.33	0.26	0.28	0.35
Adj. R^2	0.33	0.26	0.28	0.35
Num. obs.	18,654	2,342	13,088	1,766
RMSE	0.14	0.21	0.14	0.19

NOTE: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 5: Equation (2) for hours worked

	Treatment after (2)	Control after (2)	Treatment before (2)	Control before (2)
Constant	37.88^{***}	42.21^{***}	36.69^{***}	41.53^{***}
	(0.34)	(0.95)	(0.42)	(1.23)
Age	-0.04^{***}	0.87^{***}	-0.02^{***}	0.87^{***}
	(0.00)	(0.04)	(0.00)	(0.06)
R^2	0.01	0.30	0.00	0.24
Adj. R^2	0.01	0.30	0.00	0.24
Num. obs.	10,436	1,009	7,516	763
RMSE	14.41	13.45	14.63	14.33

NOTE: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 6: Equation (1) for employment rates in the post-treatment period

	Same slope (1)	Different slope (1)	Polynomial (1)
Constant	0.53^{***}	0.43^{***}	0.48^{***}
	(0.04)	(0.08)	(0.08)
Age	-0.01	-0.07	-0.01
	(0.02)	(0.05)	(0.07)
D_i	-0.05	0.03	-0.02
	(0.07)	(0.09)	(0.11)
Age * D_i		0.08	
		(0.06)	
Age^2			0.01
			(0.01)
Age^3			-0.00
			(0.01)
R^2	0.03	0.04	0.04
Adj. R^2	0.02	0.02	0.02
Num. obs.	164	164	164
RMSE	0.21	0.21	0.21
Bandwidth	2.71	2.71	2.71

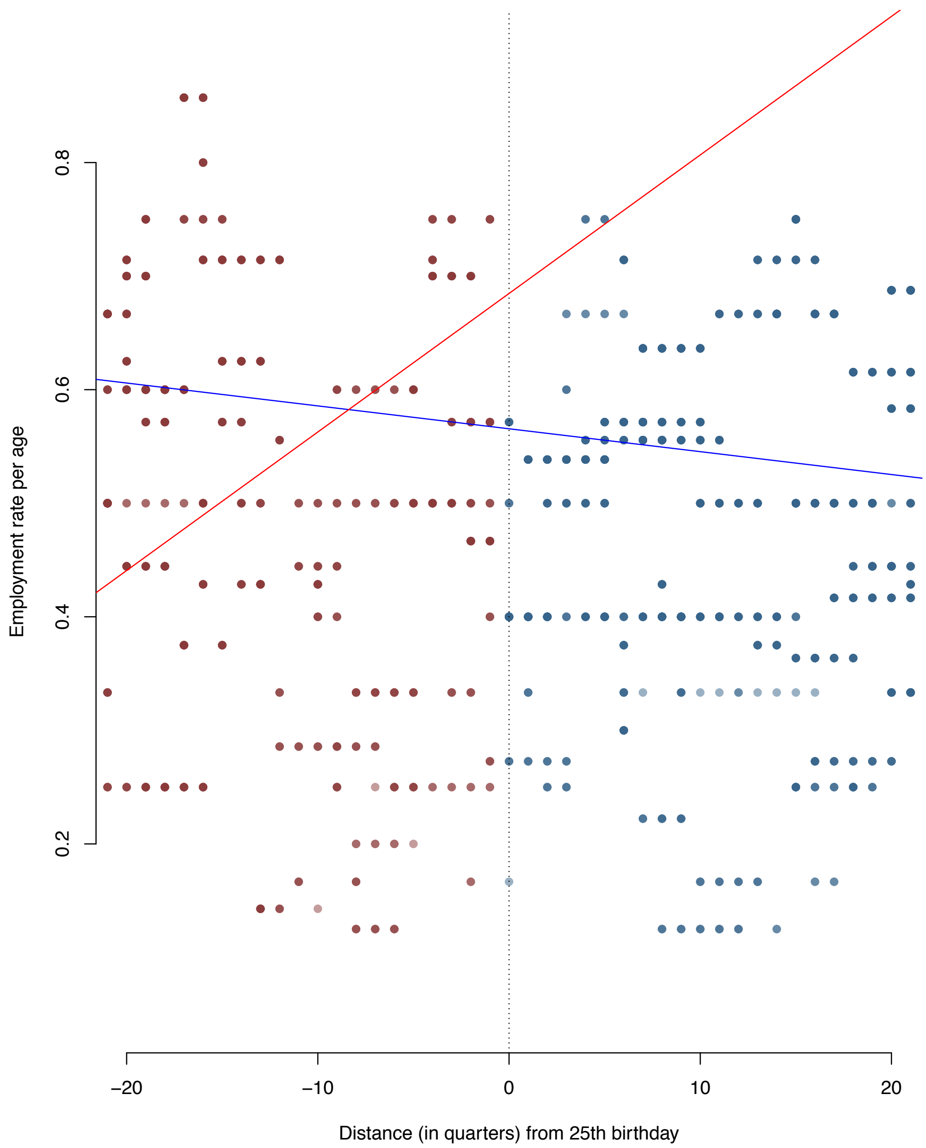
NOTE: the $p - values$ refer to the balance test between means, $H_0 : \mu_{it} - \mu_{jt} = 0$.

