Human capital investment and job creation: the role of the education and production systems

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ABSTRACT
This paper provides empirical evidence on two mechanisms through which a committed investment in human capital serves as a stepping stone into permanent employment. I verify whether regional disparities in general education and production systems affect the capacity of the apprenticeship labour contract to create job matches that persist over time. I find that when the quality of the regional education system is good, the medium-run gains in terms of permanent employment can be moderate. However, a small number of productive firms in a region limits the quantity of job entries as apprentices.

KEYWORDS
Human capital; permanent employment; education system; production system

JEL CLASSIFICATION
J24, J21, I20, D2

1. Introduction

In recent years, technological innovations and the globalisation process have posed a challenge to the labour market to create not only jobs but good jobs. One expects that a commitment to invest in human capital can contribute to the creation of a good quality job and the consequent permanent employment position. If this is the case, apprenticeships have an advantage over the other labour contracts to lead to permanent employment (Maida & Sonedda, 2019). Why are not apprenticeships more widespread? The answer is because there exist influential factors that restrict their use.

The aim of this paper is to investigate the role of the general education and production systems in shaping which labour contract serves as a stepping stone into permanent employment. I exploit the Italian regional disparities in these systems to shed light on this issue. Looking at the regional disparities is important to fill some gaps in the literature. The presence of a legally enforceable commitment of the firms to training provision explains why firm-based vocational training schemes work in some countries but not in others (Dustmann & Schönberg, 2012). However, this nation-wide institutional setting is a necessary but not sufficient condition to influence the

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willingness of firms to provide training. For instance, on the basis of this argument only, it would be hard to justify the existence of differences within and across industries. These differences are analysed by Dustmann and Schönberg (2009) who focus on the role of the degree of unionisation. The argument that unions serve as commitment and as wage floor device is convincing. Nevertheless, further explanations are still missing. Otherwise, in countries like Switzerland and Germany where the apprenticeship labour contract works, regional differences are only due to differences in the degree of unionisation (or in the degree of the enforceable commitment of the firms to training provision).

This paper contributes to the literature by presenting new empirical evidence that points to the importance of two influencing factors: the general education and production systems. Regional disparities in these systems contribute to explain not only regional differences in the apprenticeship rate but also the extent to which apprenticeships serve as a stepping stone into permanent employment. To the best of my knowledge, this is the first paper that tackles this empirical issue.

I use a very rich administrative dataset, by the Italian Ministry of Labour and Social Policies, *CICO* (the so-called *Comunicazioni Obbligatorie*). Focusing on Italy is interesting for three reasons. First, law no. 247/2007, Legislative Decree no.167/2011 and law no.92/2012 introduced a common nationwide institutional setting that fixed the rules governing the apprenticeship labour contract and increased the commitment to training and general education provision. Second, in Italy, wage floor applies *erga omnes* and not only to unionised firms. Third, Italy is characterised by a further dualism within a dual labour market[1]: the North-South divide which is possibly related to regional disparities that interact with the functioning of the labour market.

I assume that the data generating process of the permanent employment rate is related to the legal rule that in Italy a job entry as apprentice is only available, albeit not mandatory, up to 29 years and 364 days of age.[2] This yields to a discontinuity in the permanent employment rate around the cutoff of 30 years of age. This discontinuity in the permanent employment rate can depend on the apprenticeship labour contract only. There is no reason to observe such data generating process of permanent employment in case of transitions from either unemployment or from a temporary labour contract. On the top of that, I expect that the introduction of law no. 92/2012 has exogenously changed this data generating process. If fact, the law explicitly aimed at encouraging apprenticeships as the main port of entry into permanent employment. A mentoring scheme was introduced to strengthen the vocational training component of the job. This rule was complemented by a future punishment to the firm that avoided to maintain on a permanent basis at least 30% of those hired as apprentices three years before. This setting allows me to design a difference in discontinuity regression model. That is, the difference in the discontinuity around the cutoff of 30 years of age, generated by the labour market reform, creates a source of randomised variation. Since this variation is randomised, it is independent of any observable factor that can be added as a covariate in the regression model, including the indicator of the location of work. I expect that the permanent employment probability of cohorts treated by the labour market reform, around the age cutoff, has increased compared to the permanent employment probabilities of similar untreated individuals (Maida & Sonedda, 2019).

[1] According to the original definition of Doeringer and Piore (1971), labour markets are dual in nature if they are segregated into primary and secondary spheres.

[2] This implies that I am considering apprenticeships as a labour contract committed to the provision of on the job training and of general education courses outside the firm. The role of apprenticeships as part of the vocational education and training system, alternative to a more academic education track, is here neglected.

This paper adds to the literature the analysis of regional disparities in this difference in discontinuity impact. The aim is twofold. First, by estimating whether there are regional differences, it contributes to illustrate how the regional labour markets evolve. Second, from a more general perspective, it provides empirical evidence that reveals which mechanisms allow an investment in human capital to create job matches that persist over time.

This paper verifies whether regional permanent employment patterns are related to the regional production and general education systems. This analysis differs from the few existing studies using data at regional level, e.g. Brunello and De Paola (2008); Muehlemann and Wolter (2008), in four crucial aspects. First, exploiting a randomised variation, this paper overcomes one of the major problem that has to be faced when analysing regional differences in labour market outcomes: the region of work is not exogenous. Employers can decide where to locate their economic activity. Employees can migrate if there are not good employment opportunities in the region where they were born. Second, the main outcome is the individual's permanent employment probability and how it is related to the apprenticeship probability rather than the training decision of the firm. Third, I analyse the role of the quality of the regional education and production systems in determining the size of these difference in discontinuity impacts at the baseline and in the medium-run. For instance, it could be the case that it is not the number of firms or the number of employees per squared kilometer that matter *per sé*. If there are complementarities between former education and the on-the-job human capital investment, a qualitative, rather than a quantitative, measure of general education better contributes to determine the number of *potential* apprentices. This qualitative measure(s) corresponds to the percentage of individuals who scored the minimum (maximum) level in the Programme for International Student Assessment (PISA) tests in math and reading performance. By the same token, the limited number of *productive* firms in a region[3] could serve as a barrier to the quantity of successful apprenticeship labour contracts. In fact, for both employer and employees, the apprenticeship contract implies a costly investment whose future return is uncertain. It is, therefore, likely that only firms with medium-long terms production opportunities invest on it. Last but not least, there is no paper that verify whether there are regional disparities in the medium-run effect on permanent employment of the initial human capital investment. By looking at the dynamics, the paper provides an important evidence on the main argument of the paper. The combination of a committed human capital investment in a open-ended contract (as apprenticeships) drives the screening-sorting processes that lead to permanent employment, on the top of human capital accumulation. If this is true, the probability that this job match persists over time is higher than the same probability of other job matches created without the same commitment to the human capital investment (Maida & Sonedda, 2019). This holds more true if there are complementarities between the former education and the on-the-job human capital investment.

I find that the capacity of the apprenticeship labour contract to serve as a stepping stone into permanent employment is limited when the quality of the education system is low and the number of productive firms is small. Different results emerge when instead the quality of the education system is high. In such a case, the medium-run gains in terms of permanent employment are moderate. This is possibly revealing the existence of complementarities between former education and further human capital

[3]Of course, it is likely that the limited number of firms and the limited number of productive firms are correlated.

accumulation. These medium-run gains come out even in absence of any impact at the baseline.

The rest of the paper is organised as follows. Section 2 outlines the setting. Section 3 illustrates the identification strategy while section 4 describes the data. Results are reported in section 5. Finally, section 6 concludes.

2. The setting

2.1. Related literature

The article is related to at least three strands of the literature.

First, the effect of dualism on labour markets has been widely analysed, see for instance Dolado (2017). From every angle this issue is looked at, in a dual labour market employers are more reluctant to hire workers on a permanent basis. This literature focuses on the role of the employment protection legislation and reaches no clear consensus on which kind of labour contract can be used as the main port of entry into stable, high quality, employment. On the one hand, it is generally assumed that temporary contract do not bear the firing costs which have to be paid to terminate permanent contracts. This assumption, implies that employers might prefer temporary to permanent jobs. The former contracts, by decreasing firing costs, could, theoretically, be useful to young inexperienced workers to raise their job experience easing their transition towards permanent employment. After a period of screening, the firm could convert these contracts, letting them be stepping stones into permanent employment (Booth, Francesconi, & Frank, 2002; Heinrich, Mueser, & Troske, 2005; Holmlund & Storrie, 2002; Ichino, Mealli, & Nannicini, 2008). However, as suggested by Cahuc, Charlot, and Malherbet (2016), in all countries, open-ended jobs comprise probationary periods and temporary works cannot be terminated before their ending date. As a result, firms profitably screen temporary workers only if the duration of the probationary period is shorter than that of fixed term contracts. The authors consider a job search and matching model where the use of temporary contracts hinges on the heterogeneity of expected production opportunities. Short-term (even very short ones) contracts can emerge in equilibrium because they are used for production opportunities with short expected durations. Workers could, therefore, end up moving from one temporary contract to another letting these contracts be dead-end jobs (Blanchard & Landier, 2002; Boeri & Garibaldi, 2007; Cahuc & Postel-Vinay, 2002). Moreover, as the expected duration of fixed term contracts gets shorter, firms are less likely to invest in workers training because the return of this investment in human capital is low, if positive. Besides, fixed-terms workers are more likely to lose their incentives to exert more effort to accumulate better productive capabilities. As a result, the successfulness of temporary labour contracts to help employers to screen workers' ability and employees to sort in better jobs could be limited.

