Online Appendix
Breaking from the starting gate on the right foot: Employment effects of an investment in human capital

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Content

This online appendix presents additional materials organized as follows. Section A1 discusses the difference-in-discontinuity estimator. Section A2 calculates the average treatment effect. Section A3 presents the tests on the parametric functional form. Section A4 illustrates a graphical analysis on individual's imprecise control of the forcing variable. Section B1 provides additional graphical analysis. In Section C1, we report a battery of robustness checks and placebo analysis.

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A1 Difference-in-discontinuity design in a potential outcomes framework

Consider the fraction, n, of the population that starts a job episode (even one lasting just one day) during some given time interval, b, before the introduction of Law No. 92/2012. Then consider an outcome, y, and express quantities in terms of its potential, μ. Based on her year of birth, tb, an individual ages, a_i, during some given time interval $t = b$ before the introduction of the reform.

$$E[y_{1it}|a_{it}, tb_{it}] = \mu_{1b}$$
$$E[y_{0it}|a_{it}, tb_{it}] = \mu_{0b}$$

Where 1 and 0 refer to the left and right side of the age threshold level, 30. In fact:

$$\mu_{1b} = \alpha_0 + \gamma_0 + \beta_{1b} a_{it}$$
$$\mu_{0b} = \alpha_0 + \beta_{0b} a_{it}$$

We don't include other covariates for the sake of simplicity. During some given time interval before the reform, the two sides of the cutoff identify the treatment and control states since the intent to treat (i.e. the vocational apprenticeship labor contract) is based on the following selection rule:

$$d_{it} = \begin{cases} 1 & \text{if } a_{it} < a_m \\ 0 & \text{if } a_{it} \geq a_m \end{cases}$$

a_m denotes the age cutoff.

We start from the usual definition of the observed outcome for this n fraction in the population whose age is close to the threshold. We take expectations under the assumption that the intent to treat is locally randomized (this amounts to independence assumption: $y_{1it} \perp d_{it}$ and $y_{0it} \perp d_{it}$, i.e. the law could have established another age threshold):

$$y_{ib} = y_{1ib} d_{it} + y_{0ib}(1 - d_{it})$$
$$E[y_{ib}|d_{it}, a_{it}, tb_{it}] = E[y_{ib}|a_{it}, tb_{it}] = E[y_{0ib}|a_{it}, tb_{it}] + \{E[y_{1ib}|a_{it}, tb_{it}] - E[y_{0ib}|a_{it}, tb_{it}]\} d_{it}$$
$$E[y_{ib}|a_{it}, tb_{it}] = \mu_{0b} + [\mu_{1b} - \mu_{0b}] d_{it}$$

In the absence of a confounding policy, the difference $(\mu_{1b} - \mu_{0b})$ can be estimated by γ_0 in the following (first-order polynomial in age) discontinuity regression model during some given time interval t before the labor market reform:

$$y_{it} = \alpha_0 + \beta_{0b} a_{it} + \gamma_0 d_{it} + (\beta_{1b} - \beta_{0b}) d_{it} a_{it} + \epsilon_{it}$$

It is possible to extend this model specification to higher-order polynomials in age.

Consider now that Law n.92/2012 introduced another source of randomized variation based on this discontinuity rule:

$$r_{it} = \begin{cases} 1 & \text{if } tb_{it} \geq tb_c \\ 0 & \text{if } tb_{it} < tb_c \end{cases}$$

where tb_c corresponds to the year of birth of an individual who is aged a_{it} in June 2012. Observed outcome, centered around the labor market reform at the age cutoff during some given time interval t, amounts to:

$$y_{it} = y_{i,t=p} r_{it} + y_{i,t=b}(1 - r_{it})$$

p denotes post labor market reform.

Let's define potential outcomes around the age threshold in the post-reform period:

$$E[y_{1it}|a_{it}, tb_{it}] = \mu_{1p}$$
$$E[y_{0it}|a_{it}, tb_{it}] = \mu_{0p}$$

As above, 1 and 0 refer to the left and right side of the age cutoff. In fact:

$$\mu_{1p} = \alpha_0 + \gamma_0 + \gamma_1 + \alpha_1 + \beta_{1p} a_{it}$$
$$\mu_{0p} = \alpha_0 + \alpha_1 + \beta_{0p} a_{it}$$

Then we take expectations of observed outcome y_{it} under the assumption that the intent to treat of the labor market reform at the age cutoff is locally randomized[1] (i.e. independence assumption: $y_{1i,t=p} \perp r_{it}$ and $y_{0i,t=p} \perp r_{it}$ and $y_{1i,t=b} \perp r_{it}$ and $y_{0i,t=b} \perp r_{it}$):

$$E[y_{it}|d_{it}, r_{it}, a_{it}, tb_{it}] = E[y_{it}|a_{it}, tb_{it}] = E[y_{ib}|a_{it}, tb_{it}] + \{E[y_{ip}|a_{it}, tb_{it}] - E[y_{ib}|a_{it}, tb_{it}]\} r_{it}$$
$$E[y_{it}|a_{it}, tb_{it}] = \mu_{0b} + (\mu_{1b} - \mu_{0b}) d_{it} + (\mu_{0p} - \mu_{0b}) r_{it} + [(\mu_{1p} - \mu_{0p}) - (\mu_{1b} - \mu_{0b})] r_{it} d_{it}$$

$$\begin{aligned} E[y_{it}|a_{it}, tb_{it}] = {} & \alpha_0 + \beta_{0b} a_{it} + \gamma_0 d_{it} + (\beta_{1b} - \beta_{0b}) a_{it} d_{it} + \alpha_1 r_{it} + (\beta_{0p} - \beta_{0b}) a_{it} r_{it} + \\ & + \gamma_1 r_{it} d_{it} + [(\beta_{1p} - \beta_{0p}) - (\beta_{1b} - \beta_{0b})] a_{it} r_{it} d_{it} \end{aligned} \tag{A7}$$

Equation A7 corresponds to the first-order polynomial in age of the flexible parametric model specification of the difference-in-discontinuity regression design. Extension to the model to second, third, or higher-order polynomials is possible. As discussed in the main text, we cannot estimate this regression model in close (given our data) proximity to the age cutoff. In fact, in the age range ± 1 year around the threshold, the indicator d_{it} is perfectly collinear with the age variable a_{it}, implying a zero slope assumption ($\beta_{1p} = \beta_{0p} = \beta_{1b} = \beta_{0b}$=0). Anyhow, in the proximity of the threshold, this is not as strong an assumption as it is when we move farther from the age cutoff. As a result, the regression model collapses to a zero-order polynomial in age. In fact:

$$E[y_{it}|a_{it}, tb_{it}] = \alpha_0 + \gamma_0 d_{it} + \alpha_1 r_{it} + \gamma_1 r_{it} d_{it} \tag{A8a}$$
$$y_{it} = \alpha_0 + \alpha_1 r_{it} + \gamma_0 d_{it} + \gamma_1 d_{it} r_{it} + \epsilon_{it} \tag{A8b}$$

Equation A8b corresponds to Equation (2) reported in the main text.

Therefore, in the age range of ± 1 year around the threshold, because of the zero slope assumption, the stability bias assumption trivially holds, and the difference-in-discontinuity parameter coincides with the difference-in-differences parameter. In fact:

$$\begin{aligned} \gamma_1 = (E[y|d=1, r=1] - E[y|d=0, r=1]) - (E[y|d=1, r=0] - E[y|d=0, r=0]) = \\ = [(\mu_{1p} - \mu_{0p}) - (\mu_{1b} - \mu_{0b})] \end{aligned}$$

Rearranging the terms we have the usual expression for the difference-in-differences parameter:

$$\gamma_1 = (E[y|d=1, r=1] - E[y|d=1, r=0]) - (E[y|d=0, r=1] - E[y|d=0, r=0])$$

We claim that the difference in differences estimator is then a limiting case of the difference-in-discontinuity design. Locally, the common trend assumption is trivially satisfied. Moreover, the latter does not need to condition on exogenous variables that lead to differential trends as the difference in differences regression model needs. In general, in all the other age ranges, the two parameters differ. They are equal only if we impose some restrictions on a flexible model specification (which could allow not only for all possible interaction terms but also for higher-order polynomials in age).

[1] The independent assumption at the age threshold level holds also in the post-reform period, $y_{1i,t=p} \perp d_{it}$ and $y_{0i,t=p} \perp d_{it}$

A2 Average treatment effect of the population around the age threshold

Consider the fraction $1-n$ of those who were unemployed in a given year of the sample period and those employed without changing status or job. Potential outcomes are the following:

$$E[y_{10}|a_{it}, tb_{it}] = \theta_{10}$$
$$E[y_{00}|a_{it}, tb_{it}] = \theta_{00}$$

$$E[y_{11}|a_{it}, tb_{it}] = \theta_{11}$$
$$E[y_{01}|a_{it}, tb_{it}] = \theta_{01}$$

The first 1 and 0 refer to the left and the right of the threshold. The second 0 and 1 denote before and after the introduction of Law No. 92/2012.

For this $1-n$ fraction of individuals, the ITT parameter at the age threshold is $[\theta_{1t} - \theta_{0t}]$, where $t = 0$ in the before-reform period and $t = 1$ in the post-reform period. The difference-in-discontinuity ITT parameter amounts to $[(\theta_{11} - \theta_{01}) - (\theta_{10} - \theta_{00})]$ under the crucial assumption that the fraction $1-n$ is constant across pre- and post-reform periods.

It is possible to define three ATE parameters as follows:

$$ATE_b = n[\mu_{10} - \mu_{00}] + (1-n)[\theta_{10} - \theta_{00}] \tag{A12}$$

$$ATE_p = n[\mu_{11} - \mu_{01}] + (1-n)[\theta_{11} - \theta_{01}] \tag{A13}$$

$$ATE_b - ATE_p = n[(\mu_{11} - \mu_{01}) - (\mu_{10} - \mu_{00})] + (1-n)[(\theta_{11} - \theta_{01}) - (\theta_{11} - \theta_{01})] \tag{A14}$$

Equation A12 identifies the ATE at the threshold before the reform; equation A13 identifies the ATE at the threshold after the reform; and Equation A14 identifies the ATE in difference-in-discontinuity.

We assume that $\theta_{11} = \theta_{01} = \theta_{11} = \theta_{01} = 0$, which is a plausible assumption although for different reasons across the two types of individuals who belong to the $1-n$ fraction. On the one hand, it is unlikely that those who had an open-ended contract switched to the apprenticeship labor contract.[2] On the other hand, a positive outcome of a costly labor contract used to screen workers is unlikely for unemployed.[3].