Table 7: Equation (1) for hours worked in the post-treatment period

	Sample slope (1)	Different slope (1)	Polynomial (1)
Constant	35.17^{***}	35.36^{***}	35.17^{***}
	(1.31)	(1.85)	(5.71)
Age	-0.02	0.02	0.63
	(0.22)	(0.37)	(4.79)
D_i	-1.97	-2.06	-2.48
	(2.32)	(2.39)	(6.21)
Age * D_i		-0.07	0.37
		(0.46)	(5.33)
Age^2			0.31
			(1.12)
Age^3			0.03
R^2	0.01	0.01	0.01
Adj. R^2	0.00	0.00	-0.01
Num. obs.	506	506	506
RMSE	13.00	13.02	13.06
Bandwidth	9.36	9.36	9.36

NOTE: the $p - values$ refer to the balance test between means, $H_0 : \mu_{it} - \mu_{jt} = 0$.

Figure 1: Employment rate per age for low-skilled individuals in the post-treatment period



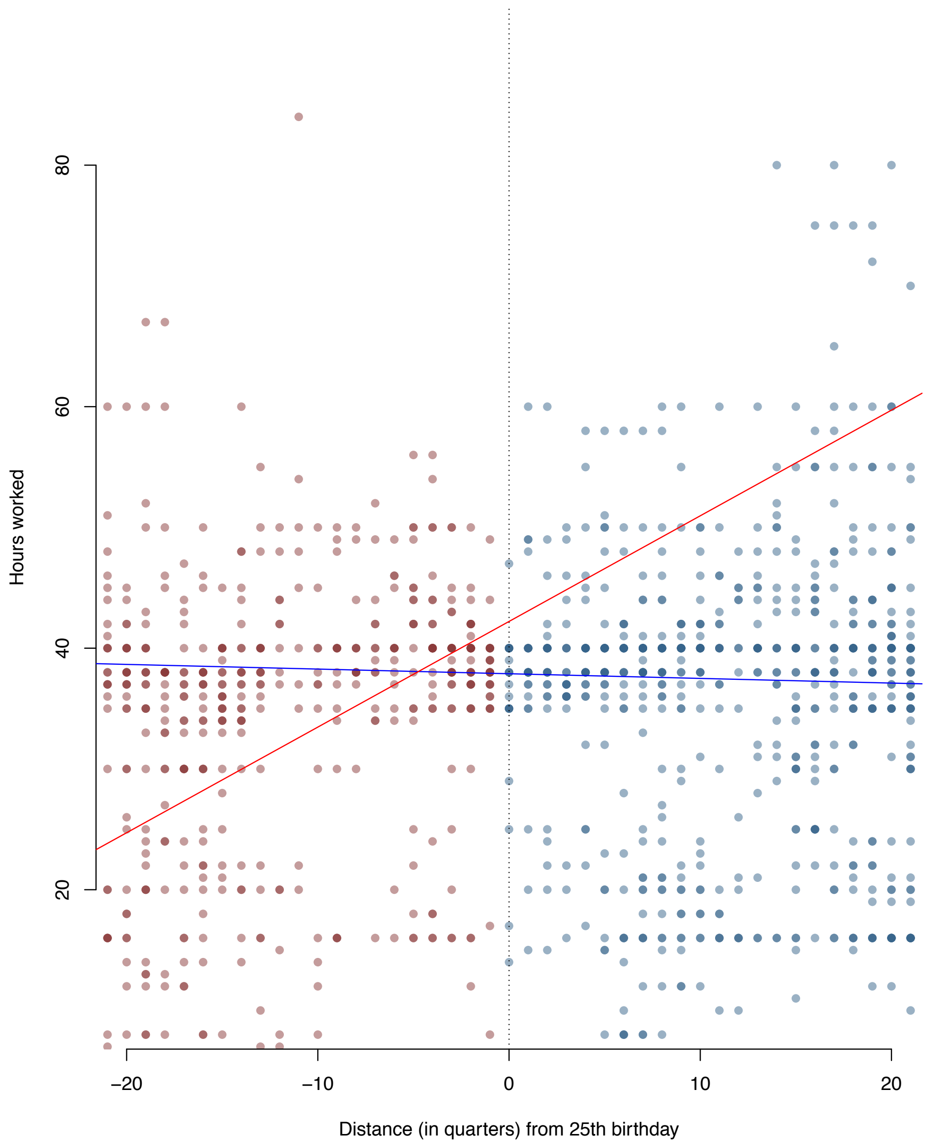
NOTE: fitted values of equation (2) for the post-treatment period.