Second, I complement the literature on the determinants of firm sponsored training. I present new empirical evidence on the factors that could make an investment in human capital be a device to optimise the screening-sorting processes that lead to permanent employment. To this extent, the apprenticeship labour contract can have an advantage over the other labour contracts.[4] Apprenticeship training allows individuals to accumulate human capital which translates into ex-post higher productivity. The informational content of the contract is crucial here. In fact, informational asymmetries

[4]In Italy since 2008 apprenticeship contracts are considered permanent labour contracts.

convert general into specific training since the current employer has an informational advantage on his employees' productivity relative to other firms (Acemoglu & Pischke, 1998, 1999). Both firms (in terms of monopsony rents) and individuals (in terms of higher wages and higher probability of permanent employment) benefit of the higher worker's productivity. Firms and workers share also the cost of this human capital investment. Firms are required, during time of work, to let apprentices attend external courses provided by local authorities or accredited training institutes sponsored by the regions. In fact, these external courses depend on the regional public funding and infrastructures. Firms are partly compensated for the training costs by a tax rebate. From the workers' perspective the apprenticeship labour contract is costly because it requires costly effort and it implies a lower initial wage. To some extent, the lower initial wage eliminates the wage rigidity which prevents an offsetting transfer from workers to firms in exchange for being insured against job losses (E. P. Lazear, 1990). In fact, there are some analogies with a contract that fix a performance related pay component of (future) earnings. The costs of the vocational training and the general education provided by the contract and the lower initial wage are compensated by a permanent labour contract and higher earnings in the future. The rationale is here similar to Macho-Stadler, Perez-Castrillo, and Porteiro (2014) who argue that long-term contracts allow the better provision of incentives because firms can credibly transfer payments from earlier to later periods in the life of the workers. The higher the worker effort is, the higher the probability of a long-lasting employment relationship, the higher future earnings will be. On the top of that, it is the combination of a costly human capital investment in a open-ended contract that could allow better sorting-screening processes. However, there might be further explanations on the successfulness of the apprenticeship labour contract over and above the informational content. In absence of these further mechanisms it would be difficult to explain differences across countries. In fact, information asymmetries and skill specificities are not likely to vary greatly across countries while institutional attributes do. An important contribution in this direction is provided by Dustmann and Schönberg (2012) who relate the successfulness of apprenticeships to the commitment to training provision guaranteed by the countries' institutional framework. While the authors focus on a mechanism which clearly explains why apprenticeship performs better in a country rather than another, it does not completely address the issue of why there might be differences across regions, sectors and occupations *within* a country. A potential explanation of the existence of within and across industries differences relies on Dustmann and Schönberg (2009) who account for such differences in terms of the degree of unionisation. In fact, unions set a wage floor, which is another influencing factor of the firm decision to provide training. From the employees' perspective, unionised firms offer a long-term wage contract. In the future, at least the union wage has to be paid. From the employer's point of view, the unions' wage floor determines wage compression. As long as the equilibrium wage structure is more compressed than the productivity differentials, the firm makes greater profits from more skilled workers. Consequently, if the training costs are not too large, it is profitable for the employer to invest in the employee's human capital (Acemoglu & Pischke, 1998, 1999). Dustmann and Schönberg (2009) provide empirical evidence that apprenticeship training is higher in unionised firms in Germany.

Third, very few papers present empirical evidence on the firm decision to provide training using data at regional level. Brunello and De Paola (2008) study the relationship between local labour market density and firm sponsored training. The local labour market density is measured by the number of employees per squared kilometer in a province. The authors show that, theoretically, the effect of economic density on the firm decision to train cannot be signed. On the one hand, a higher density of the local labour market increases productivity and consequently encourages firms to invest more in training. On the other hand, a higher density of the local labour market reduces the rents of the firms and consequently lowers the incentive to train. They use data on more than 1000 Italian manufacturing firms, drawn from the Survey of Italian Manufacturing by Mediocredito Centrale, to present estimates on such relationship. They find that the local agglomeration pattern has a negative and statistically different from zero impact on the willingness of the firms to invest in the employees' human capital. Muehlemann and Wolter (2008) use a representative firm level data set to estimate whether the local industry structure and education system affects the decision of the firm to hire apprentices in Switzerland. The local industry structure is proxied by the number of competing firms situated in the same geographical area. In the attempt to avoid endogeneity issues related to the geographical location of the firm, the authors define the geographical area in terms of travel distances rather than political borders. The local education system is measured in three different ways: by the local number of young people of school-leaving age; by the local share of pupils of foreign nationality and by the local share of young people completing compulsory education that opted for grammar schools in 1995. They find that while the number of competing firms situated in the same geographical area affects negatively the probability of apprenticeship training, the number of young people of school-leaving age in the area has instead a positive impact on it. All in all, regional disparities in the education and production systems are particularly relevant to understanding to what extent a labour contract committed to a costly human capital investment, serves as a stepping stone into permanent employment. Drawing on the North-South divide in Italy, I study the heterogeneity across Italian regions of the impact of the labour market reform (law no. 92/2012) at the threshold of 30 years of age, above which job entries as apprentices is not possible. In what follows, I will briefly describe the Italian institutional framework.

2.2. Institutional framework

Constitutional law n. 3 of 18 October 2001 brought substantial amendments to Title V of the Italian Constitution. It enhanced the powers of the Regional Governments and institutionalised the principle of the autonomy of the educational institutions. Education is included among the matters of concurrent legislation between the State and the regions. The State is exclusively responsible for general norms and sets fundamental principles. In fact, the State determines the general educational goals and it reviews the performance by evaluating whether the results obtained in the school system meet the requested standards. The State is also in charge for allocating financial and human resources to the educational institutions. The regions are responsible for building activities, educational assistance, programming how to integrate the vocational training and the school systems.[5] As a result, exclusive power to legislate over vocational training is given to the regions.

law no 30/2003 and legislative decree no. 276/2003 reformed the rules governing the apprenticeship contracts. The traditional contract (apprenticeship for vocational qualifications and diplomas, upper secondary education diplomas and high techni-

[5]Merger and closure of schools and the organization of the school systems, including the use of buildings and materials, are instead competencies assigned to local governments.

cal specialisation certificates), that can be assimilated to a vocational and education training programme, was complemented by a new form of apprenticeship, vocational apprenticeship.[6] For this new type of apprenticeship, the age limit, above which the contract cannot be signed[7], was extended from 24 years and 364 days to 29 years and 364 days. Cappellari, Dell'Aringa, and Leonardi (2012) exploit the variability across regions and across sectors to show that this apprenticeship reform had an overall productivity enhancing effect. In fact, to accomplish with these new normative requirements, regional governments had to issue regional regulations. Although, in general, regions were slow in fulfilling this task, some regions implemented the legislation earlier than others. (Autonomous Province of Bolzano in Trentino Alto Adige, Emilia Romagna, Friuli Venezia Giulia, Marche, Puglia, Sardegna, Toscana). Besides, there was a certain degree of heterogeneity in the contents of these regional regulations. As a consequence, law no. 247/2007 started the process, culminated with legislative decree no. 167/2011, of establishing a common regulation across all regions. Based on these premises, law no. 92/2012 reformed further the apprenticeship labour contract. Three aspects of the law are relevant. Two of them are expected to have a direct and intended impact on the probability of apprenticeship. First, the law enforced a mentoring scheme that might have increased the worker's productivity. Second, the law introduced a punishment on the firms which do not accomplish with the commitment of employing permanently the apprentice (with the exception of motivated lay-offs). In fact, these firms cannot hire more than one apprentice in future. This punishment increases the worker's value of apprenticeship and discourage the production-oriented, in favour of the investment-oriented, usage of the apprenticeship contract. Third, the law increased the social security contributions burdened on temporary contracts while keeping fixed the tax rebate on the apprenticeship contracts.

Given this institutional framework, I focus on the quality of the regional general education system and on the number of productive firms in a region as influencing factors in the creation of a permanent job position through the apprenticeship labour contract. These regional determinants play a role over and above differences in the quality of regional external training courses which were not affected by the labour market reform.

3. Identification strategy

Following Maida and Sonedda (2019), I start by assuming that the data generating process of the apprenticeship rate is based on the legal rule that, in Italy, job entry as apprentice is only available, albeit not mandatory, up to 29 years and 364 days of age. This yields to a deterministic process of the apprenticeship rate on one side of the cutoff of 30 years. As a consequence the data generating process of permanent employment rate exhibits a discontinuity around this age threshold. On the top of that, I expect that the introduction of law no. 92/2012 has exogenously changed this data generating process. This setting allows me to design the following difference in discontinuity regression model:[8]

[6] The reform introduced also a third type, the higher education and research apprenticeship.

[7] The minimum length of the apprenticeship contract is six months. This implies that there are individuals aged more than age limit working as apprentices. That is, the rule sets the age limit to job entries as apprentices. The maximum length of the contract is three years, although there could be some exceptions.

[8] The preliminary analysis discussed in Section 4 shows that a *local* linear model specification fits the data. In the on-line Appendix I will show how to derive this model specification using the potential outcomes framework,

$$y_{i,t} = \alpha_0 + \alpha_1 k_{it} + \beta_0 a_{it} + \gamma_1 d_{it} k_{it} + \gamma_0 d_{it} + \epsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is the outcome for individual i at time (year, month) t; a_{it} is the forcing variable age parameterised as deviation from 30; k_{it} is an indicator function which takes the value of 1 if the individual, given her age and year of birth, is treated by law no. 92/2012 and d_{it} is an indicator function that takes the value of 1 if the person is aged less than 30 years.[9]

In what follows, I will consider as outcomes y: the employment probability, the permanent employment probability and the apprenticeship probability.

The difference in the discontinuity around the cutoff of 30 years of age, generated by the labour market reform, creates a source of randomised variation. In fact, since the forcing variable, age, is observed, there is little room for discretion from an identification standpoint. The only choice is to estimate the expectation of the outcome, y, conditional on the forcing variable, age, on either side of the cutoff before and after the introduction of law no. 92/2012. The interpretation of the Intention To Treat, ITT, parameter, γ_1, simplifies to measuring to what extent, around the age threshold, the outcome of interest changes for individuals treated by law no. 92/2012 compared to similar individuals born in contiguous cohorts, who reached the threshold age before the introduction of the law. This differential impact is compared across similar individuals, who differ because of their age, in the possibility to enter into a job as apprentice and who differ because of their year of birth which assigns them to the treatment of law no 92/2012. This is very appealing for two reasons. First, it allows to avoid to take strong stance about which covariates to include in the analysis. In fact, the design predicts that the observable covariates are irrelevant and unnecessary for identification. Second, within the design all the relevant factors are controlled for and the crucial assumption that no omitted variables are correlated with the treatment is trivially satisfied. When the individual's age is lower (higher) than 30 the intention to treatment dummy, d, is always equal to 1 (0). Conditional on age, there is no variation left in the assignment into intention to treat. It cannot, therefore, be correlated with any other factor. This implies a conditional independence assumption with respect to the individual's region of work (and birth) and generates a suitable environment to estimate whether regional disparities in the apprenticeship probability exist and to what extent these differentials translate into regional disparities in permanent labour contracts.

Regression model 1 is, therefore, augmented to allow for heterogenous effects across regions:

$$y_{i,t} = \alpha_{1r} + \alpha_1 k_{it} + \beta_0 a_{it} + \gamma_1 d_{it} k_{it} + \gamma_0 d_{it} + \beta_{1r} a_{it} r_{it} + \gamma_{1r} d_{it} k_{it} r_{it} + r_{it} + \epsilon_{i,t} \tag{2}$$

where r_{it} are the regional dummies which corresponds to the individual's region of work.