Then, around the age threshold, the difference-in-discontinuity ATE static parameter amounts to $n[(\mu_{11} - \mu_{01}) - (\mu_{10} - \mu_{00})]$, that is, the fraction n times the ITT static parameter.

Clear identification requires that the source of the randomized variation (i.e., Law No. 92/2012 at the age cutoff) had no impact on the selection into employment (i.e., the employment probability) across treated and untreated cohorts around the age threshold. The data support this hypothesis.

A3 Identification through a parametric functional form

Figure 1 paves the way to build an identification strategy that relies on the difference-in-discontinuity around the age threshold. To validate our analysis, we must discuss an important issue. We have information on the individual's year of birth only. As a consequence, we have to deal with a regression difference-in-discontinuity inference with discrete support and specification error. Since the randomization process of the data does not change across repeated samples, if the employment rate, at a given age and for each birth month, is constant across affected and unaffected cohorts, the difference-in-discontinuity at the threshold of 30 years cancels out these error terms. In such a case,

[2]Moreover, in this case, the individual would have belonged to the n fraction of the population.

[3]Besides, we cannot exclude that some of these individuals are even out of the labor force

Table A1: Functional form restrictions to flexible parametric specifications.

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First (Zero for ±1) Order Polynomial						
FPFF	Polynomial degree zero	NO	YES	Polynomial degree zero	NO	YES
Second Order Polynomial						
FPFF	NO	NO	NO	NO	NO	NO
Third Order Polynomial						
FPFF	NO	NO	NO	NO	NO	NO
Fourth Order Polynomial						
FPFF	NO	NO	NO	NO	NO	NO

Notes: FPFF stands for a Flexible Parametric Functional Form that allows for all possible interaction terms. No implies that there are not enough degrees of freedom to calculate the F statistic suggested by Lee and Card (2008) using the flexible parametric functional form.

the specification error vanishes since the same specification error prevails in the counterfactual world of contiguous similar, albeit untreated, cohorts. If, instead, the employment rate, at a given age and for each birth month, is not constant, the difference in these error terms between contiguous affected and unaffected cohorts might be random. We followed Lee and Card (2008), who argue that discreteness in the treatment-determining covariate implies to identify the treatment with parametric functional form assumptions. We performed their goodness-of-fit F statistic test,[4] to help us choose a reasonably accurate regression model. That is, we tested if the functional form adopted is statistically equal to a regression of the outcome on the full set of age dummy variables[5]. We use one dummy variable for all the possible values of age in the age range. If the statistic exceeds the critical values CV, we reject the null hypothesis implying that the polynomial function was too restrictive. The lower the test than the critical value is, the higher the confidence on the validity of the estimated effect is. Since we had information only on the year of birth, we had to use a bandwidth of 1 year of age. Around the age threshold, there were not enough degrees of freedom to carry out this test on several parametric functional forms. The unrestricted model could include a limited number of age dummies. Besides, the forcing variable (deviation of age from 30) and the cutoff indicator (i.e. being below or above) are highly collinear. Then, we could not often adopt a flexible parametric functional form to approximate the conditional expectation function. Table A1 summarizes the functional form restrictions imposed by our data. We could test the more general flexible parametric model specification for the linear model only in the range of ±3 years around the threshold. In the age range of ±1 year, the local linear regression collapses to a polynomial of degree zero (in age) regression model because of the perfect collinearity between the cutoff indicator and the forcing variable.[6]

Table A2 illustrates the F goodness-of-fit statistic applied to the permanent employment probability. To perform the test, we impose some restrictions for polynomial functions of degree higher than 1. We control for the polynomial in age but not for all possible interactions. Then, we are assuming that the slopes around the age cutoff and before/after the reform are equal. The table reports the p-values of the F statistics on the joint significance of the age dummies in the auxiliary regression.[7] As expected, the two F tests provide the same information. However, the advantage of the p-value is that we can always calculate it. When it is equal to 1, and the corresponding F statistic

[4]We calculate the F statistic as $\frac{\frac{ESS_R - ESS_{UR}}{G}}{\frac{ESS_{UR}}{N-J}} \overset{H_0}{\sim} F(\text{G,N-J})$, where $G = J - K$ are the number of restrictions, i.e., the difference between the number of parameters J in the unrestricted model and the number of parameters K in the restricted model.

[5]full set of dummies times the indicator function of the labor market reform for the difference-in-discontinuity model specification

[6]The cutoff indicator is equal to 1 if the forcing variable assumes the value of -1. The former is equal to 0 if the latter is 0.

[7]We test the interaction between age dummies and the treatment indicator for the difference-in-discontinuity specification.

Table A2: F goodness-of-fit test: probability of having an open-ended contract

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First (Zero for ±1) Order Polynomial						
F			26.966			16.041
CV			4.605			3.319
p val	1.000	1	2.057×10^{-10}	1.000	1	1.569×10^{-9}
Second Order Polynomial						
F			59.765		0.493	26.024
CV			4.605		4.605	2.802
p val		1	4.035×10^{-24}		0.995	8.348×10^{-28}
Third Order Polynomial						
F			100.780		0.986	25.534
CV			6.635		6.635	3.017
p val		1	3.490×10^{-20}		0.995	5.236×10^{-22}
Fourth Order Polynomial						
F						4.685
CV						3.319
p val		1	1		0.995	0.067

Notes: The null hypothesis of the F goodness-of-fit statistic test is that the functional form adopted is statistically equal to a regression of the permanent employment probability on the full set of dummy variables for the all the possible values of age (age times the indicator function for being treated by the labor market reform for the difference-in-discontinuity model specification) which define the range. If the statistic exceeds the critical values CV, we reject the null. The p-value refers to the p-value of an F test on the joint significance of the age dummies (age dummies times the labor market reform treatment indicator) in the auxiliary regression.

approaches 0. Then, we can be relatively confident that the estimated difference-in-discontinuity parameter approximates the difference-in-discontinuity in the averaged raw data.

Moreover, Table A2 shows that we can adopt a local linear regression model when we restrict the sample to an age range of ±1 and ±2 year(s) only. Panel (b) of Figure 1 displays that average raw data do not fall inside the confidence intervals for all the other age intervals.[8] The statistic fails to reject the null hypothesis in the age range of ±2 years around the cutoff polynomials in age higher than zero. Then, this test confirms the graphical analysis of Figure 1. In this analysis, standard errors are heteroskedastic robust. Results do not change if we cluster them by age, year and region of birth to account for within-group correlation at this level.

[8]Overall, Figure 1 indicates that, only in the age range of ±1 year, are the averaged raw data well centred the polynomial fit.

Table A3: Goodness of fit F statistic for the polynomial functional form: apprenticeship probability

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
F			177.777			103.287
CV			4.605			3.319
p val	1.000	1	1.068×10^{-74}	1	1	9.588×10^{-82}
Second Order Polynomial						
F			467.835		2.278	170.616
CV			4.605		4.605	2.802
p val		1	5.075×10^{-200}		0.718	1.368×10^{-212}
Third Order Polynomial						
F			772.452		4.556	163.480
CV			6.635		6.635	3.017
p val		1	1.033×10^{-164}		0.718	3.399×10^{-168}
Fourth Order Polynomial						
F		0				3.803
CV						3.319
p val		1	1		0.718	0.172

Notes: The null hypothesis of the F goodness-of-fit statistic test is that the functional form adopted is statistically equal to a regression of the apprenticeship probability on the full set of dummy variables for the all the possible values of age (age times the indicator function for being treated by the labor market reform for the difference-in-discontinuity model specification) which define the range. If the statistic exceeds the critical values CV, we reject the null. The p-value refers to the p-value of an F test on the joint significance of the age dummies (age dummies times the labor market reform treatment indicator) in the auxiliary regression.

Table A4: Goodness of fit F statistic for the polynomial functional form: employment probability

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
F			4.347			2.615
CV			4.605			3.319
p val	1.000	1.000	0.120	1.000	1	0.494
Second Order Polynomial						
F			2.824		1.397	2.710
CV			4.605		4.605	2.802
p val		1.000	0.337		0.901	0.135
Third Order Polynomial						
F			2.913		2.795	2.652
CV			6.635		6.635	3.017
p val		1.000	0.713		0.901	0.277
Fourth Order Polynomial						
F						2.485
CV						3.319
p val		1.000	1		0.901	0.542

Notes: The null hypothesis of the F goodness-of-fit statistic test is that the functional form adopted is statistically equal to a regression of the employment probability on the full set of dummy variables for the all the possible values of age (age times the indicator function for being treated by the labor market reform for the difference-in-discontinuity model specification) which define the range. If the statistic exceeds the critical values CV, we reject the null. The p-value refers to the p-value of an F test on the joint significance of the age dummies (age dummies times the labor market reform treatment indicator) in the auxiliary regression.

Table A5: Goodness of fit F statistic for the polynomial functional form: permanent employment probability, same firm

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
F			1.261			4.301
CV			4.605			3.319
p val	1.000	1.000	0.779	1.000	1	0.103
Second Order Polynomial						
F			4.325		1.055	4.911
CV			4.605		4.605	2.802
p val		1.000	0.126		0.955	0.002
Third Order Polynomial						
F			6.574		2.110	5.910
CV			6.635		6.635	3.017
p val		1.000	0.248		0.955	0.002
Fourth Order Polynomial						
F						6.113
CV						3.319
p val		1.000	1		0.955	0.011

Notes: The null hypothesis of the F goodness-of-fit statistic test is that the functional form adopted is statistically equal to a regression of the employment probability on the full set of dummy variables for the all the possible values of age (age times the indicator function for being treated by the labor market reform for the difference-in-discontinuity model specification) which define the range. If the statistic exceeds the critical values CV, we reject the null. The p-value refers to the p-value of an F test on the joint significance of the age dummies (age dummies times the labor market reform treatment indicator) in the auxiliary regression.

Table A6: Goodness of fit F statistic for the polynomial functional form: permanent employment probability, same sector

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
F			1.653			2.605
CV			4.605			3.319
p val	1.000	1	0.651	1.000	1	0.488
Second Order Polynomial						
F			6.831		0.595	4.133
CV			4.605		4.605	2.802
p val		1	0.019		0.992	0.010
Third Order Polynomial						
F		0	10.607		1.190	4.773
CV			6.635		6.635	3.017
p val		1	0.060		0.992	0.013
Fourth Order Polynomial						
F		0				3.645
CV						3.319
p val		1	1		0.992	0.203

Notes: The null hypothesis of the F goodness-of-fit statistic test is that the functional form adopted is statistically equal to a regression of the permanent employment probability in the same sector of previous job on the full set of dummy variables for the all the possible values of age (age times the indicator function for being treated by the labor market reform for the difference-in-discontinuity model specification) which define the range. If the statistic exceeds the critical values CV, we reject the null. The p-value refers to the p-value of an F test on the joint significance of the age dummies (age dummies times the labor market reform treatment indicator) in the auxiliary regression.