Table 8: Balance check for covariates in the post-treatment period

Balanced covariates	Employment rate		Hours worked	
	LATE	$p - value$	LATE	$p - value$
Ethnicity	-0.50	0.76	1.08	0.11
Residence	-0.50	0.78	-1.10	0.24
Enrolled	-0.07	0.33	0.02	0.38
Industry	0.53	0.83	-0.44	0.19
Qualification	0.15	0.86	0.06	0.84

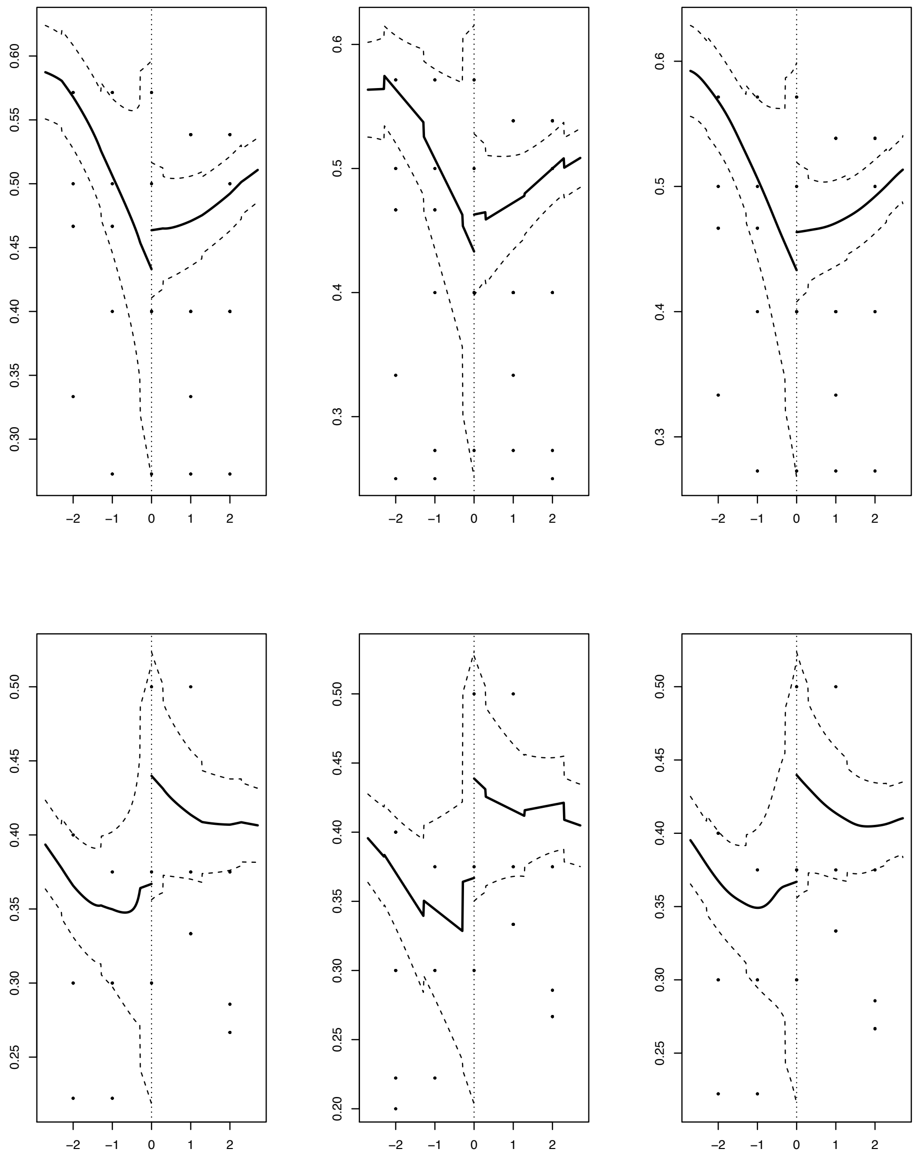
NOTE: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Figure 2: Hours worked for low-skilled individuals in the post-treatment period