The parameter γ_{1r} measures the static and instantaneous at the baseline ITT effect which is specific to each region. I extend the analysis to a dynamic setting. The

(Maida & Sonedda, 2019)

[9]Equation 1 refers to the general linear model specification. However, since the analysis is restricted to the range of ±1 year of age around the cutoff, it is not possible to include both the forcing variable (parameterised as deviation from 30) and the indicator function for being under (above) the age threshold.

following regression model takes into account the persistency in outcome generated by the exogenous shock of the reform at the age threshold[10] and allows to retrieve the dynamic ITT parameter:

$$
\begin{aligned}
y_{i,t} = \alpha_{1r} + \alpha_1 k_{it} + \beta_0 a_{it} + \gamma_1 d_{it} k_{it} + \gamma_0 d_{it} + \beta_{1r} a_{it} r_{it} + \gamma_{1r} d_{it} k_{it} r_{it} + \\
+\phi_\tau \Big(\sum_{\tau=1}^{\tilde{\tau}} (\alpha_1 k_{i,t-\tau} + \beta_0 a_{i,t-\tau} + \gamma_\tau^{TOT} d_{i,t-\tau} k_{i,t-\tau} + \gamma_0 d_{i,t-\tau}) + \\
+\phi_\tau \Big(\sum_{\tau=1}^{\tilde{\tau}} (\gamma_\tau^{TOT} d_{i,t-\tau} k_{i,t-\tau} r_{i,t-\tau}) + \epsilon_{i,t}
\end{aligned}
\tag{3}
$$

The above model specification allows for estimating whether the difference in discontinuity impact is heterogenous across Italian regions. However, it does not help clarifying why these differential effects might occur. I attempt at shedding light on the mechanisms which could generate regional disparities in outcomes. I start by investigate whether the impact on the labour outcomes is different for those who were born in the same region where they work compared to the effect on those who migrate. The static regression model is the following:

$$
\begin{aligned}
y_{i,t} = \alpha_{1r} + \alpha_1 k_{it} + \beta_0 a_{it} + \gamma_1 d_{it} k_{it} + \gamma_0 d_{it} + \beta_{1r} a_{it} r_{it} + \gamma_{1r} d_{it} k_{it} r_{it} + r_{it} + \\
+\beta_{1r} a_{it} r_{it} l_{it} + \gamma_{1r} d_{it} k_{it} r_{it} l_{it} + l_{it} + \epsilon_{i,t}
\end{aligned}
\tag{4}
$$

where l_{it} is an indicator function which takes the value 1 if the individual is born in the same region where she works.[11]

I, then, decompose further the effect for those who migrate distinguishing between neighbouring and non-neighbouring regions. The aim is to verify whether similar individuals born in a region rather than another have an advantage in their labour market performances. Still, this evidence clarifies whether there is heterogeneity across Italian regions but it does not explain why. To achieve this goal, I focus on two possible explanations.

First, I consider the role of the characteristics of the production system. The static model described by equation 1 is modified to grant for heterogenous effects which rely on the number of productive firms in a region and on the variance of firms' total revenues in a region:

$$
y_{i,t} = \alpha_{1r} + \alpha_1 k_{it} + \beta_0 a_{it} + \gamma_1 d_{it} k_{it} + \gamma_0 d_{it} + v_{it} + \beta_{1r} a_{it} v_{it} + \gamma_{1r} d_{it} k_{it} v_{it} + \epsilon_{i,t} \tag{5}
$$

where v_{it} are the dummies for the quartiles of the distribution of the regional number of firms with a non-missing record in total revenues or the dummies for the quartile of the distribution of the regional variance in total revenues. That is to say, for instance,

[10] That is to say that I expect that if job entry as apprentice serves as stepping stone into permanent employment, in the months following the baseline, the current permanent employment position depends also on the permanent employment position at the baseline which in turn is related to the impact of the labour market reform around the age cutoff.

[11] To provide a comprehensive view of the issue, I consider also the dynamic version of equation 4 which amounts to equation 3 augmented by the dummy l_{it}.

that the dummy for the second quartile takes the value of 1 if a certain region sits in the second quartile of the distribution of the regional number of productive firms.

Second, I analyse the role of the quality of the regional education system. By the same token, the variable v_{it} refers to the quartiles of the distribution of the regional percentage of those who scored the minimum (maximum) level in the PISA test in math and reading performance.

4. Data

4.1. Description of the data

Data are taken from a very rich administrative dataset by the Ministry of Labour and Social Policies, *CICO* (the so-called *Comunicazioni Obbligatorie*). In a given year, for each cohort of birth, the dataset gathers all individuals who are born on the 1st, the 9th, the 10th and the 11th of each month. It includes, since 2009, detailed information on the flow of all job contracts, activated, transformed and dismissed, for dependent and independent (individuals with VAT number) workers for all sectors including the Agricultural sector and the Public Administration. The relevant dates (day, month, year) of each event are available in the database together with the type of labour contract, the sector, the region of work and an anonymous identifier for both the firm and the worker and the type of benefit associated to the contract, if granted. For each worker, I have information on the gender, the year of birth, the region of birth, citizenship and education.

The working sample is centered in a ± 30 months interval around June 2012 when law no. 92 was issued. This implies that those treated (untreated) by the reform are those who reach a given age between July 2012 to December 2014 (January 2010 to June 2012) ending up with two and half affected and unaffected cohorts. Since there is not precise information on the date of birth of the individual, to minimize measurement error in the definition of age, the latter is measured at the 31st December of the previous year. That is to say, for example, that in 2012 an individual is aged 29 with certainty if she is born in 1982 and she is turning to 30 in an unknown month during that year.

Using the information on the region of work, the database is merged with Bureau Van Dijk (AIDA) data and with data on regional human capital indicators provided by the Italian Statistical Office (ISTAT).[12] Aida contains comprehensive information on all Italian companies required to file their accounts, approximately 1 million companies. I consider companies with a non-missing value on revenues amounting to $919,456$ (2010), $939,488$ (2011), $937,170$ (2012), $940,106$ (2013) and $947,449$ (2014) firms.

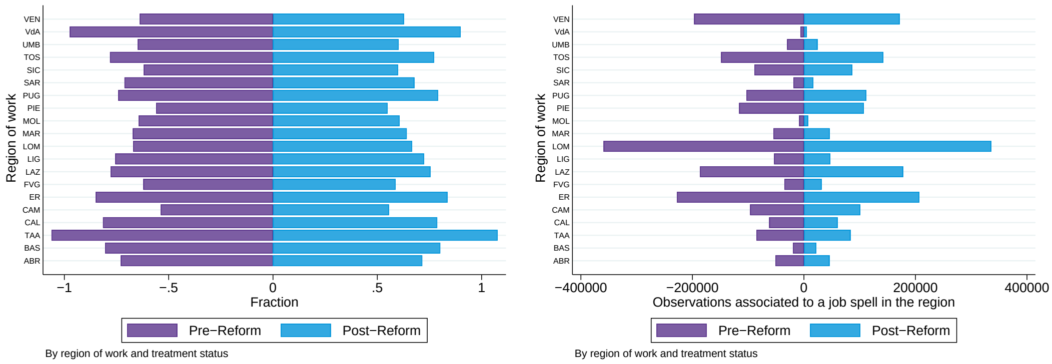
I start from restricting the age interval of ± 5 years around the age threshold. After this selection the sample includes $39,216,787$ observations involving 1,015,069 workers and 693,662 firms. In the same age range, considering only those who started either a job spell or a self-employment activity[13] in a given year, the sample is made of 11,874,149 observations involving 649,525 individuals and 500,514 firms. The preliminary analysis will show that the local linear regression model fits well the data in the age range of ± 1 year around the cutoff. The working sample, therefore, amounts to $2,132,899$ observations gathering 168,542 individuals and 152,225 firms.

[12]ISTAT data are taken from the web site *http://dati-capumano.istat.it/?lang=en*

[13]I have information on self-employment activities by merging CICO data with two datasets recording self-employment and independent jobs episodes in the professional orders.

4.2. Preliminary analysis

In what follows I present suggestive evidence on the absence of strong compositional change of the working sample before and after the labour market reform.



(a) Share.

(b) Distribution of those born abroad.

Figure 1. Regional distribution of the number of individuals in the working sample.

Panel (a) of Figure 1 depicts for each region of work the share of the number of individuals in the working sample over the residential population at a given age.[14] This quota could differ across regions for three reasons. First, because labour market participation is quite heterogeneous. Second, because the age profile in the access to the labour market is not homogenous.[15] Third, if the migration process is not similar. The ratio is higher than 1 in Trentino Alto Adige suggesting that there are workers inflows. It is instead quite low in Campania where there might be outflows of workers. Panel (b) of the Figure considers the migration process from another perspective. It illustrates the region where foreign workers migrate. Foreign workers migrate most to northern and central regions. This is expected since it is a well known stylised fact that the labour market is more dynamic in the northern and central part of Italy. All in all, the Figure shows that pre- and post-reform cohorts are quite balanced out.

Figure B1, reported in the on-line Appendix B1, gives a sense of the importance of the phenomenon of migration of Italian workers across national regions. It displays the regional distribution of workers by region of birth. In all regions, the highest frequency is associated to those working in the same region where they were born. Southern born individuals migrate to the centre-north of Italy while those born in the northern and central regions migrate towards the neighbouring regions. As expected, migration is a larger phenomenon for those born in the South. It is confirmed that pre- and post-reform cohorts are balanced out. This is reassuring and it suggests that the migration process is independent from the labour market reform around the age cutoff. Compared to other empirical strategies, the difference in discontinuity design fits better to pursue the main objective of the paper. I carry out two preliminary tests to validate the empirical model. These tests are reported in the on-line Appendix A1.

First, when implementing the difference in discontinuity design, this study relies on age based cutoff. Following Lee and Card (2008) I use parametric regression to estimate

[14]Data on the residential population are ISTAT census data.

[15]CICO data are representative of the universe of job flows but they do not account for the stock of job episodes. This implies that I cannot observe those who have permanently (without losing the job) entered in the labour market before 2009.