Table A7: Goodness of fit F statistic for the polynomial functional form: self-employment probability

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
F			0.664			1.857
CV			4.605			3.319
p val	1.000	1.000	0.937	1	1	0.767
Second Order Polynomial						
F			1.927		9.886	7.873
CV			4.605		4.605	2.802
p val		1.000	0.561		0.006	1.986×10^{-6}
Third Order Polynomial						
F			3.489		19.772	9.156
CV			6.635		6.635	3.017
p val		1.000	0.641		0.006	3.734×10^{-6}
Fourth Order Polynomial						
F						10.852
CV						3.319
p val		1.000	1		0.006	9.110×10^{-6}

Notes: The null hypothesis of the F goodness-of-fit statistic test is that the functional form adopted is statistically equal to a regression of the permanent employment probability in the same firm of previous job on the full set of dummy variables for the all the possible values of age (age times the indicator function for being treated by the labor market reform for the difference-in-discontinuity model specification) which define the range. If the statistic exceeds the critical values CV, we reject the null. The p-value refers to the p-value of an F test on the joint significance of the age dummies (age dummies times the labor market reform treatment indicator) in the auxiliary regression.

A4 Graphical analysis on individual's imprecise control of the forcing variable.

Thirty years of age is the limit for possible hirings using the apprenticeship labor contract. This setting matches up with a specific case of fuzzy regression discontinuity design for reasons of requiring the same identifying assumptions of a sharp RDD. It has an advantage over other identification strategies. For instance, let's now design an RDD that uses the reform to generate a discontinuity across years of birth (Malamud and Pop-Eleches 2010). At a given age, the cohort of birth randomly assigns the individual to the treatment (i.e., the reform). It is then possible to exploit the variability across cohorts by considering exogenously defined groups exposed to different rules for obtaining an apprenticeship labor contract. Estimating a causal parameter within the age range 15-29 would require functional form assumptions on how the effect evolves across ages. It is not an easy task to rationalize the imposed identifying restrictions through substantive knowledge about the selection process. Moreover, this is a fuzzy RDD that requires a monotonicity assumption. Marginal benefits and costs (including opportunity costs) of the apprenticeship labour contract are likely to vary over the age dimension.

Besides, VET schemes and vocational apprenticeships coexist between 18 to 25 years of age. Their marginal costs and benefits are likely to differ. The difference-in-discontinuity design applied in the age interval of ± 1 year around 30 allows us to overcome these issues.

In the presence of essential heterogeneity, the optimal age at which starting a new job as an apprentice is not the same across individuals and firms. Nevertheless, under the difference-in-discontinuity design, it is not relevant if the age threshold is suboptimal. Both individuals and firms have some influence on the vocational apprenticeship probability since they know the age cutoff in advance. To validate the model, workers and employers cannot precisely manipulate the timing (optimal or not) of the hiring event (if it occurs). Then, the variation in treatment around the threshold is randomized similarly to a randomized experiment (see Lee and Lemieux 2010). Ignorability, or the unconfoundedness assumption, is therefore satisfied. Besides, in the difference-in-discontinuity design, the imprecise control over the forcing variable does not substitute but rather complements the overlap condition because the comparison is between contiguous, and then similar, cohorts.

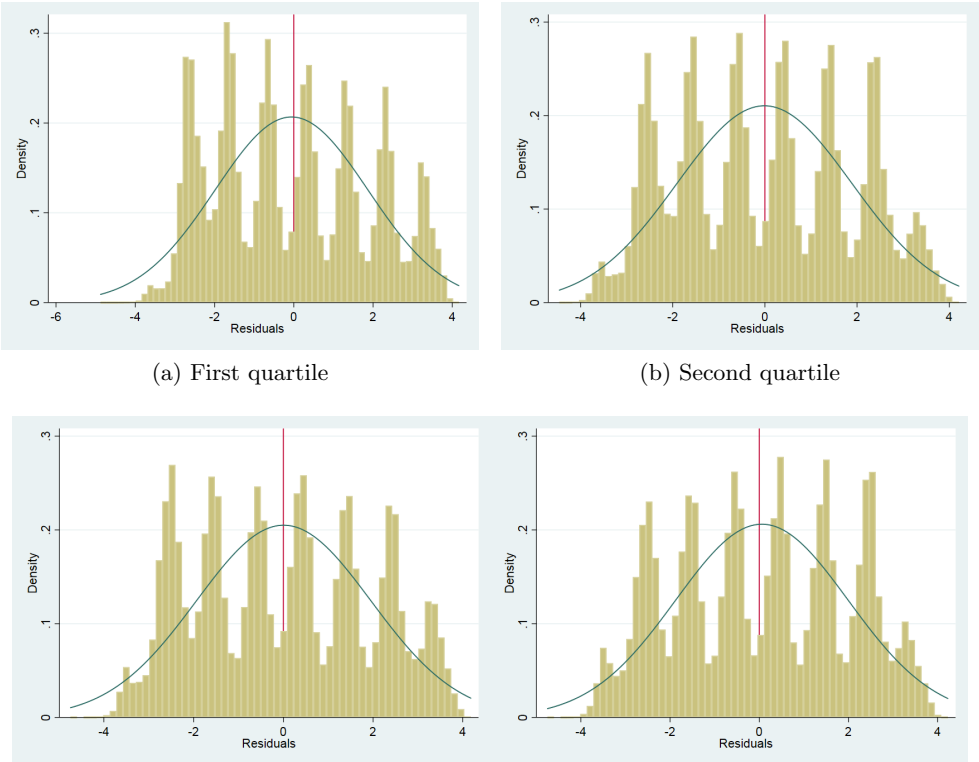
Evidence on this imprecise control over the forcing variable can be suggested by the density of the residuals V of the forcing variable (age) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity, and level of education) and on the quartiles of the distribution of the residuals U of the permanent employment probability regression model (Equation (2), augmented by our covariates (Lee and Lemieux 2010). According to the Bayes' Rule, $Pr[X = x, U = u|A = a] = Pr[a|X = x, U = u]\frac{Pr[X=x,U=u]}{Pr(a)}$, where Pr(a) and Pr[a|X=x, U=u] are marginal and conditional densities. We consider the density of V rather than the density of age a. Anyhow, the two distributions are equivalent up to a translation shift. V are residuals of a regression of age on observable characteristics X. If individuals do not control the forcing variable, Pr[a|X=x, U=u] is identical on either side of the cutoff in the limit of the threshold. Then, the distributions of U, V are not truncated in age. Here, we propose two different versions of this density plot.

In the first (Figure A1), we consider all individuals in the age range between 25 and 35 years of age who have started a job episode of at least one day in a given year of the sample period. As expected, observable X and unobservable U characteristics affect the shape of the densities. However, while the discrete character of the forcing variable is apparent, the histograms indicate that observed and unobserved pre-determined characteristics have identical conditional distributions on either side of the age cutoff in the limit of the threshold.

We then restrict the sample to the age range of ± 1 year around the threshold for those who have an apprenticeship labour contract. We exploit the fact that this labour contract can last more than one year (i.e., and hence we are also including those who started an apprenticeship contract in previous years).

The purpose is to show that, even in the selected sample of vocational apprentices, individuals do not manipulate the age at which this event occurs (i.e., we do not observe any truncation of the conditional distributions). The results of these model validation tests are reassuring and make us confident that we are comparing similar individuals who differ only in terms of the random variation

Figure A1: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of static main regression of permanent employment probability.



(a) First quartile

(b) Second quartile

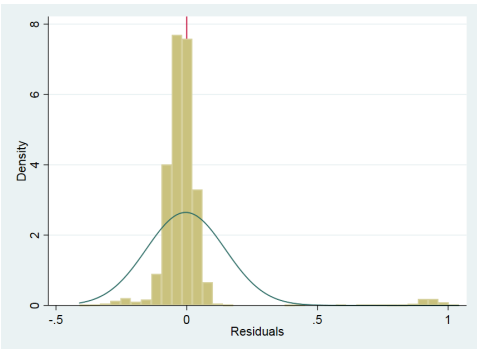
(c) Third quartile

(d) Fourth quartile

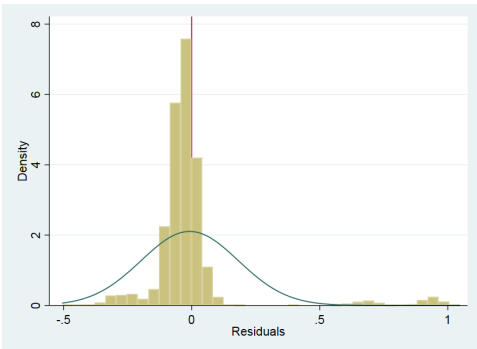
Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of permanent employment probability regression model (equation (2)) augmented by our covariates.

in the intention to assign to treatment.

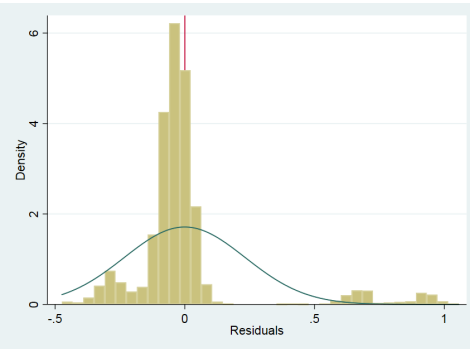
Figure A2: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of static main regression of permanent employment probability. Apprentices in the age range of ±1 year around the threshold only.