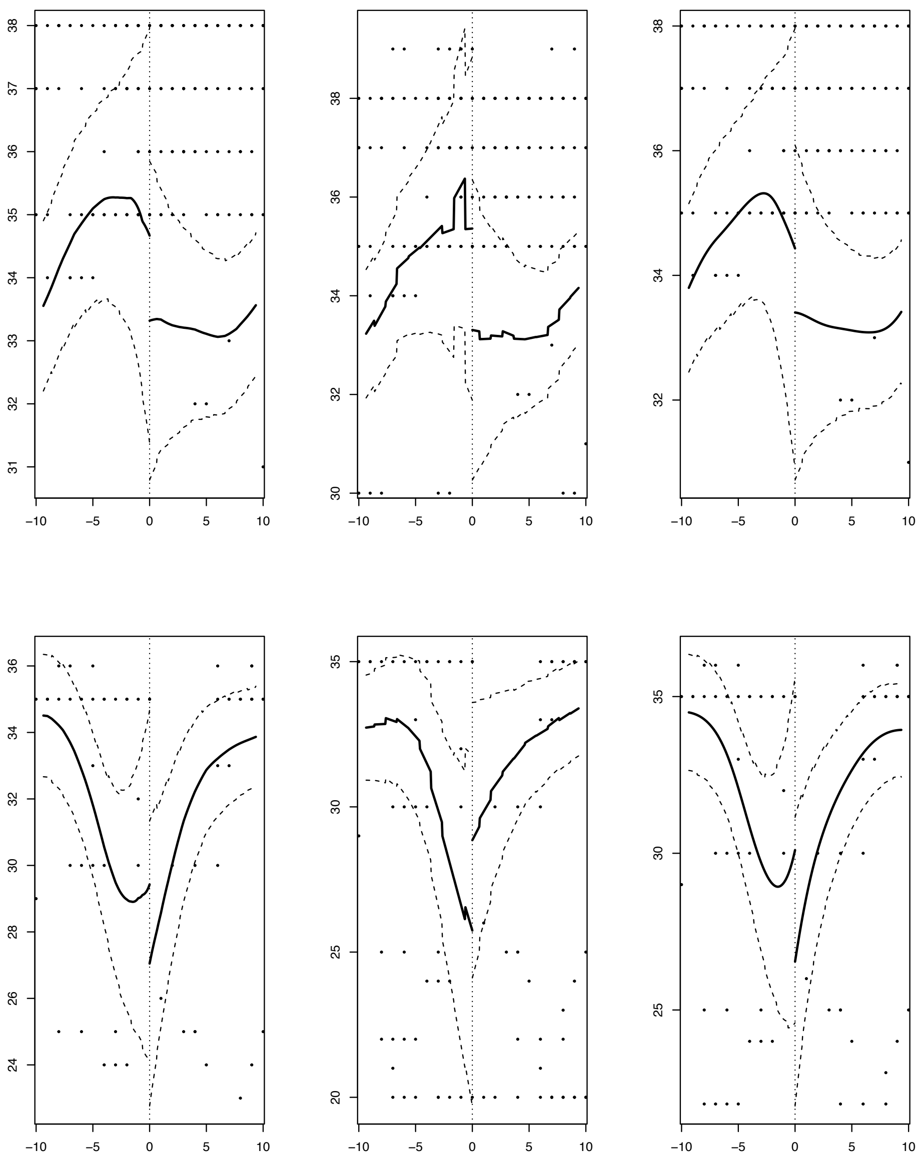
NOTE: fitted values of equation (2) for the post-treatment period.