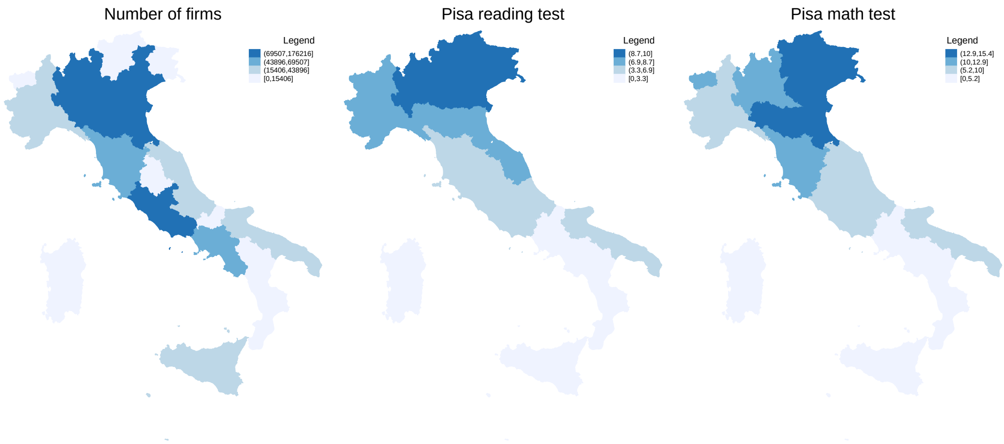
the conditional expectations of the outcome variable (the apprenticeship probability, the employment probability and the permanent employment probability) at the cutoff point comparing treated and untreated cohorts by extrapolation. The discreteness of the assignment variable provides a natural way of testing whether the regression model is well specified by comparing the fitted model to the raw dispersion in mean outcomes at each value of the assignment variable. As suggested by Lee and Card (2008) I present a goodness of fit statistics which tests whether the restricted model (e.g. local linear regressions or polynomial regressions) is statistically identical to the unrestricted model where a full set of dummies (one for each value of the assignment variable, age) is included. Standard errors are clustered by age and year of birth. The lower the value of the test than the critical value, the higher the confidence on the validity of the estimated effect. All the tables, illustrated in the on-line Appendix A1, clearly show that for each region and for each outcome of interest a (local) linear model specification is always supported by the data when the sample is restricted to an age range ± 1 year around the threshold. There is not, instead, an homogeneous data generating process across regions and within region across outcomes when the age range is enlarged. In fact, a second (third or fourth or even higher) order polynomial in age is necessary when the sample is extended to the age range $\pm 2(3)$ years around the cutoff.

Second, I examine whether the observed baseline covariates are locally balanced on either side of the age threshold before and after the introduction of the labour market reform. This should be the case if the treatment is locally randomised. I consider the following observable characteristics: gender, region of birth, education and an indicator for missing information on education, past experience and an indicator for missing information on past experience, an indicator of changing sector with respect to the previous job, an indicator of regional mobility and a bulk of dummy variables capturing the position of the job episode in the age specific distribution of some characteristics, measured in a given month and year, such as the number of multiple job spells; the number of job separations; the number of net job flows (hirings minus separations), the number of job episodes which benefitted of hiring incentives, a reduction of labour costs or social insurance benefits.

For each region of work, I report the Tables which show that, with very few exceptions, in the age range of ± 1 year around the cutoff, differences in discontinuity of the covariates are statistically equal to zero. That is, overall the covariates are balanced out and continuous at the threshold implying that there is not precise control of the assignment variable, the age at which the apprenticeship labour contract is signed.[16]

The discreteness of the age simplifies the problem of the bandwidth choice when graphing the data. In fact, I can simply compute and graph the difference in means between treated and untreated cohorts of the outcome variable for each value of the discrete assignment variable. The graphical analysis is important since it gives a rough sense of the relationship and the shape of this relationship between the assignment variable, the individual's age, and the difference in the outcome variable before and after the labour market reform. It thus indicates what functional form is likely to be supported by the data. In fact, considering the age range of ± 1, the linear regression model fits very well the data since the estimated parameter perfectly matches the raw data. Because of space constraints (I have to plot this relationship for three outcomes in each of the 20 regions of work) these graphs are reported in the on-line Appendix

[16]Worries on precise sorting are related to the age at which job entry as apprentices occurs (if occurs). The same assumption on the other source of random variation is trivially satisfied. In fact, individuals cannot have precise manipulation over their year of birth.



(a) Number of firms. (b) Percentage with high scores (c) Percentage with high scores

Figure 2. Distributions of number of firms and PISA test scores in reading and math.

A1. They reveal the existence of an instantaneous difference in discontinuity positive impact on the apprenticeship probability for the large majority of the Italian regions. The exceptions are Basilicata, Trentino Alto Adige, Molise, Sardegna, Umbria and Valle d'Aosta. These regions, rather than reflecting a North-South divide, have in common the small dimension of their labour markets. The difference in discontinuity detected for the apprenticeship labour contract translates in the majority of the cases into difference in discontinuity for the permanent employment probability. The figures confirm the goodness of fit of the parametric fit of the (local) linear regression in the range of ± 1 year of age around the cutoff. Overall, there is not clear graphical evidence on a difference in discontinuity effect on the employment probability. These figures constitute the bulk of the static empirical analysis which sets the premises for the estimates of the dynamic impact.

The working sample excludes those who have started working or a self-employment activity, in previous year(s) and those who were unable to have a job spell, even of one day, in a given year. This is because the discontinuous age requirement refers to the entrance into apprenticeship. I replicate the previous graphs including also these individuals. Since a crucial assumption of the difference in discontinuity design is the continuity around the threshold of the potential outcome, I expect that the age profile of the apprenticeship labour contract is continuous.[17] In fact, there is no indication of a discontinuity around the age cutoff.

Finally, Figure 2 displays how the number of firms with non-missing values in total revenues distributes over the Italian regions. Different colours refer to different quartiles of the distribution: from the lightest to the darkest blue. The size of the regional markets plays clearly a role with smaller or low density regions sitting in the lowest quartile. From this angle, the north-south divide does not emerge. In contrast, it appears looking at panel (b) and (c) of the same Figure. All the southern part of Italy, including main islands, is below the median value of the distribution of the percentage of students who scored the highest level in math and reading PISA tests.[18] All these preliminary analyses constitute good grounds for the estimation results that follow.

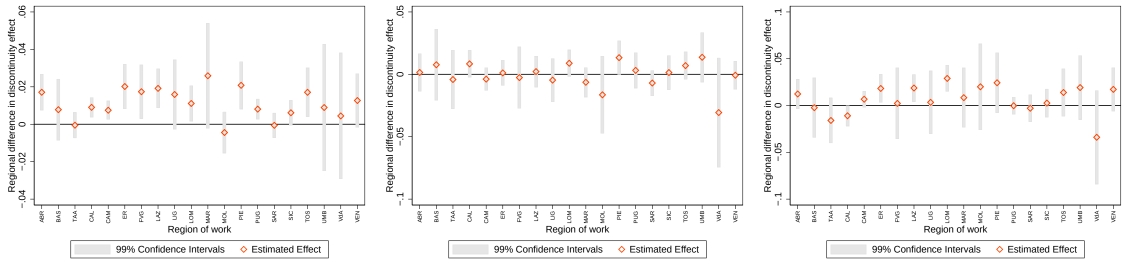
[17]This is because the apprenticeships can last more than one year.

[18]Similar pictures can be provided for the distribution of students who scored the minimum level in the math and reading PISA tests. All southern regions are above the median of the distribution.

5. Estimation results

5.1. Static model accounting for differential impact across regions

The estimated coefficients on the apprenticeship and permanent employment probability match the difference in discontinuity in raw data illustrated in the figures reported in the on-line Appendix A1. In fact, with the exceptions of Basilicata, Trentino Alto Adige, Molise, Sardegna, Umbria and Valle d'Aosta the instantaneous impact is positive and statistically significant at 0.05 level.[19]



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

Figure 3. Difference in discontinuity: differential impact across regions of work

In the on-line Appendix I report for each region a Table whose columns correspond to different model specifications ranging from a regression model where only region of work and region of birth dummies are included (column 1), to regression models which add further baseline characteristics: time fixed effects (month and year dummies in column 2); sector fixed effects (column 3); firm fixed effects (polynomial of degree 1 in the employer identification code in column 4); time invariant characteristics (column 5) and time-varying baseline characteristics (column 6). Time invariant characteristics are the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education and past-experience. Time varying characteristics are a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past-experience is higher than the 75th percentile of the past-experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations, in a given month and year, higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations), in a given month and year, higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode gained from social insurance benefits more than the 25th percentile of the corresponding distribution at a given age in a given month and year.

[19]In Figure 3, I compute the 99% confidence intervals to delimit the shaded area.

The estimated instantaneous impact goes from about 2.6% for Marche to 0.6% for Sicilia.[20] Overall, the estimated coefficients and standard errors[21] are quite stable across all model specifications. There is more heterogeneity across regions on the estimated impact on the permanent employment probability. At the baseline of entrance into the labour market, the permanent employment rates of treated individuals increases from 0.6% (Campania) to about 2 (Lazio and Emilia Romagna) percentage points above the permanent employment rates of similar untreated individuals. In some regions, the positive instantaneous impact on the apprenticeship probability translate to an almost corresponding difference in discontinuity impact on the permanent employment probability. This is the case for Abruzzo, Campania, Emilia Romagna, Lazio, Piemonte and Veneto. However, in other regions, such as Friuli Venezia Giulia, Liguria, Puglia, Sicilia, Toscana, the effect on permanent employment is not statistically different from zero and it is even negative and statistically different from zero at 0.05 level in Calabria. Moreover, it could seem puzzling that the difference in discontinuity impact on permanent employment probability in Lombardia is larger than the estimated effect for the apprenticeship probability. In principle there could be a larger jump at the threshold if the permanent employment rate of those aged 30 and untreated by the labour market reform would be higher than the corresponding rate of similar individuals affected by the reform. However, the graphical analysis clearly shows that this argument is not supported by the data. Legislative decree no 76/2013, issued in June, introduced an incentive to hire on a permanent basis individuals aged less than 30 years. However, age was not the main requirement. Individuals had either to be unemployed in the previous six months or had to have a dependent family member. Resources devoted to finance this hiring incentive were limited and administered by the regional governments. Therefore, the timing and the intensity of the firms' response to this policy intervention vary across regions. Month and year dummies and an indicator function, capturing whether the individual sits above the 25th percentile of the age distribution of recipients of hiring incentives, are not able to disentangle the impact at the age threshold on the cohort affected by both law no 92/2012 and legislative decree no 76/2013 from the difference in discontinuity effect on the cohort affected by law no 92/2012 only. As a matter of fact, the introduction of time fixed effects reduces sampling variability while the estimated coefficient is quite stable across model specification. This is the expected consequence of the randomised variation generated by the 2012 labour market reform at the age cutoff. If the ITT impact on permanent employment is entirely related to this randomised source of variation I do not expect an effect which is statistically different from zero on the employment probability. Legislative decree no 76/2013 introduced a discontinuity at the age threshold not only in the permanent employment probability (through apprenticeships) but also in the employment probability targeting those who were at least 6 months unemployed.[22] Overall, there is not a statistically different from zero impact on the employment probability. The exceptions are Calabria, Lombardia, Piemonte, Toscana and Umbria whose static ITT parameters on the employment probability are positive and, albeit rather small, they are statistically different from zero at 0.1 significance level. The effect is instead

[20] However, for the subset of regions, where the ITT static parameter on the apprenticeship probability is positive and statistically different from zero, the confidence intervals mostly overlap.

[21] Standard errors are clustered at age, year of birth and region of birth level to account for possible autocorrelation in the environment where the individuals were born.