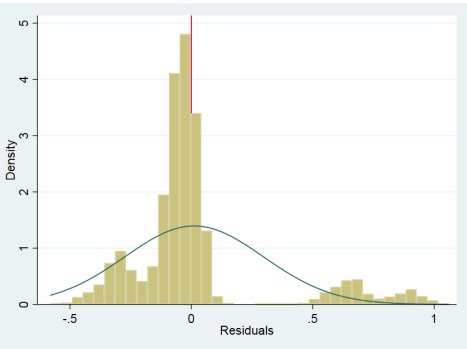
(a) First quartile



(b) Second quartile



(c) Third quartile



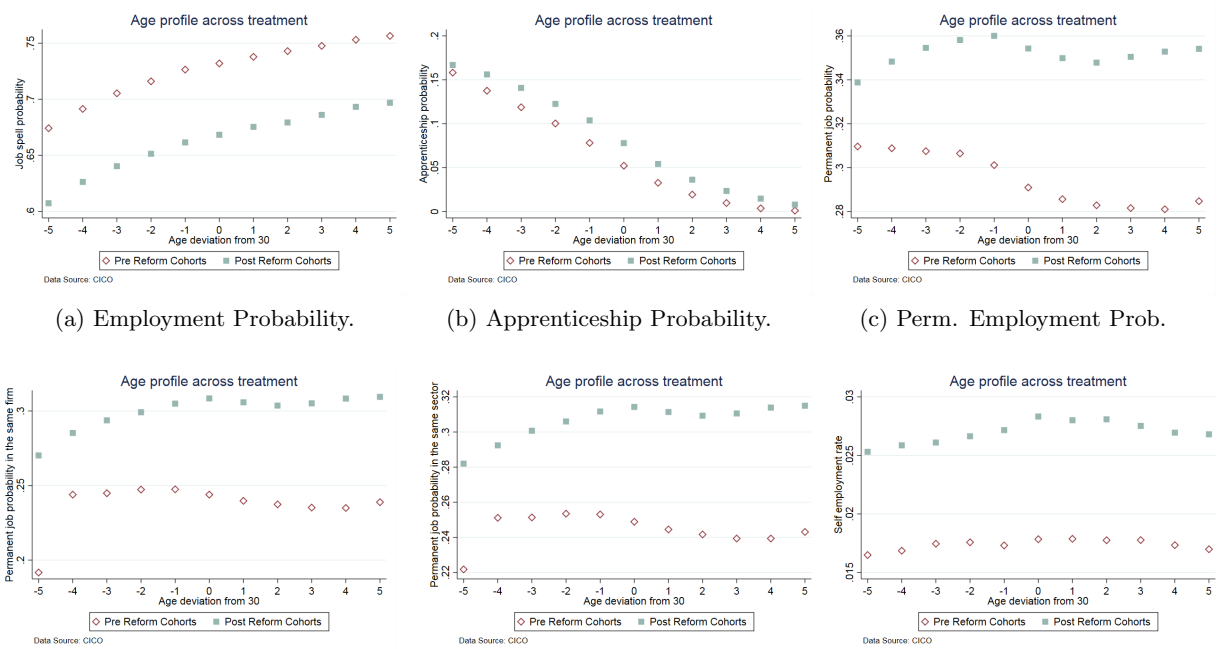
(d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of permanent employment probability regression model (equation (2)) augmented by our covariates.

B1 Additional graphical analysis

In this Section, we complement the graphical analysis presented in Section 3.1 in the main text. We start approximating the age profile, in the age interval 25-35, of the stocks of our employment outcomes. It plots the employment outcomes of workers followed over time once entered in the panel.[9]

Figure B1: Age profiles across contiguous cohorts generated by Law No. 92/2012



(a) Employment Probability. (b) Apprenticeship Probability. (c) Perm. Employment Prob.

(d) Permanent Empl. Prob. in the same firm of last job. (e) Permanent Empl. Prob. in the same sector of last job. (f) Self-Employment Probability.

Notes: The dots are averaged raw data points.

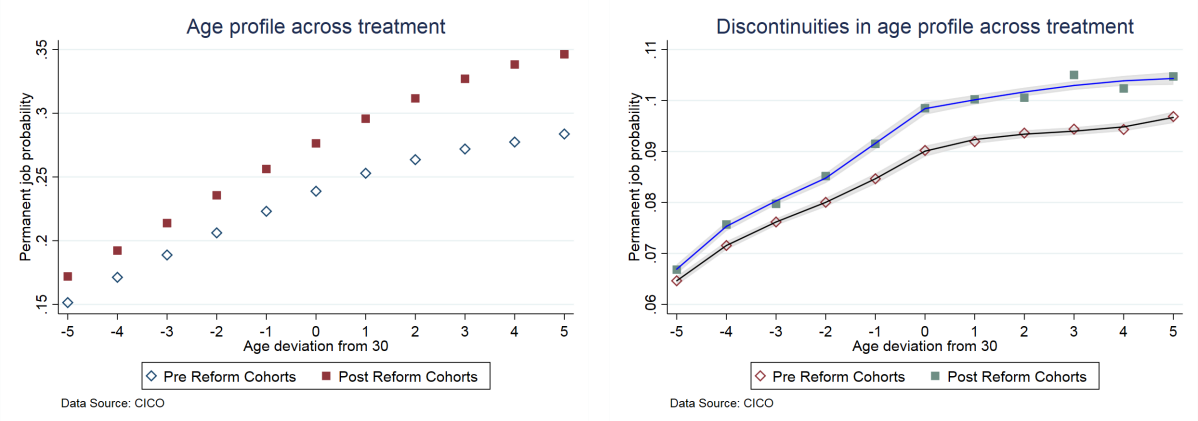
The employment probability (panel (a)) is increasing in age and higher for untreated cohorts. This panel does not show any discontinuity at the age cutoff. Panel (b) of the figure displays that, when we follow workers over time, since training period for apprentices lasts more than one year [10] the apprenticeship probability is continuous in age at the threshold, albeit, is a decreasing function of age because of the age limit. Hence, this graph provides suggestive evidence of continuity of potential apprenticeship rates. Finally, the treated cohorts always have a higher apprenticeship rate, thus providing suggestive evidence of an overall positive effect of the reform. In contrast, while approaching the threshold of 30 years of age, the probability of having an open-ended contract (panel (c)) decreases, and this pattern holds for both treated and untreated cohorts. Moreover, at all ages, treated cohorts have a higher permanent employment probability.

We now plot the age profiles of flows and the proxy of stocks of permanent employment rate without including apprenticeships in its definition. Both graphs are increasing in age, and there is no sign of a discontinuity around 30 years of age.

[9] We could not observe those who had a job (or a self-employment activity) that started before 2009 and that either did not cease or transform between 2009 and 2017. Then, we are approximating the employment stocks.

[10] The maximum duration of the apprenticeship contract is six years before the reform and three years after the reform. Collective agreements can extend this length

Figure B2: Age profiles across treatment status generated by law n.92/2012



(a) Perm. Employment Probability: proxy for stocks

(b) Perm. Employment Probability: flows

Notes: The dots indicate raw data while the line and the gray area refer to the parametric fit (third order polynomial in age) and its 99% confidence intervals. Heteroskedasticity robust standard errors. Here we do not include apprenticeships in the definition of permanent employment labor contract, even if they are recorded as open-ended.

Table B1: Main estimates, covariates: static model

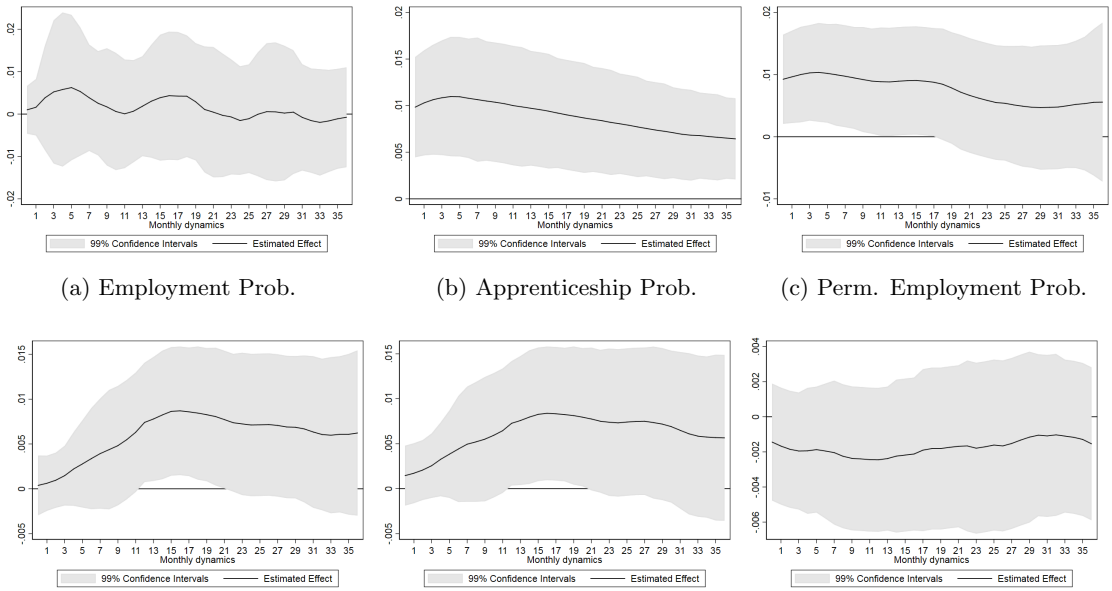
	Dependent Variable:					
	Emp.	Appr.	Perm. Emp.	Same Firm Perm.	Same Sect. Perm.	Self Emp.
Model specification in Table (2)	(7)	(7)	(7)	(7)	(7)	(7)
Gender	-0.008***	0.002***	-0.009***	-0.005***	-0.005***	-0.016***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Missing education	0.005***	-0.001*	-0.001	-0.001**	-0.002**	-0.006***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Real first earnings	-0.000***	-0.000***	0.000***	0.000***	0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Missing first earnings	0.026***	-0.017***	-0.005	0.009***	0.007***	0.023***
	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.002)
Missing past exp.	-0.042***	0.004***	0.031***	0.069***	0.069***	0.017***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Higher education than 25	0.009***	0.007***	0.026***	0.003***	0.005***	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Higher education than 75	0.026***	0.004***	0.019***	0.001	0.002*	-0.020***
	(0.002)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
Higher past experience than 75	0.072***	-0.002***	0.046***	-0.010***	-0.003***	-0.009***
	(0.002)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)
Changing sector	-0.006***	0.003***	0.014***	-0.006***	-0.017***	-0.004***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Higher 25 per. monthly job spells	-0.794***	-0.022***	-0.095***	-0.034***	-0.028***	0.067***
	(0.003)	(0.002)	(0.004)	(0.001)	(0.001)	(0.002)
Higher 25 per. monthly sep. flows	-0.252***	-0.019***	-0.137***	-0.033***	-0.037***	0.012***
	(0.005)	(0.002)	(0.004)	(0.001)	(0.001)	(0.001)
Higher 25 per. monthly net job flows	0.147***	-0.004***	-0.004**	-0.004***	-0.000	-0.007***
	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Higher than 25 perc. costs reduction	0.106***	-0.026***	0.105***	0.049***	0.055***	-0.001
	(0.003)	(0.003)	(0.007)	(0.004)	(0.005)	(0.001)
Higher than 25 perc. soc. insurance benefits	0.058***	-0.023***	0.066***	-0.009*	-0.004	-0.010***
	(0.008)	(0.004)	(0.019)	(0.005)	(0.007)	(0.001)

Notes: see notes in Table (2).