Figure 3: RDD estimates of employment rates for low-skilled individuals



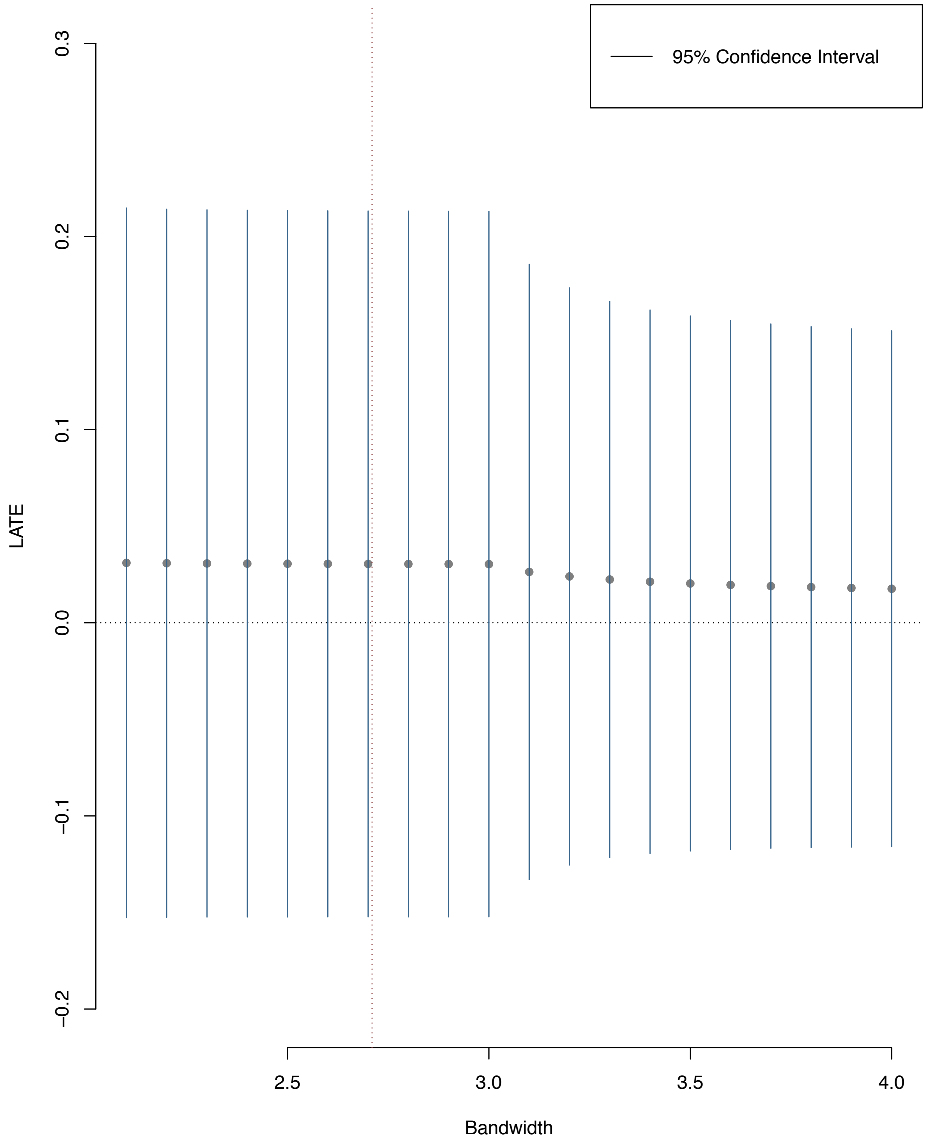
NOTE: the top row is the post-treatment period and the bottom row is the pre-treatment period; depicting IK local linear, local linear and cubic specifications respectively on each row.