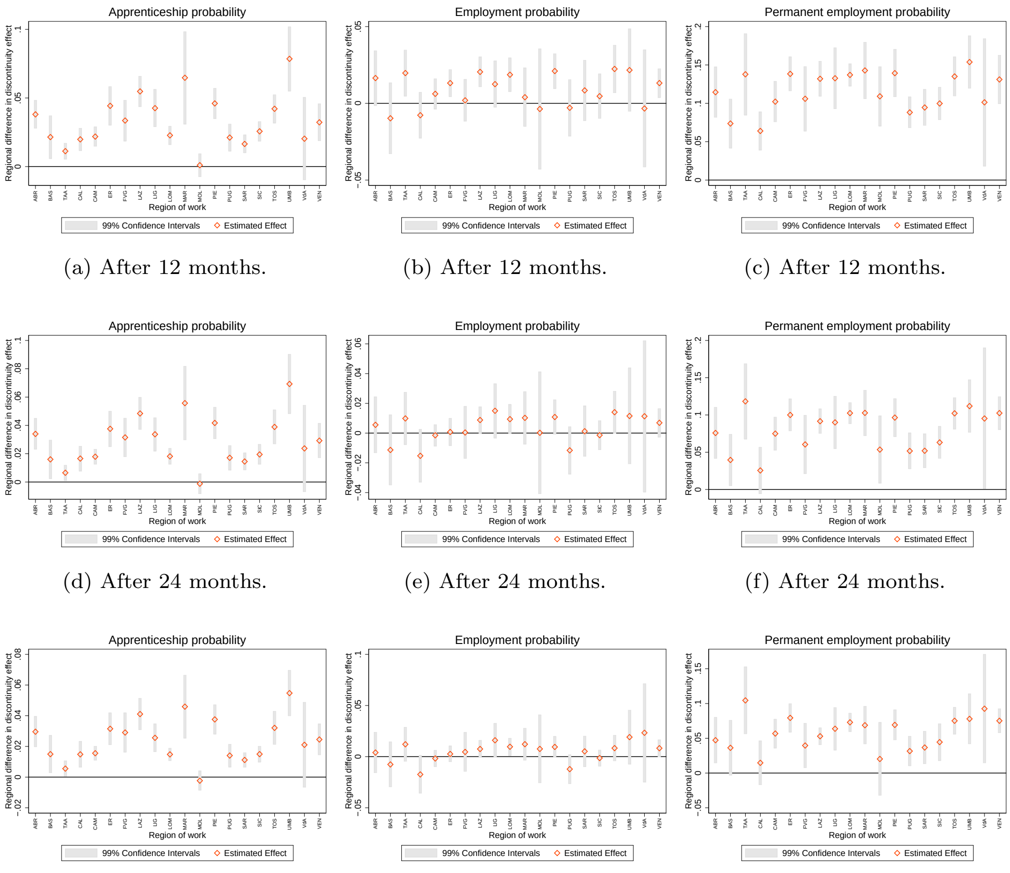
[22] There is, instead, no evidence that this Legislative Decree could have increased, at the age cutoff, the rate of conversions from temporary to permanent contracts. In fact, there are no statistically different from zero effects on the permanent employment probability conditional on staying in the same firm of the previous job spell. These results are available from request from the author.

negative in Sardegna and Valle d'Aosta (at 0.1 significance level).

This evidence suggests that there is considerable heterogeneity across regions on the type of labour contract used to enter in the labour market on a permanent basis. In some regions the apprenticeship labour contract serves as the main port of entry, while in others it seems to play a relevant but not exclusive role. To provide a comprehensive view, it is important to look at the dynamic effects.

5.2. Dynamic model accounting for differential impact across regions

A statistically different from zero medium-run impact can be estimated even in absence of an instantaneous effect. This occurs if the labour market reform has improved the quality of the apprenticeship labour contract. In fact, law no 92/2012 has strengthened the commitment of the contract on the training provided.



(a) After 12 months. (b) After 12 months. (c) After 12 months.

(d) After 24 months. (e) After 24 months. (f) After 24 months.

(g) After 30 months. (h) After 30 months. (i) After 30 months.

Figure 4. Difference in discontinuity: differential impact across regions of work over time

To underline and discuss the main results, I will focus on the ITT parameters after 12, 24 and 30 months from the baseline on the apprenticeship probability, on the employment probability and on the permanent employment probability.[23]

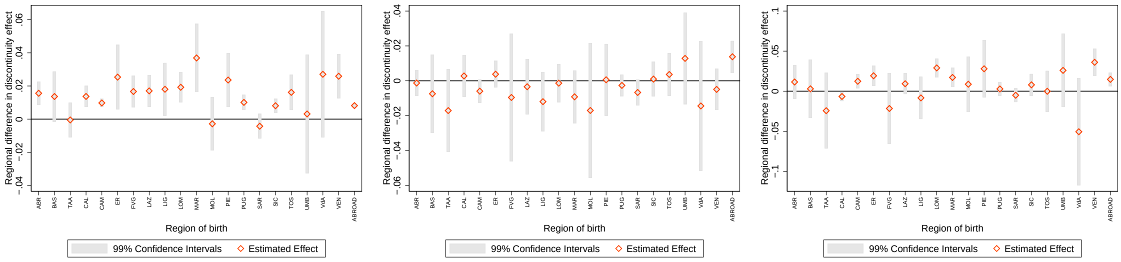
[23]It is worth estimating the dynamic model also for the apprenticeship rate since the maximum length of the contract is 3 years. This length could be extended by collective agreements.

Figure 4 shows that Molise is the only region where a positive difference in discontinuity impact on the apprenticeship probability is never estimated. In all the other regions, over time, the apprenticeship probability of those treated by the labour market reform at the age cutoff, is higher than the same probability of similar untreated individuals. The existence of a tax rebate for apprenticeships can not explain these medium-run positive effects. In fact, the tax rebate was also present before the labour market reform. Yet, these findings could possibly indicate that the commitment to providing vocational training and general education has increased. Consequently, the human capital component of the apprenticeship labour contract has risen leading to a moderate medium-run impact on the permanent employment probability. In fact, with the exception of Calabria and Molise, the medium run ITT parameters on the permanent employment of all the other regions after 12, 24 and 30 months from the baseline is positive and statically different from zero. In contrast, overall there is no medium-run effect on the employment probability. After 30 months from the baseline, the permanent employment probability of those treated at the age cutoff, increased from about 11% in Trentino Alto Adige to 3.2% in Puglia, compared to the same probability for similar untreated individuals. Evidence from Trentino Alto Adige seems to indicate that the labour market reform could have affected not only the quantity but also the quality of the human capital component of the apprenticeship labour contract. In fact, any statistically different from zero effect on permanent employment probability is detected at the baseline, while the medium-run impact is much larger than the same impact in other regions (e.g. it is about 7.3% in Lombardia).

All in all, these findings support the view that a labour contract which invests in human capital serves as a stepping stone into permanent employment. However, the impact is quite heterogenous across regions. In the medium-run, the North-South divide clearly emerges with southern regions experiencing much lower permanent employment gains over time. To better interpret these results I move in two directions. First, I will compare heterogeneity in the ITT parameters across regions of work to heterogeneity in these coefficients across regions of birth. This is not because the migration decision is related to the labour market reform evaluated at the age cutoff. Yet, the region of birth in the majority of cases constitutes the environment where the individual grew up and was educated. If there are complementarities between former education at school and vocational training, some regions could experience larger permanent employment gains than others. On the top of that, the region of birth is the main local labour market where the individual searches for job opportunities. Second, I study whether the quantity of apprentices in a given region may depend on the regional production system.

5.3. Does the environment where the individual was born matter?

I now replicate the previous analysis verifying whether there are differential impact across regions of birth rather than regions of work. Trentino Alto Adige, Molise and Sardegna are the only regions where the instantaneous ITT parameter is not statistically different from zero. In contrast, for Calabria, Campania, Emilia Romagna, Liguria, Piemonte, Puglia and Sicilia the static impact on the apprenticeship rate is slightly higher than the corresponding effect estimated for those who are working in these regions. This positive gain is, instead, moderate for Basilicata, Lombardia, Marche, Valle d'Aosta and Veneto. The 21th region of birth gathers all foreign workers. For them, the static ITT impact is positive and statically different from zero. However,



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

Figure 5. Difference in discontinuity: differential impact across regions of birth

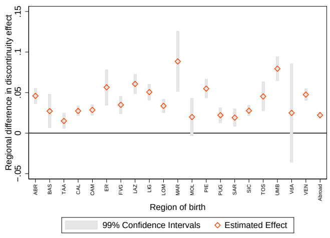
it is smaller when compared to the corresponding impact for individuals born in all the other regions. The previous analysis has pointed to the importance of heterogenous static ITT parameters across the regions of work. To what extent a static positive impact on the apprenticeship rate translates into an effect on the permanent employment probability depends also on the region where migrants work.[24] I do not expect, consequently, that the impact on the permanent employment probability matches the effect on the apprenticeship rate. Figure 5 illustrates that the static ITT parameter on the permanent employment probability is positive and statistically different from zero for Campania, Emilia Romagna, Lazio, Lombardia, Marche, Piemonte, Veneto and for those born abroad. Overall there is no effect on the employment probability with the exception of foreign workers who could possibly be the recipients of the hiring incentive fixed by legislative decree no 76/2013.

Figure 6 presents the dynamic ITT parameters on the outcomes of interest after 12, 24 and 30 months from the baseline allowing for heterogenous effects across regions of birth. The Figure confirms the picture presented in the previous paragraph.

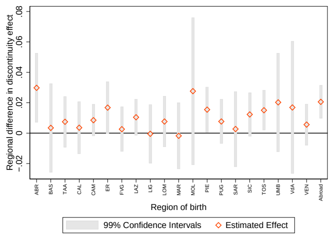
With the only exception of Molise, individuals treated by the labour market reform at the age cutoff increased their permanent employment rate compared to untreated individuals. While there are no significant effects for those working in Molise, the difference in discontinuity impact on the apprenticeship probability for those who were born there, is positive and statistically different from zero after 12, 24 and 30 months. However, the corresponding positive gain in terms of permanent employment vanishes out after 24 months. At 30 months from the baseline, those born in Trentino Alto Adige benefit of the highest impact on the permanent employment rate (about 12.7%) followed by Emilia Romagna, Veneto, Umbria, Piemonte and Toscana (around 8%). The difference in discontinuity medium-run impact for those born in Sardegna and Puglia is in the same order of magnitude of the corresponding impact for those working in these regions. Those who were born in Abruzzo, Trentino Alto Adige, Campania, Friuli Venezia Giulia and Sicilia (Liguria) and treated by the labour market reform at the age threshold increased their permanent employment probability more (less) than 1% compared to the corresponding impact on those working in these regions. Finally, workers born in Calabria and Basilicata gain more if they migrate but less than 1% compared to those who work in these regions.