B2 Dynamic effects without controlling for outcome persistence

Figure B3 depicts the dynamic effects estimated by equation (3). The dynamic *ITT* on the apprenticeship probability is positive and decreasing over time. We expected this because the training period is not indefinite. Anyhow, it is always statistically different from zero. Then, the reform succeeded in encouraging the use of the apprenticeship labour contract compared to the previous regime.

Figure B3: Difference-in-discontinuity: dynamic effect up to 36 months without controlling for persistency in outcomes.



(a) Employment Prob. (b) Apprenticeship Prob. (c) Perm. Employment Prob.

(d) Perm. Emp: same firm. (e) Perm. Emp: same sector. (f) Self Employment Prob.

Notes: See notes in Table (2). The gray area indicates 99% confidence intervals. Standard errors clustered at year of birth, age and region of birth level.

Without controlling for the persistence in the outcome generated by the exogenous shock of the reform, Panel (c) shows that after 36 months from the baseline, the permanent employment probability of treated cohorts is still 0.6% higher than the permanent employment rates of similar untreated cohorts. The t-statistics fails to reject the null hypothesis of a coefficient equal to zero at 10% level from the 23rd month onwards. On the one hand, this relates to the inefficiency of equation (3). Standard errors increase because the error term has a large fixed component. On the other, once the apprenticeship labour contract is no longer available, we expect the impact as estimated by equation (3) to vanish over time. The dynamic impact on the permanent employment rates at the firm or sector for which each worker last (month) worked is positive and statistically different from zero (panels (d) and (e)). It reaches a maximum just after 12 months and then it stabilizes at about 0.6 percentage point.[11] The other two panels ((a) and (f)) confirm that the labor market reform has not generated around the age threshold any differential impact on the employment and self-employment probability.

B3 Difference-in-discontinuity impact across education groups.

In Table B2, we show the existence of balancing-out of both low-educated and high-educated workers. We define low-educated individuals those with lower secondary education only. High-educated workers are those with a higher education degree.

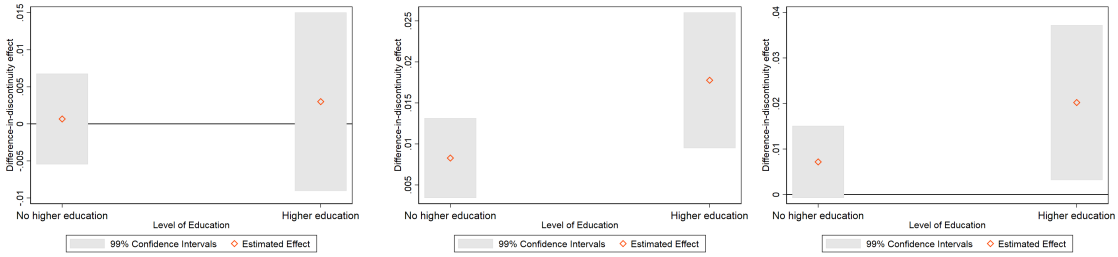
Figures B4 and B9 displays the static difference-in-discontinuity impact on employment, vocational apprenticeship, and open-ended contract probability.

[11] It is statistically different from zero at 10% level after 36 months.

Table B2: Balancing-out the shares of education groups.

	Main Sample			
	Raw data		**Polynomial fit**	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD	DiD	DiD	DiD
	(Std. Dev.)	(Std. Dev.)	(Std. Err.)	(Std. Err.)
Low educated	0.006^***	0.006^***	0.006	0.005
	0.001	0.001	0.009	0.009
Highly educated	−0.004^***	−0.002^***	−0.004	−0.005
	0.001	0.000	0.007	0.007

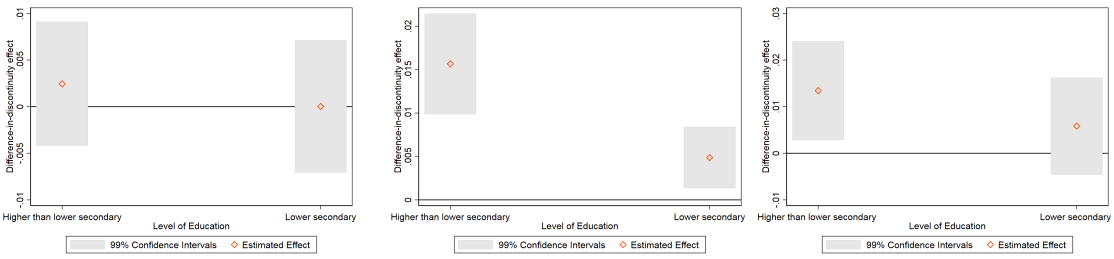
Figure B4: Difference-in-discontinuity: static effect higher versus no-higher education



(a) Employment Prob. (b) Apprenticeship Prob. (c) Perm. Employment Prob.

Notes: See notes in Table (2). The gray area indicates 99% confidence intervals. Standard errors clustered at year of birth, age and region of birth level.

Figure B5: Difference-in-discontinuity, static effect lower secondary education versus higher than lower secondary degree

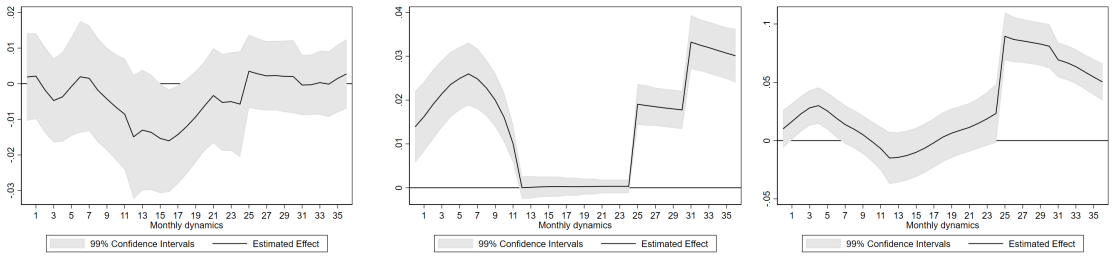


(a) Employment Prob. (b) Apprenticeship Prob. (c) Perm. Employment Prob.

Notes: See notes in Table (2). The gray area indicates 99% confidence intervals. Standard errors clustered at year of birth, age and region of birth level.

The following graphs illustrate the dynamic ITT.

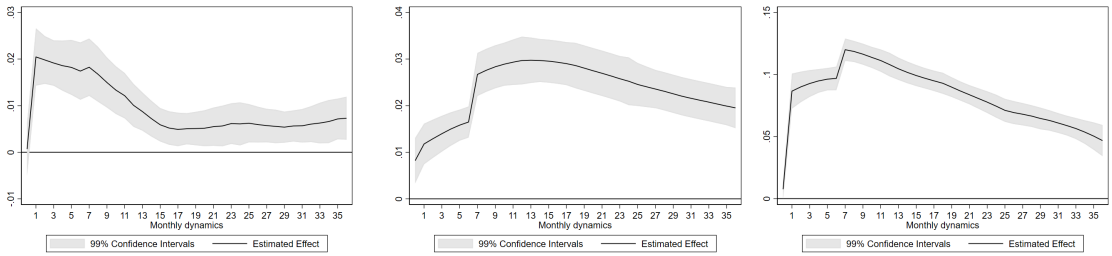
Figure B6: Dynamic ITT: higher education



(a) Employment Prob. (b) Apprenticeship Prob. (c) Perm. Employment Prob.

Notes: See notes in Table (2). The gray area indicates 99% confidence intervals. Standard errors clustered at year of birth, age and region of birth level.

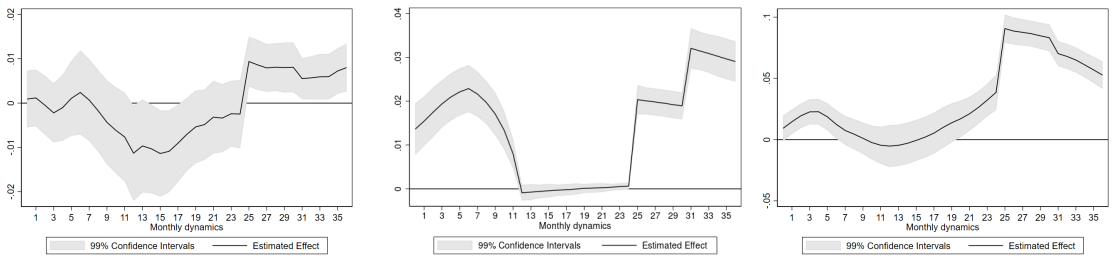
Figure B7: Dynamic ITT: no higher education



(a) Employment Prob. (b) Apprenticeship Prob. (c) Perm. Employment Prob.

Notes: See notes in Table (2). The gray area indicates 99% confidence intervals. Standard errors clustered at year of birth, age and region of birth level.

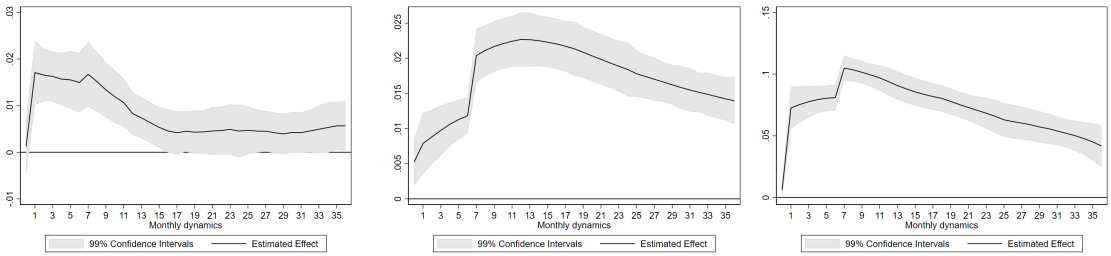
Figure B8: Dynamic ITT: education degree higher than lower secondary education



(a) Employment Prob. (b) Apprenticeship Prob. (c) Perm. Employment Prob.

Notes: See notes in Table (2). The gray area indicates 99% confidence intervals. Standard errors clustered at year of birth, age and region of birth level.

Figure B9: Dynamic ITT: lower secondary degree



(a) Employment Prob. (b) Apprenticeship Prob. (c) Perm. Employment Prob.

Notes: See notes in Table (2). The gray area indicates 99% confidence intervals. Standard errors clustered at year of birth, age and region of birth level.

B4 Difference-in-discontinuity: static impact on tenure.

Table B3: Static model estimates on job tenure

	Model Specification:						
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tenure	-.03531	-.03043	-.02645	-.03209	-.03414	-.02732	.01317
	.238	.1341	.1527	.0783	.078	.0781	.0629
Time fixed effect	NO	YES	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES	YES
Region of birth fixed effect	NO	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	NO	YES

Notes: See notes in Table (2).