Figure 4: RDD estimates of hours worked for low-skilled individuals



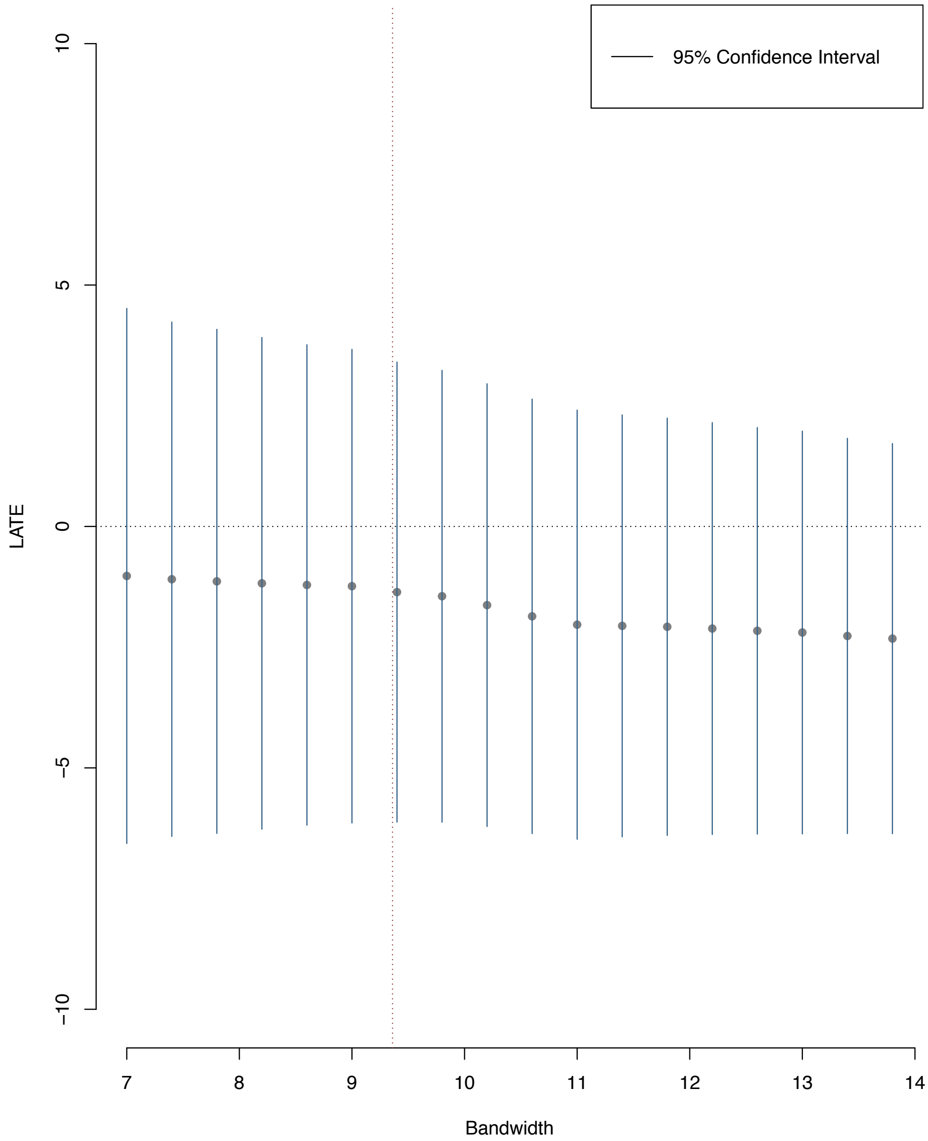
NOTE: the top row is the post-treatment period and the bottom row is the pre-treatment period; depicting IK local linear, local linear and cubic specifications respectively on each row.

Figure 5: Bandwidth sensitivity for employment rates in the post-treatment period



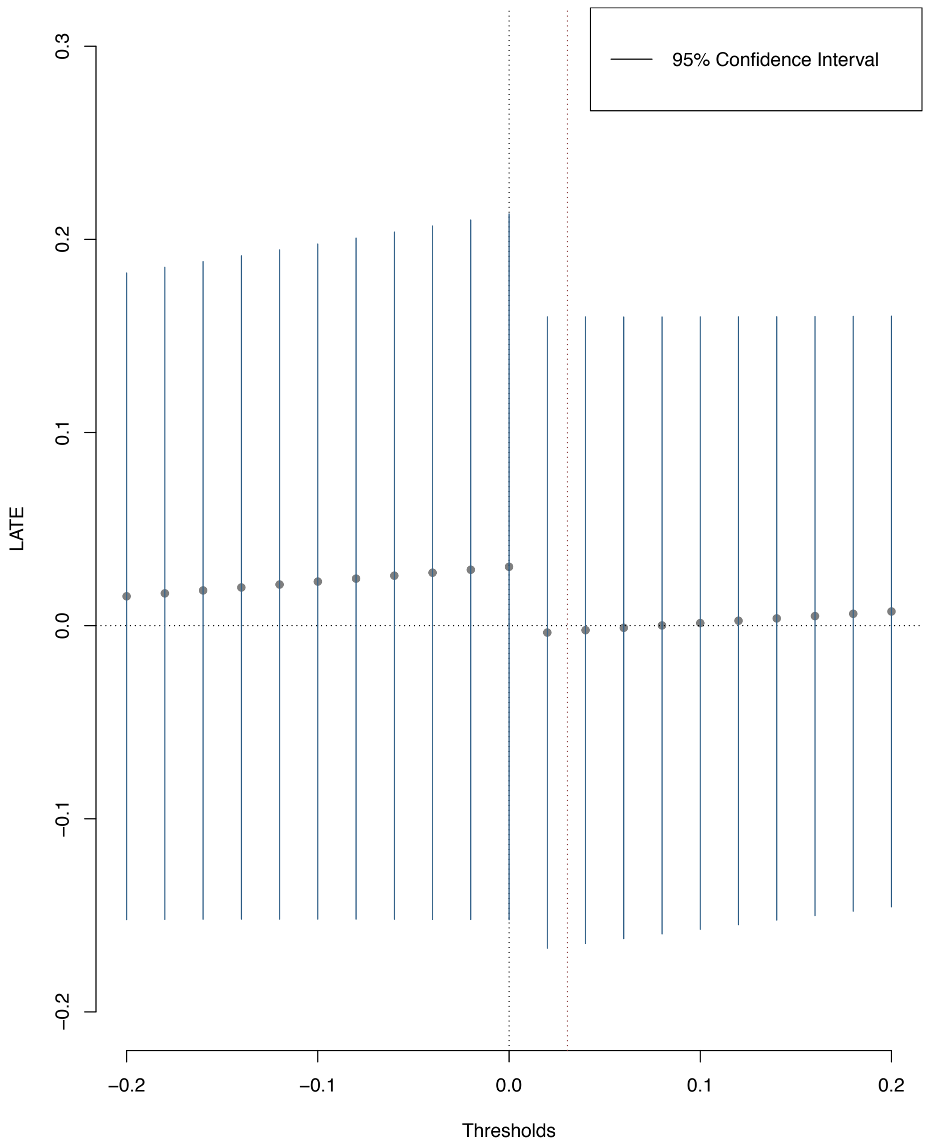
NOTE: checking sensitivity to size of the bandwidth determined by different values of k. Very stable LATE and confidence intervals overlap zero, thus the null effect. No confusion about a linear relation interpreted as a lack of jump around the threshold.