The current literature on the determinants of a labour contract which increases human capital has mainly emphasised the role of commitment (Dustmann & Schönberg, 2012) to the training and education provision in a framework of asymmetric infor-

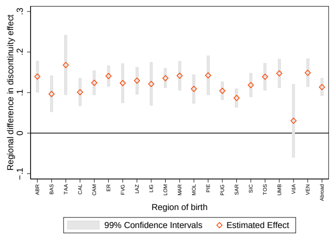
[24]The data do not contain the information on the timing of migration. The balancing-out of covariates, however, suggest that the migration decision is independent from the treatment.



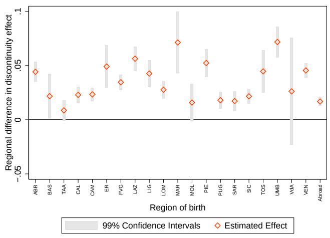
(a) After 12 months.



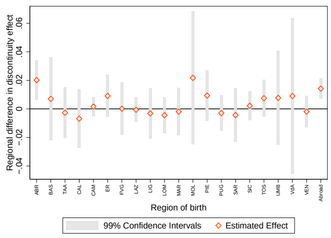
(b) After 12 months.



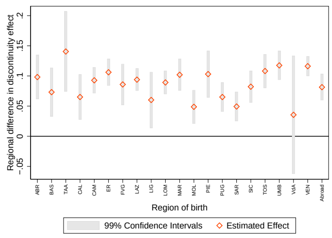
(c) After 12 months.



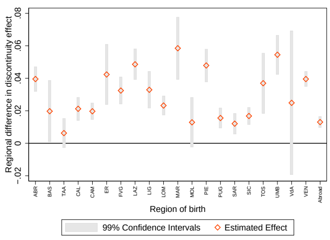
(d) After 24 months.



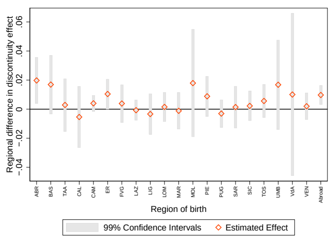
(e) After 24 months.



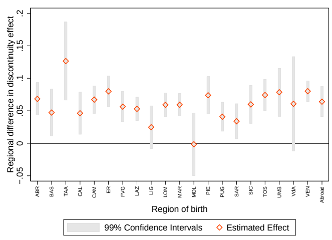
(f) After 24 months.



(g) After 30 months.



(h) After 30 months.



(i) After 30 months.

Figure 6. Difference in discontinuity: differential impact across regions of birth over time

mation (Acemoglu & Pischke, 1998, 1999). In such a setting the commitment to the human capital investment constitutes a necessary requirement. The successfulness of the apprenticeship labour contract to serve as a port of entry into permanent employment could also depend on whether and to what extent the complementarities between the on-the-job human capital accumulation and the individual's competencies and skills are related to the sorting of the individuals and to the screening of the firms in a given job. These sorting-screening processes could be driven by signals which are observable. The general education level, and where it was achieved, stands above all the other signals. If this true, the educational and other observational signals of the migrants could be much weaker than that of the locals because firms are much better informed on the educational and environmental context of the region where they operate.

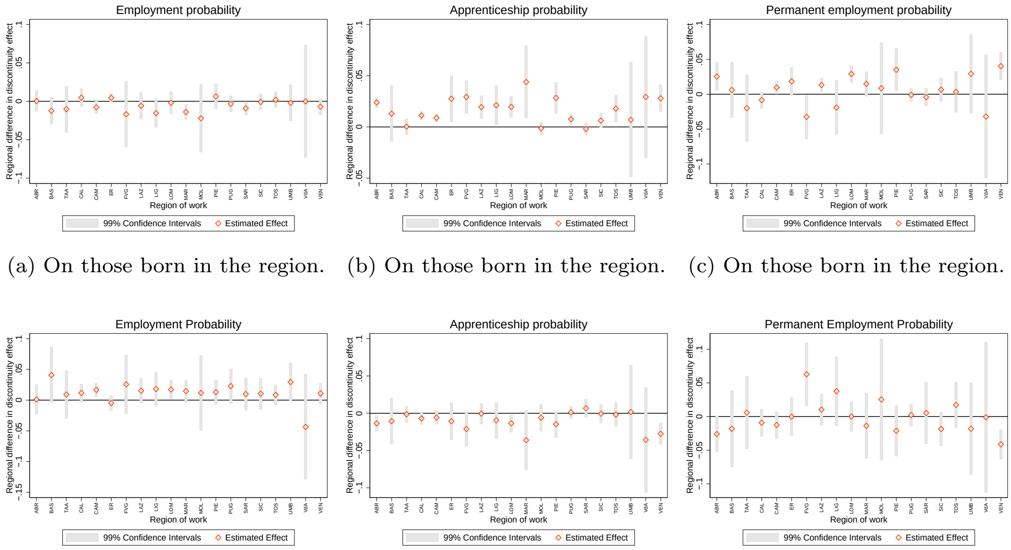
Figure 7 displays the differences in discontinuity on the outcomes of interest allowing for a differential impact across regions conditioning on the migration status. That is, it is verified whether the effect is different for those who were born (and likely grew up) in the region where they work compared to those who were born outside the region. Consistently with previous findings Basilicata, Trentino, Molise, Sardegna, Umbria and Valle d'Aosta are the only regions where the static ITT parameter is not statistically significant from zero neither for those born in the region nor for all the others. In all the other regions at the age cutoff, the apprenticeship probability for regional natives, treated by the labour market reform, increased compared to the apprenticeship rate of untreated individuals. In contrast, the corresponding impact for those who were born outside the region is either statistically identical to zero or negative. These positive effects on the apprenticeship rate translate into a positive effect on the permanent employment probability of the natives in Campania, Emilia Romagna, Lazio, Lombardia, Marche, Piemonte and Veneto. Estimates for Friuli Venezia Giulia seem puzzling. On the one hand, the ITT impact on the apprenticeship rate of those born in the region is positive while it is negative for those born outside. On the other hand, at the age cutoff the permanent employment rate of those born in the (outside) region and treated by the labour market reform is lower (higher) than the permanent employment rate of untreated individuals. Estimates of the ITT impact on the permanent employment probability conditional on staying in the same firm (sector) of the previous job spell are quite similar[25] revealing that the effect on the permanent employment probability is mainly driven by conversions from temporary to permanent labour contracts. Articles 30-33 of the regional law no 18/2005 settled on several incentives to encourage firms to convert temporary into open-ended contracts. The age limit was fixed to 35 years. In principle, a difference in discontinuity impact in the conversion rate might not be observed and estimated. In practise, the data show that this is the case, possibly, as a result of the imperfect balancing-out of the gender dummy.

In the on-line Appendix, I disentangle further the impact at the baseline around the age cutoff for those treated individuals who were not born in the same region where they work, distinguishing between those who were born in a neighbouring region and non-neighbouring regions. There is no statistically different from zero impact neither for those coming from neighbouring regions nor for all the others coming from non-neighbouring regions.[26] A possible explanation is that the labour market reform encouraged the investment-oriented usage of the apprenticeship labour contract reinforcing the commitment to provide vocational training and to maintain the worker on a permanent basis. These conditions are more likely met if the sorting-screening processes of individuals and firms improves. The distance between the region of birth and the region of work does not help improving this process. In fact, this distance, while it surely reduces mobility costs, it unlikely provides an informational advantage on the workers-firms unobservable characteristics.

All in all, this evidence points to the importance of the informational content of the apprenticeship labour contract. The observational signals of those born in the region where the firm operates are stronger. This let the sorting-screening processes of individuals and firms be more successful because asymmetric information are reduced and, possibly, because there could be complementarities between former education and the on-the-job human capital accumulation process. If this is the case, the same individual with the same observable and unobservable characteristics would increase more her productivity in a firm rather than in another. Consequently, disparities across regions emerge because the strength of these complementarities differs across regions. This evidence contributes to provide an explanation on why the same type of contract is more successful to serve as a stepping stone into permanent employment in a region rather than in another. It helps clarifying why Trentino Alto Adige has the highest dynamic ITT impact on the permanent employment. Nevertheless, it does not explain

[25] These results are available from request from the author.

[26] In Veneto, for instance, this latter impact is statistically different from zero but small and negative.



(a) On those born in the region. (b) On those born in the region. (c) On those born in the region.

(d) On those born outside. (e) On those born outside. (f) On those born outside.

Figure 7. Difference in discontinuity: differential impact across natives and those born outside

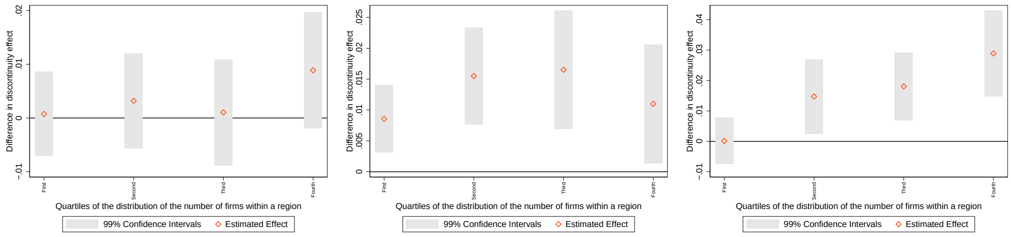
completely why in this region there are not significant effects at the baseline. As a final analysis I consider some characteristics of the regional labour market which could work as a barrier to increase the quantity and the quality of the apprenticeship labour contracts.

5.4. The role of the regional labour market

At first glance, the instantaneous ITT impact on the apprenticeship labour contract is statically not different from zero when the dimension of the regional labour market is limited (Basilicata, Trentino Alto Adige, Molise, Sardegna, Umbria and Valle d'Aosta). The number of productive firms in a region could fix the quantity of the apprenticeship labour contracts by limiting the successfulness of the screening of the firms and the sorting of the workers. In fact, considering the framework presented by Cahuc et al. (2016), the lower the number of productive firms, the lower the expected production opportunities, the higher the number of temporary job contracts which are created to fulfill these production opportunities with short expected durations.

I use the AIDA (Bureau van Dijk) database to determine the number of firms with a non-missing record of total revenues in each region from 2010 to 2014. These amounts are averaged out across time to possibly smooth out excess of variability in the number of non-missing information. I then draw the distribution of the resulting quantities assigning a value equal to 1 to the quartile of the distribution to which the region belongs.