C1 Robustness

C1.1 Permutation tests

Table C1: Permutation test: static model estimates

	Permutation test:						
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Employment prob.	.00544ˆ**	-.00026	.00598ˆ**	.001	-.00154	.00991ˆ***	.00656ˆ***
	.0022	.0023	.0026	.002	.0025	.002	.0025
Apprenticeship prob.	.00027	.00008	-.00139	.00149	.0001	-.00289	-.00164
	.002	0002	.0015	.0019	.0003	.0019	.0017
Perm. Employment prob.	.00172	-.0023	.00039	.00302	-.00089	.0003	-.00224
	.0033	.0031	.0035	.0042	.0034	.0031	.0024
Perm. Empl. same firm prob.	-.00071	-.0023	.00486	-.00115	-.00028	.00013	-.00098
	.0015	.0031	.0052	.0013	.0014	.0043	.0026
Perm. Empl. same sector prob.	-.00154	.0004	.0058	.00083	-.00056	.00072	-.00073
	.0015	.0015	.0055	.0015	.0016	.0046	.0027
Self employment	.0002	.00242ˆ*	-.0016	-.0007	.0016	-.00272ˆ***	-.00324ˆ***
	.0011	.0014	.0012	.0012	.0021	.0009	.0011
Time fixed effect	YES	YES	YES	YES	YES	YES	YES
Sector fixed effect	YES	YES	YES	YES	YES	YES	YES
Region of birth fixed effect	YES	YES	YES	YES	YES	YES	YES
Firm fixed effect	YES	YES	YES	YES	YES	YES	YES
Time invariant covariates	YES	YES	NO	YES	YES	YES	YES
Time varying covariates	YES	YES	YES	YES	YES	YES	YES

Notes: column 1 ± 1 *year of age threshold 27* ± 24 *months around june 2012, column2* ± 1 *year of age threshold 33 and* ± 24 *months around june 2012, column 3* ± 1 *year of age threshold 27* ± 18 *months around june 2010 , column 4* ± 1 *year of age threshold 29* ± 12 *months around june 2011, column5* ± 1 *year of age threshold 32* ± 12 *months around june 2013.*

C1.2 Static placebo estimates

In Table C2, we show that placebo estimates are small and statistically insignificant, with standard errors of the same order of magnitude as those in Table (2). We made a comparison between the dynamic pattern of treated and untreated individuals, mainly within the cohort of birth. Then, we cannot present dynamic estimates for this placebo sub-sample. In other words, as long as we have no information on the month of birth, we cannot precisely control for the differences in current and past outcomes between affected and unaffected individuals.

Table C2: Placebo: static model

	Model specification:						
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Employment Prob.	-.00233	.00085	.00035	.00059	.00055	.00049	.00025
	.0657	.0157	.0168	.0177	.0177	.0174	.0058
Apprenticeship Prob.	-.00155	.00154	.00154	.00153	.00153	.00155	.00153
	.0021	.0019	.0017	.0014	.0014	.0014	.0014
Perm. Employment Prob.	-.00237	.00202	.00166	.00184	.00182	.00177	.00163
	.0201	.0061	.0031	.004	.004	.004	.0029
Perm. Employment Prob. same firm	-.00013	.00006	.00001	.00002	.00002	.00002	.00013
	.0042	.0013	.0011	.0011	.0011	.0011	.0014
Perm. Employment Prob. same sector	-.00125	.00115	.00108	.00107	.00107	.00107	.00113
	.0052	.0015	.0013	.0011	.0011	.001	.0014
Self Employment	.00253	.00251	.00231	.0022	.00219	.00222	.00219
	.0025	.0029	.0026	.0016	.0016	.0016	.0014
Time fixed effect	NO	YES	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES	YES
Region of birth fixed effect	NO	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	NO	YES

Notes: The placebo sample comprises -6/+6 months around September 2011. See notes in Table (2).

C1.3 Sample centered ± 12 months around June 2012

Table C3 shows the balancing-out of covariates. Static effects (Table C4) are consistent with our main findings. The dynamic TOT (Figure C2) parameters are of the same order of magnitude of those reported in the main text, albeit here estimates are noisier in correspondence of the announcement of the introduction of a hiring incentive on permanent labor contracts. This policy corresponds to a time fixed effect that separates, within treated cohorts, individuals affected by both policies from those affected only by Law No. 92/2012. As for any other covariate, the exclusion/inclusion of time fixed effects did not impact the consistency of the estimates in a difference-in-discontinuity regression design (Lee and Lemieux 2010). Then, the dynamic ITT parameters (Figure C3) are robust to those reported in Figure 4, as expected.

Table C3: Main observable characteristics: difference-in-discontinuity in the robustness sample

	Main Sample			
	Raw data: t-test		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD	DiD	DiD	DiD
	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)
Gender	−0.003***	−0.003***	−0.003	0.000
	0.001	0.001	0.045	0.076
Region of birth	−0.121	−0.288***	−0.121	−0.610
	0.088	0.062	21.570	36.781
Education	−0.221***	−0.089**	−0.221	−0.306
	0.049	0.035	5.862	10.092
Missing education	0.001	0.001*	0.001	−0.002
	0.001	0.001	0.108	0.186
Past experience	−13.522***	−72.597***	−13.522	92.317
	1.525	1.068	63.633	104.256
Missing past exp.	−0.004***	0.006***	−0.004	−0.020
	0.001	0.001	0.018	0.031
Region of work	−0.000	−0.008	−0.000	0.012
	0.012	0.008	0.759	1.324
Changing sector	0.001	−0.001*	0.001	0.006
	0.001	0.001	0.019	0.034
Regional mobility	−0.003**	−0.004***	−0.003	−0.006
	0.001	0.001	0.186	0.318
Higher 25 per. monthly job spells	−0.002	0.001	−0.002	−0.006
	0.001	0.001	0.066	0.112
Higher 25 per. monthly sep. flows	−0.001	−0.000	−0.001	0.001
	0.001	0.000	0.016	0.028
Higher 25 per. monthly net job flows	−0.001	−0.003***	−0.001	0.002
	0.001	0.001	0.016	0.027
Higher than 25 perc. costs reduction	0.001**	−0.001**	0.001	0.001
	0.000	0.000	0.011	0.019
Higher than 25 perc. soc. insurance benefits	0.000***	−0.000***	0.000	0.001
	0.000	0.000	0.001	0.001

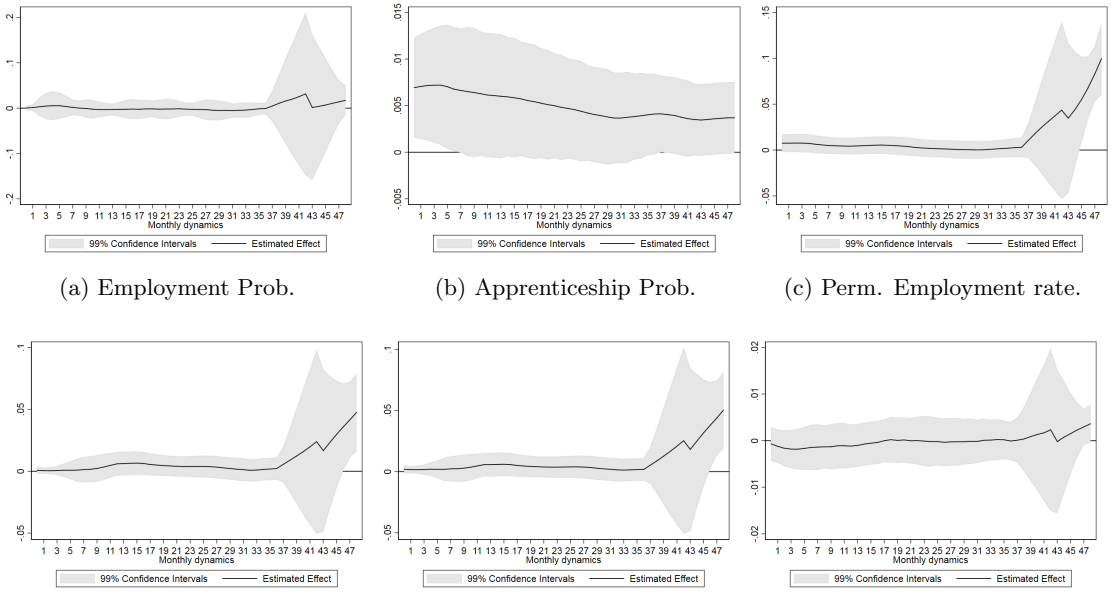
Notes: The independent samples t-test compares the difference in the means from the two groups (treated and untreated cohorts) around the age threshold to zero. The polynomial fit corresponds to a zero (first) order polynomial in age when the age range is $\pm 1(2)$*. Each variable, defined as higher than the 25th percentile, is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of each covariate in a given month and year. See also notes in Table (2).*

Table C4: Robustness sample: static model estimates

	Model Specification:						
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Employment Prob.	.00144	.00003	.00077	.00032	.00018	-.0006	.00035
	.0696	.0143	.012	.0072	.0072	.0074	.0019
Apprenticeship Prob.	.00685**	.00685**	.00693**	.00689***	.00689***	.00692***	.00694***
	.003	.003	.0027	.0021	.0021	.0021	.0021
Perm. Employment Prob.	.00707	.00674	.00776	.00738	.00733	.00707	.00753**
	.0182	.0138	.0102	.0047	.0047	.0047	.0037
Perm. Empl. prob. same firm	.00056	.00049	.0007	.0007	.0007	.00093	.00075
	.0038	.0013	.0015	.001	.001	.001	.0011
Perm. Empl. prob. same sector	.00157	.00148	.00175	.00172	.00173	.00194	.00183
	.0048	.0017	.0017	.0012	.0012	.0012	.0013
Self employment	-.00053	-.00049	-.00059	-.00075	-.00072	-.00059	-.00068
	.0033	.0028	.0026	.0015	.0015	.0015	.0014
Time fixed effect	NO	YES	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES	YES
Region of birth fixed effect	NO	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	NO	YES

Notes: See notes in Table (2).