Figure 6: Bandwidth sensitivity for hours worked in the post-treatment period



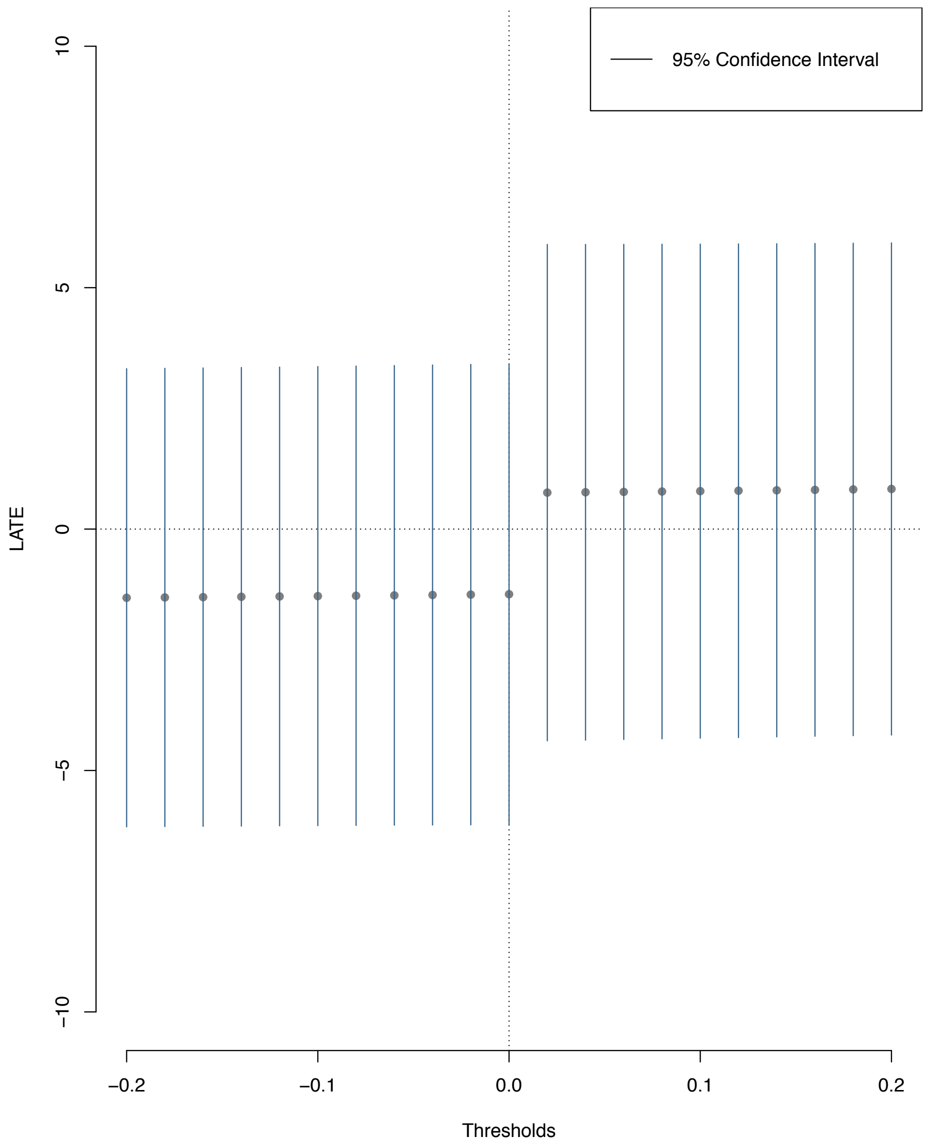
NOTE: checking sensitivity to size of the bandwidth determined by different values of k. Very stable LATE and confidence intervals overlap zero, thus the null effect. No confusion about a linear relation interpreted as a lack of jump around the threshold.