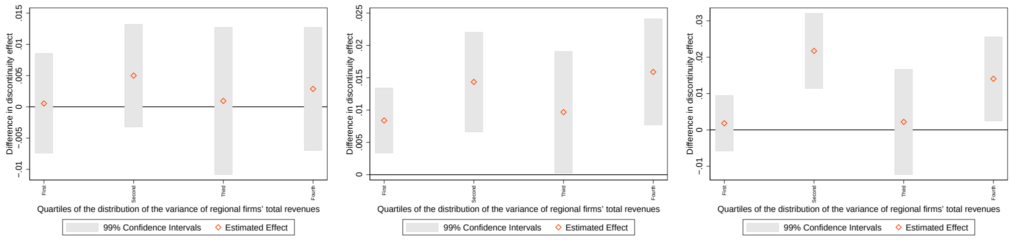
Figure 8 clearly shows that the instantaneous effect on the apprenticeship rate is lower at the lowest quartiles albeit it is not much different from the one estimated at the fourth. However, heterogenous behaviour emerges when looking at the impact on permanent employment. In fact, there are no difference in discontinuity effects on permanent employment for those regions that are characterised by a lower (compared to the other regions) number of productive firms. The dimension of the regional labour



(a) Employment Prob. (b) Apprenticeship Prob. (c) Permanent employment Prob.

Figure 8. Difference in discontinuity: differential impact across the dimension of the regional labour market

market can be a barrier to the quantity of potential successful apprenticeship labour contract. The instantaneous ITT impact on the apprenticeship rate for the second and third quartiles matches the effect on the permanent employment while it is lower for the fourth quartile. This result might be due to Lombardia region.[27] As discussed in subsection 5.1, Lombardia was the only region where the difference between the impact on the permanent employment and the effect on the apprenticeship rate approximates the increase in the employment probability for treated individuals compared to the employment rate of those untreated.[28] Therefore, the dimension of the regional labour market could be one of the reasons that limits the quantity of the apprenticeship labour contract.



(a) Employment Prob. (b) Apprenticeship Prob. (c) Permanent employment Prob.

Figure 9. Difference in discontinuity: differential impact across variance of the regional firms' total revenues

Apprenticeships, rather than other labour contracts, serve as a stepping stone into permanent employment if its human capital component translates into an increase in productivity shared between the firm (higher rents) and the workers (higher future earnings). These shared future returns are conditional to a higher probability of working on a permanent basis in the firm that provided the training. From the employee perspective there are some analogies with a contract that fix a performance related pay component of the (future) earnings. The costs of the vocational training and the general education provided by the contract and the lower initial wage could be compensated by higher future earnings only if the worker's productivity increases. A well-known result of the literature is the negative relationship between uncertainty and performance related pay. The state of the regional market, an exogenous factor of production, and other sources of luck, cause the worker's output to vary even if

[27]Lombardia is the Italian region with the largest number of firms.

[28]This positive impact on the employment probability is due entirely to legislative decree no 76/2013. The graph displays 99% confidence intervals. The ITT static impact on the employment probability at the fourth quartile is statistically different from zero at 0.05 significance level.

she provides effort, (E. Lazear, 1986). Consequently, individuals with the same level of ability and the same degree of risk aversion could find the apprenticeship labour contract less appealing in regions where uncertainty is high. I use AIDA data to calculate the variance (averaged out across time) of the distribution of non-missing total revenues of firms within a region.[29] Total revenues are normalised by the number of firms in the region. I then calculate the quartiles of the distribution of such regional variances and estimate whether the static ITT impact differs across these quartiles. Figure 9 shows that there is not a monotonic relationship between the static estimates of the difference in discontinuity effects and the quartiles of the distribution of variance. This finding is indicating that there could another possible interpretation of the role of a high regional variance of the distribution of firms' total revenues in a region. In fact, a higher variance could also signal the presence of high productive firms, (E. Lazear, 2000). If high uncertainty (high variance) could be detrimental to a human capital investment, a low heterogeneity (low variance) in total revenues could be detrimental as well, if associated to low firms' productivity. The combination of these two counteracting mechanisms could generate the non-monotonic relationship observed in the data. Although the difference in discontinuity impacts on the apprenticeship rates are always precisely estimated and statistically different from zero, these effects are higher at the second and fourth quartiles of the variance distribution. This non-monotonic relationship maps into the effects on permanent employment that are statistically different from zero at the second and fourth quartiles of the variance distribution only.[30] All in all, this evidence suggests that uncertainty could play a role but the screening-sorting processes that let the apprenticeship labour contract be the main port of entry into permanent employment is related to a context where firms' productivity (i.e. firms with long-term expected production opportunities) is not low. Although these long-term expected production opportunities might be considered as a necessary condition, they could not be sufficient to completely explain the regional differences in the dynamic difference in discontinuity impacts.

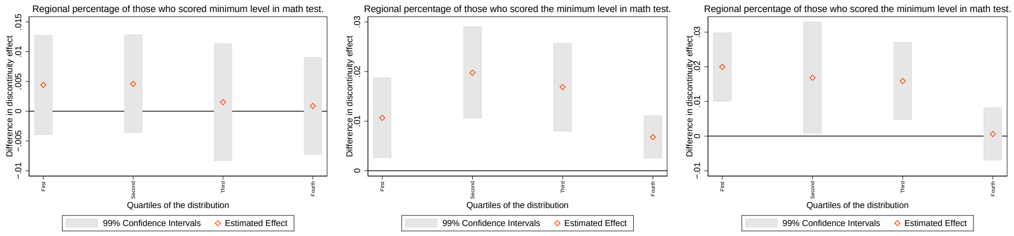
The quality of the regional educational system could potentially be a springboard to permanent employment if there are complementarities between former education, training and labour market experience. These complementarities could reinforce the informational content of the observational signals that individuals can provide. If this the case, the probability that the screening-sorting processes succeed increase. Moreover, in regions, where the quality of the regional education system is higher, these complementarities strengthen the initial advantages leading to a higher permanent employment gain over time. I use ISTAT data on the regional percentage of those, aged 15, who scored the minimum and the maximum level in the PISA test in mathematics and reading. These percentages are then averaged out over time (2006-2015).[31]

The first (second) row of Figure 10 displays the difference in discontinuity effects on the outcomes of interest across quartiles of the distribution of the percentage of those who scored the minimum (maximum) level in the math test. That is, the quality is higher, the lower (higher) the quartile which the region belongs to (i.e. the lower (the

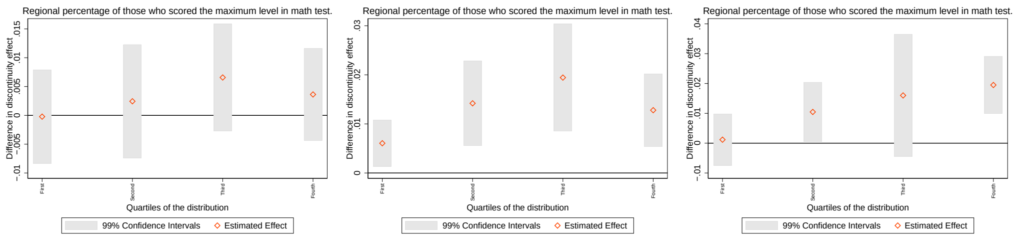
[29] Firms' productivity could be proxied by the firm's per worker value added. However, the number of firms with a non-missing record shrinks too much when alternative measures to the firms' total revenues are used.

[30] The effect on permanent employment at the fourth quartile matches the impact on the apprenticeship probability. It is instead higher at the second quartile. The latter is the only quartile where a positive impact on the employment probability could be observed albeit it is imprecisely estimated since it is statistically different from zero at 0.12 significance level.

[31] Even though students involved in these tests are younger than those considered in my analysis, this might not be an issue. In fact, what is relevant to the analysis that will follow is the regional ranking (quartiles of the distribution of the average regional score) that is quite stable over time.



(a) Employment Prob. (b) Apprenticeship Prob. (c) Permanent employment Prob.

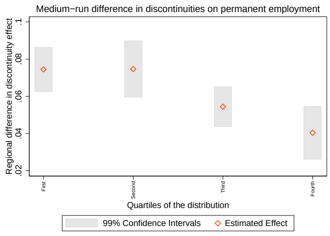


(d) Employment Prob. (e) Apprenticeship Prob. (f) Permanent employment Prob.

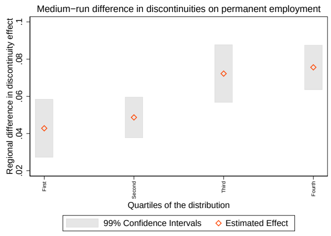
Figure 10. Difference in discontinuity: differential impact across regional level of math PISA test scores

higher) the percentage is). Clearly, the lowest quality is associated to the smallest ITT impact on the apprenticeship rate. Moreover, the permanent employment probability at the age cutoff of treated individuals compared to the permanent employment rate of those untreated are not statistically different when the regional quality of the education system is low. Similar results, reported in the on-line Appendix, can be found when I use the score in the reading performance test. This evidence suggests that it is more likely that the apprenticeship labour contract serves as a stepping stone into permanent employment in a context where the quality of the former education system is not too low. Differences in the impact across quartiles of the distribution of the regional percentage of those who scored the minimum (maximum) level in the math and reading performance amplify over time. After 30 months from the baseline, the positive dynamic ITT impact associated to the regions with the lowest educational performance is equal to 4% and it doubles to about 8% for the regions with the highest educational achievements. The size of this differential is consistent across the four indicators of performance used. That is the North-South divide on the impacts on permanent employment discussed in subsection 5.2 can be mapped to the clear North-South strong divide in schooling performances. For instance regions that have the highest (lowest) percentage of students who just scored the minimum level in the math test are: Basilicata, Calabria, Campania, Puglia, Sardegna and Sicilia (Trentino Alto Adige, Friuli Venezia Giulia, Lombardia and Veneto). This North-South divide dualised further the Italian dual labour market.

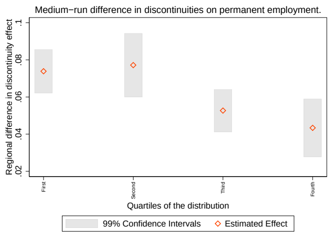
When complementarities between former education and further human capital accumulation are strong, the medium-run gain in terms of permanent employment can be moderate. This holds true even if the quantity of the potential successful matches is limited by a fixed number of productive firms, as the estimates for Trentino suggests. When the quality of the education system is low, the capacity of the apprenticeship labour contract to serve as a stepping stone into permanent employment is limited.



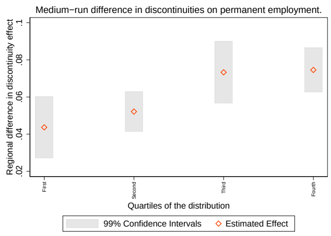
(a) Minimum level math.



(b) Maximum level math.



(c) Minimum level reading.