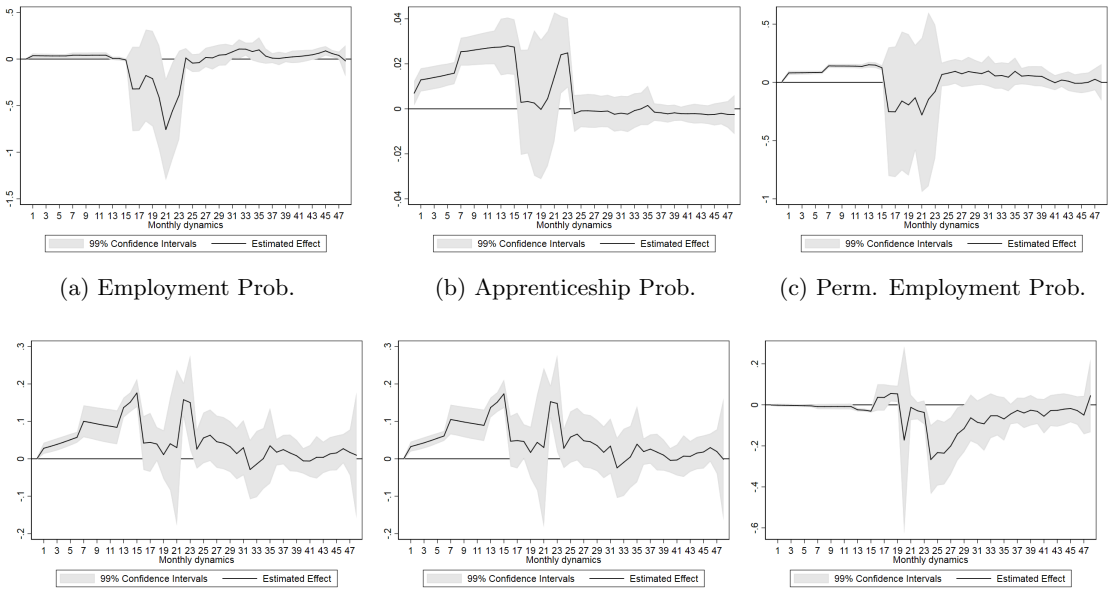
Figure C1: Robustness sample: difference-in-discontinuity, dynamic effect, without controlling for outcome persistency up to 47 months.



(a) Employment Prob. (b) Apprenticeship Prob. (c) Perm. Employment rate.

(d) Perm. Emp: same firm. (e) Perm. Emp: same sector. (f) Self Employment Prob.

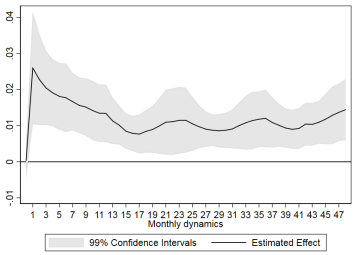
Figure C2: Robustness sample: difference-in-discontinuity, TOT parameters up to 47 months.



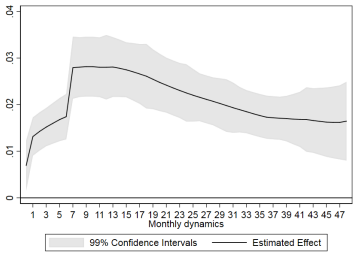
(a) Employment Prob. (b) Apprenticeship Prob. (c) Perm. Employment Prob.

(d) Perm. Emp: same firm. (e) Perm. Emp: same sector. (f) Self Employment Prob.

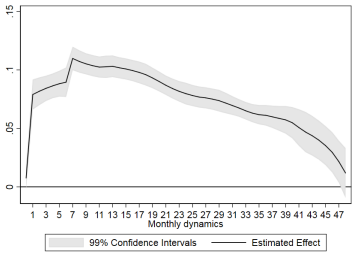
Figure C3: Robustness sample: difference-in-discontinuity, ITT parameters up to 47 months.



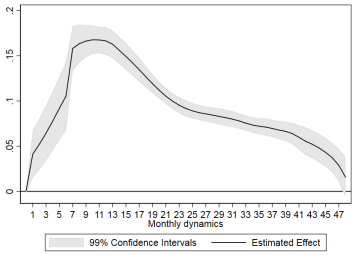
(a) Employment Prob.



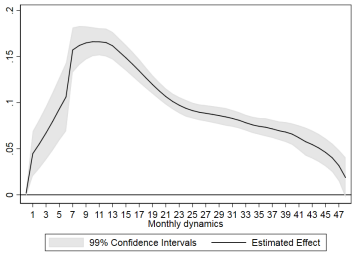
(b) Apprenticeship Prob.



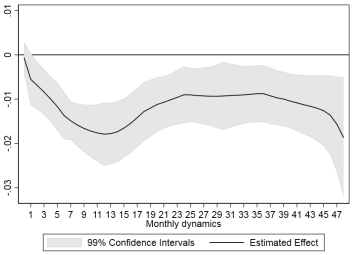
(c) Perm. Employment Prob.



(d) Perm. Emp: same firm.



(e) Perm. Emp: same sector.



(f) Self Employment Prob.

C1.4 Clustering standard errors differently and using heteroskedasticity robust standard errors

We clustered standard errors by age, year and region of birth. Individuals born in the same calendar year and region, share background characteristics (such as the quality of the education system) and the local labor market. Then, their employment outcomes tend to correlate. As discussed by Angrist and Pischke (2009), heteroskedasticity rarely leads to dramatic changes in inference. Clustering, instead, matters when the correlation of regressors within groups is high. Then, we replicated our results using a different group structure (based on age and year of birth only), and the heteroskedasticity-robust standard errors. The latter are more conservative when the window widths (i.e., the age range) are small, and the forcing variable is discrete (Kolesár and Rothe 2018). Besides, standard errors clustered by the running variable may not guard against model misspecification in RDD setting with discrete support (Kolesár and Rothe 2018). These clustered standard errors could cause the accuracy of the fitted specification to vary for small and moderate numbers of discrete values of the running variable. Then, confidence intervals based on heteroskedasticity-robust (EHW) standard errors could be larger than the corresponding intervals based on standard errors clustered by the running variable. Besides, EHW confidence intervals perform well and have good coverage. Then, we replicated our analysis using EHW standard errors and different clustering based on age and year of birth to provide further evidence on the validity of our estimates. Clustering on age and year of birth amounts to clustering on the two running variables in the difference-in-discontinuity regression design (Lee and Card 2008).

The following results illustrate that, in our data, clustering made all the difference. In the estimation of the static model, standard errors dropped by about 11% (4%) when switching from grouping individuals by age, year and region of birth to EHW standard errors (clustering by age and birth cohort only). In our data, the group structure matters. This issue is even more relevant for the dynamic estimates when the regressor of interest does not vary much within groups (see also Angrist and Pischke 2009). In all cases, our estimates are the most conservative.

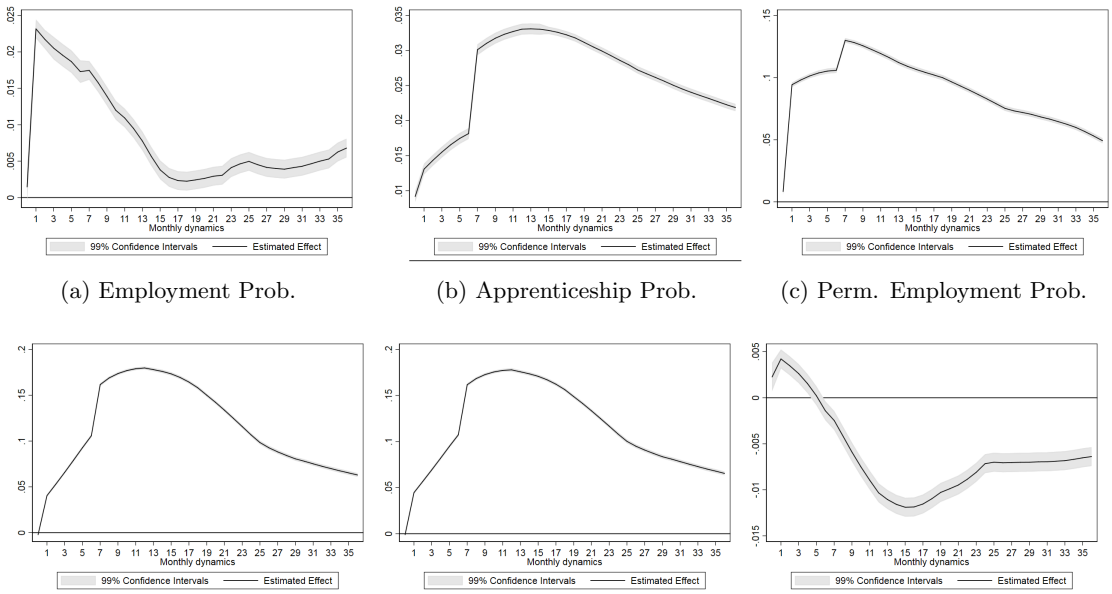
C1.4.1 Heteroskedasticity robust standard errors

Table C5: Static model estimates

	Model Specification:						
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Employment prob.	.00189	.0015	.00212	.00176	.00164	.00192	.00101
	.0015	.0014	.0014	.0014	.0014	.0014	.0008
Apprenticeship prob.	.01003***	.01004***	.01004***	.00998***	.00998***	.00993***	.00984***
	.0003	.0003	.0003	.0003	.0003	.0003	.0003
Perm. Employment prob.	.00861***	.00855***	.00905***	.00869***	.00866***	.00835***	.00925***
	.0009	.0009	.0009	.0009	.0009	.0009	.0009
Perm. Empl. prob. same firm	.00099**	.00095*	.00106**	.00109**	.00109**	.00088**	.00038
	.0005	.0005	.0005	.0005	.0005	.0004	.0004
Perm. Empl. prob. same sector	.00183***	.0018***	.00193***	.00195***	.00195***	.00172***	.00145***
	.0005	.0005	.0005	.0005	.0005	.0005	.0005
Self employment	-.00121**	-.00116*	-.00137**	-.00151**	-.00149**	-.00143***	-.00144***
	.0006	.0006	.0006	.0006	.0006	.0005	.0005
Time fixed effect	NO	YES	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES	YES
Region of birth fixed effect	NO	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	NO	YES

Notes: See notes in Table (2). Heteroskedasticity robust standard errors

Figure C4: Heteroskedasticity robust standard errors: difference-in-discontinuity, ITT parameters up to 36 months.



(a) Employment Prob. (b) Apprenticeship Prob. (c) Perm. Employment Prob.

(d) Perm. Emp: same firm. (e) Perm. Emp: same sector. (f) Self Employment Prob.