Figure 7: Placebo thresholds for employment rates in the post-treatment period



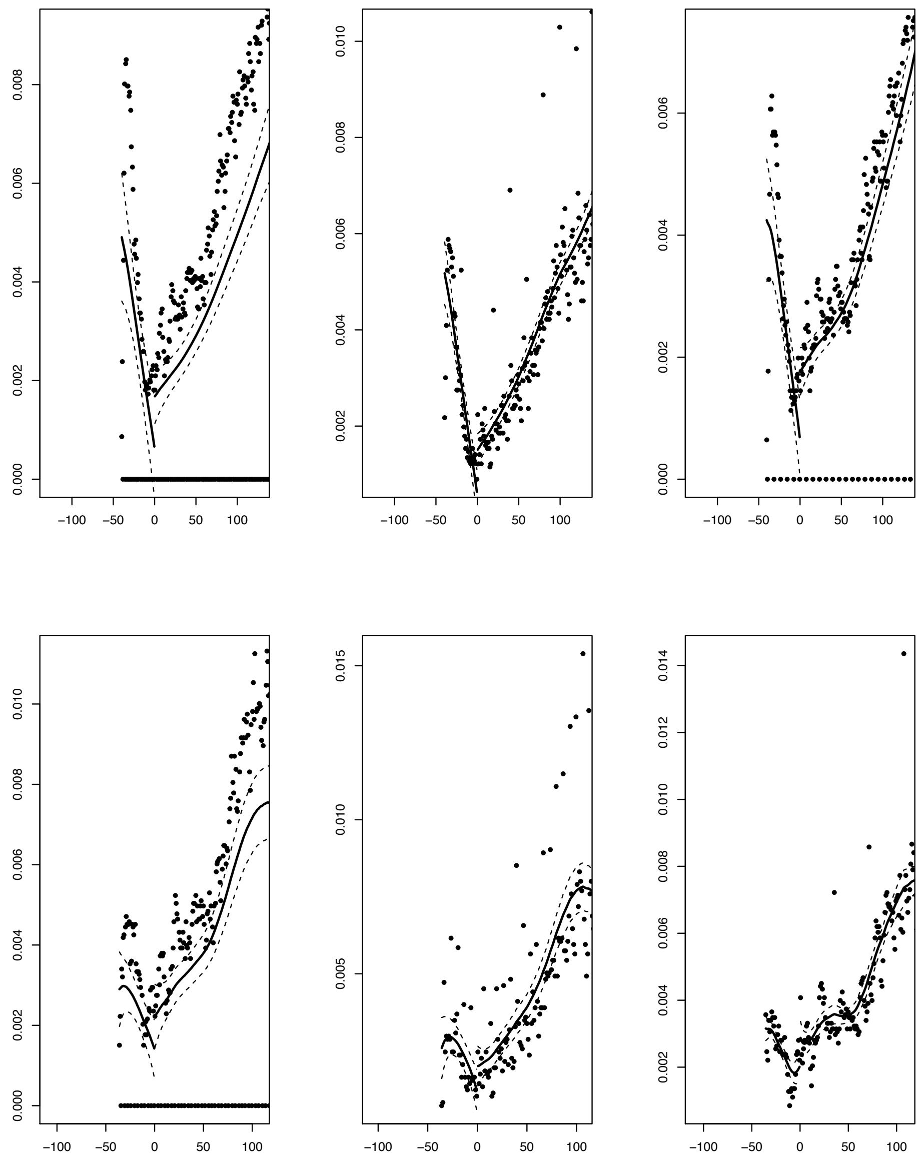
NOTE: testing whether the treatment effect is zero at different thresholds i.e. no significant LATE found at a different threshold. Suggesting no other jumps occurring at a different age.

Figure 8: Placebo thresholds for hours worked in the post-treatment period



NOTE: testing whether the treatment effect is zero at different thresholds i.e. no significant LATE found at a different threshold. Suggesting no other jumps occurring at a different age.

Figure 9: Sorting around the cutoff for employment rates and hours worked respectively



NOTE: sorting around the threshold can reject the null of no discontinuity at the cutoff. The top row is the employment rate and the bottom row is hours worked. The graphs are showing the whole panel, the pre-treatment period and the post-treatment period respectively on each row. The $p - values$ for all the tests tend to zero; except for when testing the whole panel.