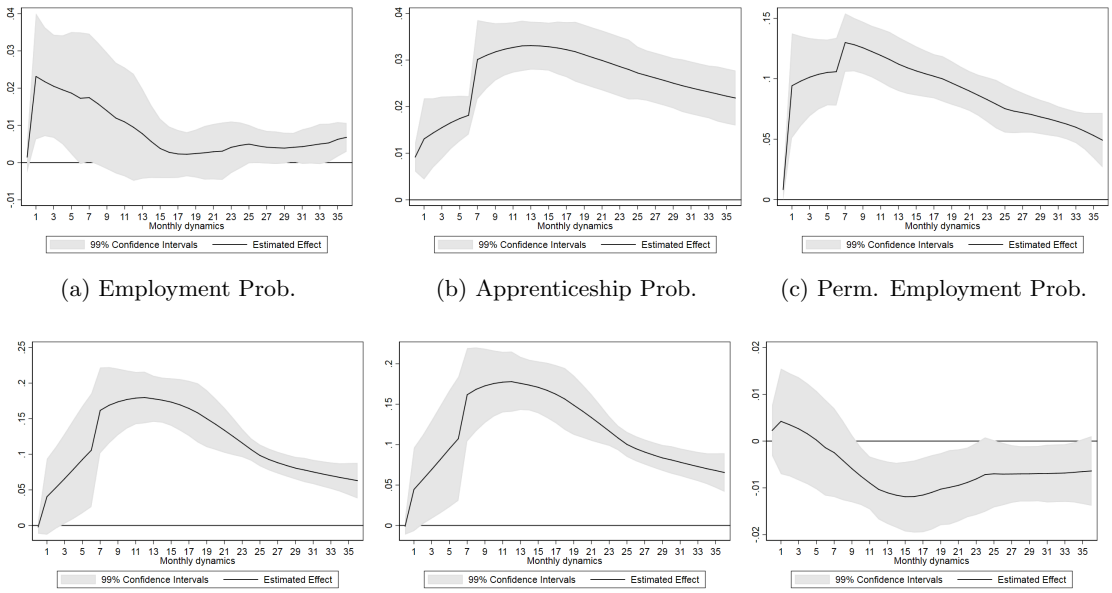
C1.4.2 Clustering by age and year of birth

Table C6: Static model estimates

	Model Specification:						
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Employment prob.	.00189	.0015	.00212	.00176	.00164	.00192	.00101
	.1067	.0016	.0018	.0018	.0017	.0018	.0016
Apprenticeship prob.	.01003***	.01004***	.01004***	.00998***	.00998***	.00993***	.00984***
	.0014	.0009	.001	.001	.001	.001	.001
Perm. Employment prob.	.00861	.00855***	.00905***	.00869***	.00866***	.00835***	.00925***
	.0202	.0007	.0006	.0005	.0005	.0005	.001
Perm. Empl. prob. same firm	.00099	.00095**	.00106***	.00109***	.00109***	.00088***	.00038
	.0055	.0004	.0003	.0003	.0003	.0002	.0003
Perm. Empl. prob. same sector	.00183	.0018***	.00193***	.00195***	.00195***	.00172***	.00145***
	.0065	.0003	.0003	.0003	.0003	.0004	.0004
Self employment	-.00121	-.00116*	-.00137*	-.00151**	-.00149**	-.00143*	-.00144
	.0045	.0007	.0007	.0007	.0007	.0008	.0009
Time fixed effect	NO	YES	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES	YES
Region of birth fixed effect	NO	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	NO	YES

Notes: See notes in Table (2). Standard errors clustered at age and year of birth level.

Figure C5: Standard errors clustered at age and year of birth level: difference-in-discontinuity, ITT parameters up to 36 months.



(a) Employment Prob. (b) Apprenticeship Prob. (c) Perm. Employment Prob.

(d) Perm. Emp: same firm. (e) Perm. Emp: same sector. (f) Self Employment Prob.

C1.5 Extending the age range to ±2 years around the threshold

We extended the age range to ±2 years around the cutoff. The main drawback to carrying out this analysis rests in the functional form restrictions imposed by the discreteness of the age variable. We started by adopting a first-order polynomial-in-age model specification. Table C7 shows that the difference-in-discontinuity parameter on the apprenticeship probability is statistically significantly different from zero at the 5% level and coincides (up to four decimal places) with that displayed in Table (2). The difference-in-discontinuity coefficient on permanent employment probability is also slightly smaller (at the fourth decimal places) when compared to that reported in Table (2). However, it is no longer statistically significant at conventional levels because of the high degree of collinearity between the difference-in-discontinuity term and its interaction with age inflates the standard errors. These two terms are almost identical on each side of the threshold. All in all, this it is reassuring. This evidence indicates that the polynomial-of-degree-zero model specification estimated in the neighborhood of the age cutoff identifies an effect that can be generalized to higher age ranges.[12]

Table C8 shows that, for both the apprenticeship and permanent employment probability equations, the t-test on the interaction term $a * r * d$ does not differ with statistical significance from zero. Then, there is no statistically significant difference in the slope coefficients around the cutoff between treated and untreated cohorts: $([(\beta_{1p} - \beta_{0p}) - (\beta_{1b} - \beta_{0b})] = 0)$. In other words, the data seem to support the stability bias hypothesis in the age range ±2 years around the threshold. Table C9 replicates the analysis for the restricted model which excludes the interaction term $a * r * d$. The difference-in-discontinuity parameters are stable, and standard errors are smaller. The impact on permanent employment probability is statistically significantly different from zero at the 10% level. Excluding also the interaction between $a * r$, the difference-in-discontinuity parameters are stable, and standard errors are even smaller. In such a case, the effect on both apprenticeship and permanent employment probability is significant at the 1% level (Table C10).

We did not estimate the dynamic treatment effects using the age range of ±2 years around the threshold (o larger than 2), because we were not confident of the model specification given the restrictions imposed by the discreteness of the age variable. Dynamic treatment effects rely on the persistence in the outcome generated by the reform at the age cutoff. That is, they depend upon the labor market history of the individual from the baseline onwards. The inability of the model specification to control for it could lead to inconsistent dynamic treatment effects.

Table C7: Static model estimates: range ±2 years around the threshold

	Model Specification:						
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Employment prob.	.00396	.00319	.00377	.0033	.00347	-.00048	-.00365
	.0653	.022	.0184	.009	.009	.0091	.0037
Apprenticeship prob.	.00923	.00923	.00916	.00907**	.00907**	.00911**	.00928**
	.0072	.0072	.0063	.0043	.0043	.0042	.0042
Perm. Employment prob.	.00952	.00937	.00961	.0091	.00915	.009	.00808
	.0254	.0235	.0161	.0059	.006	.006	.0052
Perm. Empl. prob. same firm	.00075	.00071	.0008	.00087	.00086	.00235	.00228
	.0041	.0027	.0032	.0022	.0022	.0022	.0021
Perm. Empl. prob. same sector	.00193	.00188	.00199	.00205	.00204	.00352	.00331
	.0052	.0035	.0036	.0024	.0024	.0024	.0023
Self employment	.00015	.00019	-.00016	-.00032	-.00035	.00028	.00039
	.0049	.0046	.0044	.0024	.0024	.0023	.0023
Time fixed effect	NO	YES	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES	YES
Region of birth fixed effect	NO	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	NO	YES

Notes: See notes in Table (2).

[12]The difference-in-discontinuity parameter is instead much less stable on all other employment outcomes, which, as the graphical analysis displays, do not exhibit a discontinuity at the age threshold.

Table C8: Range ±2 years around the threshold: interaction terms

	Model specification:			
Dependent Variable:	age	age*d	age*r	age*d*r
Employment prob.	.0033**	.0033*	.0002	-.0049*
	.0014	. .0020	.0020	.0030
Apprenticeship prob.	-.0006	-.0135***	.00043	-.0009
	.0014	.0018	.0019	.0033
Perm. Employment prob.	.0037**	-.0085***	.0001	-.0013
	.0017	.0028	.0027	.0040
Perm. Empl. prob. same firm	-.0003	-.0006	-.0001	.0025
	.0010	.0013	.0013	.0018
Perm. Empl. prob. same sector	-.0007	-.0014	-.0004	.0022
	.0010	.0015	.0013	.0020
Self employment	.0014	-.00002	-.0017	.0035*
	.0009	.0012	.0015	.0020
Time fixed effect	YES	YES	YES	YES
Sector fixed effect	YES	YES	YES	YES
Region of birth fixed effect	YES	YES	YES	YES
Firm fixed effect	YES	YES	YES	YES
Time invariant covariates	YES	YES	YES	YES
Time varying covariates	YES	YES	YES	YES

Notes: See notes in Table (2).

Table C9: Range ±2 years around the threshold: restricted model I

	Model Specification:						
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Employment prob.	.0038	.00366	.00431	.00394	.00403	.00179	-.00128
	.06	.0199	.0167	.008	.0081	.0082	.0032
Apprenticeship prob.	.00981*	.00982*	.00978**	.00974***	.00973***	.00971***	.00974***
	.0051	.0051	.0045	.0036	.0036	.0035	.0035
Perm. Employment prob.	.00929	.00925	.00968	.00937*	.0094*	.00898*	.00869*
	.0221	.0203	.0138	.0054	.0054	.0054	.0046
Perm. Empl. prob. same firm	.00056	.00056	.00067	.00069	.00069	.00143	.00109
	.004	.0027	.0031	.0023	.0022	.0022	.0021
Perm. Empl. prob. same sector	.00171	.00171	.00184	.00186	.00186	.00257	.00225
	.0048	.0032	.0033	.0024	.0024	.0024	.0022
Self employment	-.00153	-.00152	-.00179	-.00188	-.0019	-.00144	-.0013
	.0048	.0043	.0042	.0023	.0022	.0022	.0022
Time fixed effect	NO	YES	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES	YES
Region of birth fixed effect	NO	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	NO	YES

Notes: See notes in Table (2).

Table C10: Range ±2 years around the threshold: restricted model II

	Model Specification:						
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Employment prob.	-.00003	-.00063	-.00011	-.00052	-.00085	.00195	.00326**
	.0269	.0089	.0075	.0037	.0037	.0037	.0015
Apprenticeship prob.	.01023***	.01025***	.01028***	.01019***	.0102***	.0101***	.00982***
	.0024	.0024	.0021	.0017	.0017	.0017	.0017
Perm. Employment prob.	.00794	.00786	.00839	.00795***	.00785***	.00767***	.00977***
	.0102	.0092	.0062	.0023	.0023	.0023	.002
Perm. Empl. prob. same firm	.00141	.00134	.00145	.00146	.00147	.00033	-.00029
	.0019	.0012	.0013	.001	.0009	.0009	.0009
Perm. Empl. prob. same sector	.00196	.00189	.00203	.00202**	.00203**	.00088	.0007
	.0023	.0014	.0015	.001	.001	.001	.001
Self employment	-.00084	-.00079	-.00096	-.00108	-.00103	-.00136	-.00154
	.002	.0019	.0018	.001	.001	.001	.001
Time fixed effect	NO	YES	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES	YES
Region of birth fixed effect	NO	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	NO	YES

Notes: See notes in Table (2).

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