(d) Maximum level reading.

Figure 11. Dynamic difference in discontinuity: differential impact across regional level of PISA test scores

6. Conclusions

This paper investigates under which circumstances a labour contract, committed to the provision of human capital investment, succeeds in creating a job match that persists over time. I analyse the role of the quality of the regional general education and production systems. I exploit the conditional independent assumption between the location of work and the randomised variability introduced by a labour market reform at the age cutoff of 30 years, above which job entry as apprentice is not possible. This setting allows me to design a difference in discontinuity regression model that cannot suffer from endogeneity issues when dealing with heterogeneous effects across regions. I find that the Italian North-South divide in the quality of general education maps into and further amplifies the North-South divide in labour market performances. This is possibly because of the existence of complementarities between former education and on-the-job human capital accumulation. Moreover, the limited number of productive firms in a region is a barrier to the quantity of job entries as apprentices. The rich administrative dataset used for the analysis does not contain information on earnings. For this reason, the paper focuses on (permanent) employment effects only. An evaluation of the impact on earnings would be important to strengthen the interpretation that the apprenticeship labour contract has an advantage over other contracts in creating good quality jobs. This is left to future research.

7. Acknowledgement(s)

I am indebted to Giorgia Casalone and Emanuela Marrocu for very useful comments and discussions. I thank Barbara Dettori for her precious help and useful advice on AIDA data. I also thank Giorgio Pedrazzi and the SuperComputing Applications and Innovation Department, CINECA for providing access to the supercomputer Marconi, ISCRA Class C Project n.EWEiHC and Cristiano Padrin for his excellent technical support. I am fully responsible for any errors.

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Human capital investment and job creation: the role of the education and production systems
(Appendix for Online Publication)

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ARTICLE HISTORY
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Content

This appendix is organised as follows. Section A1 is devoted to illustrating the empirical analysis region by region. For each region, I start from the statistical tests and the descriptive statistics which validate the analysis. The Lagrange Multiplier tests are based on the procedure suggested by Lee and Card (2008) and apply to all the outcomes of interest (apprenticeship probability, employment probability and permanent employment probability). The main descriptive statistics is displayed in the tables which report the test on the balancing out of covariates at the threshold and in the graphs that illustrate the difference in discontinuity on the outcomes. Tables on the static model estimates are then presented.

Section B1 supplies additional Figures to those presented in the main text. Moreover, it draws on Maida and Sonedda (2019) to derive the difference in discontinuity parameter using the potential outcomes framework.

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Appendix A1. Empirical analysis region by region

A1.1. Abruzzo

Table A1. Apprenticeship probability.

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	124.068	252.270	0	40.076	112.854
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		82.124	165.776		9.940	69.618
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	61.608		0.043	14.925
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	50.327		0	2.322
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A2. Employment probability.

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	0.932	2.944	0	1.035	16.279
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.274	0.951		0.291	14.652
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	0.720		0.224	13.422
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.410		0	1.133
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A3. Permanent employment probability.

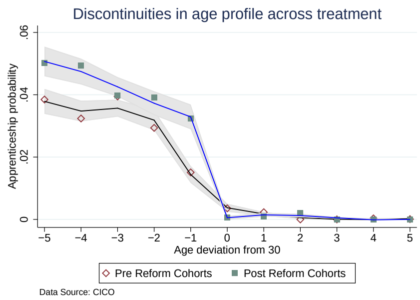
	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	0.756	54.854	0	11.634	65.081
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.356	30.684		11.893	45.231
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	0.957		2.594	22.050
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.137		0	7.733
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

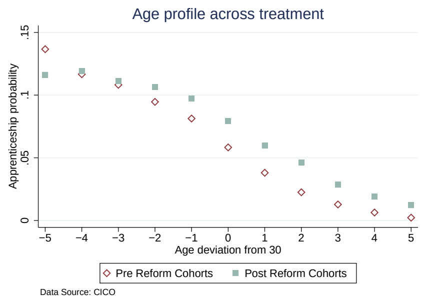
Table A4. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	0.018***	−0.008***	0.018	0.011
	0.004	0.003	0.021	0.023
Region of birth	−1.681***	−0.234	−1.681	−2.908
	0.400	0.282	3.354	3.169
Education	0.194	−0.786***	0.194	−0.367
	0.204	0.143	1.418	1.212
Missing education	−0.016***	0.005**	−0.016	0.006
	0.004	0.003	0.021	0.021
Past experience	−133.832***	−209.598***	−133.832	−119.361
	5.842	4.135	101.198	94.884
Missing past exp.	0.030***	0.011***	0.030	0.011
	0.004	0.003	0.054	0.054
Region of work	0	0	0	0
	0	0	0	0
Changing sector	−0.009***	−0.001	−0.009	−0.000
	0.004	0.003	0.012	0.012
Regional mobility	−0.042***	−0.008**	−0.042	−0.046
	0.004	0.003	0.040	0.037
Higher 25 per. monthly job spells	−0.001	−0.013***	−0.001	−0.005
	0.004	0.003	0.078	0.073
Higher 25 per. monthly sep. flows	−0.005**	0.000	−0.005	−0.007
	0.002	0.002	0.012	0.011
Higher 25 per. monthly net job flows	−0.004	−0.003	−0.004	−0.004
	0.003	0.002	0.015	0.015
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	0.013***	0.005***	0.013	0.011
	0.002	0.001	0.014	0.013
Higher than 25 perc. soc. insurance benefits	−0.002***	0.001*	−0.002	−0.001
	0.001	0.000	0.002	0.002

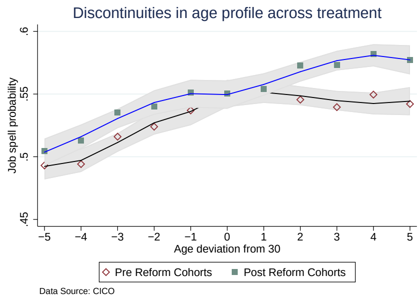
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is $\pm 1(2)$. Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



(a) Apprenticeship Probability.

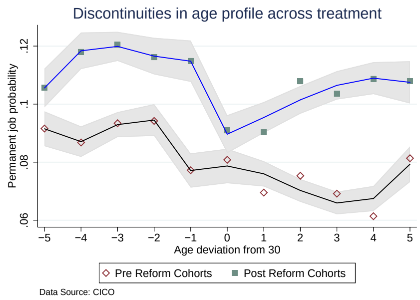


(b) Apprenticeship Probability.

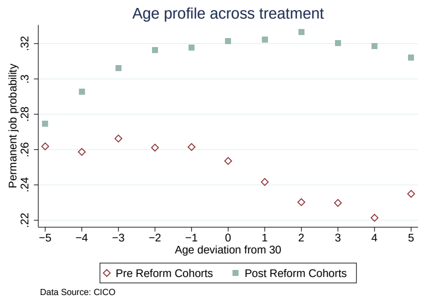


(c) Employment Probability.

(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A1. Difference in discontinuities.

Table A5. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	-.00877	-.00856	-.00874	-.01018	-.01006	.00152
	.03597	.01204	.01217	.01217	.01165	.00592
Apprenticeship prob.	.01677***	.0168***	.01678***	.01682***	.01669***	.01709***
	.00422	.00412	.0039	.00389	.00368	.00377
Perm. Employment prob.	.00928	.00942	.00915	.00877	.00849	.01234**
	.01142	.0078	.00677	.00677	.00683	.00623
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

A1.2. Basilicata

Table A6. Apprenticeship probability.

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	42.468	79.674	0	36.749	65.368
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		27.885	50.415		32.625	46.663
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	21.550		0.468	33.634
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	17.609		0	29.860
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A7. Employment probability.

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	0.696	4.949	0	10.659	38.466
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.587	1.265		11.095	27.892
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	0.539		0.010	23.072
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.406		0	21.412
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A8. Permanent employment probability.

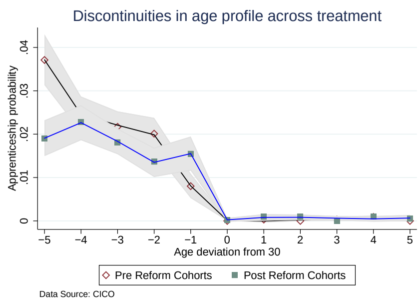
	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	2.696	12.022	0	34.607	53.944
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		1.614	8.612		30.164	47.809
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	8.167		6.133	43.654
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	2.131		0	36.345
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

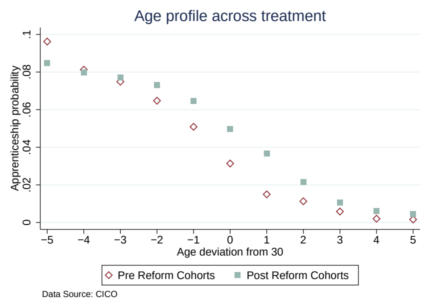
Table A9. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	0.041***	0.006	0.041	0.025
	0.006	0.004	0.029	0.031
Region of birth	2.689***	1.963***	2.689	1.045
	0.544	0.384	3.047	2.949
Education	0.202	−0.113	0.202	0.386
	0.274	0.194	1.146	0.943
Missing education	−0.016***	0.006	−0.016	−0.011
	0.006	0.004	0.026	0.021
Past experience	−138.036***	−221.749***	−138.036	−93.856
	7.633	5.339	116.198	102.814
Missing past exp.	0.046***	0.044***	0.046	0.042
	0.005	0.004	0.057	0.058
Region of work	0	0	0	0
	0	0	0	0
Changing sector	−0.019***	−0.011***	−0.019	−0.012
	0.005	0.004	0.032	0.026
Regional mobility	−0.017***	0.001	−0.017	−0.022
	0.006	0.004	0.029	0.023
Higher 25 per. monthly job spells	0.002	0.017***	0.002	−0.007
	0.006	0.004	0.057	0.055
Higher 25 per. monthly sep. flows	−0.001	−0.005*	−0.001	−0.001
	0.004	0.003	0.015	0.015
Higher 25 per. monthly net job flows	0.004	−0.006**	0.004	0.005
	0.004	0.003	0.021	0.018
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	0.015***	0.007***	0.015	0.009
	0.003	0.002	0.016	0.015
Higher than 25 perc. soc. insurance benefits	0.004***	0.002***	0.004**	0.004**
	0.000	0.000	0.002	0.002

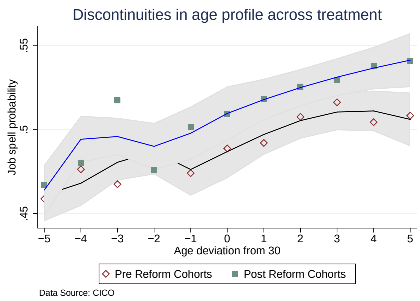
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is $\pm 1(2)$. Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



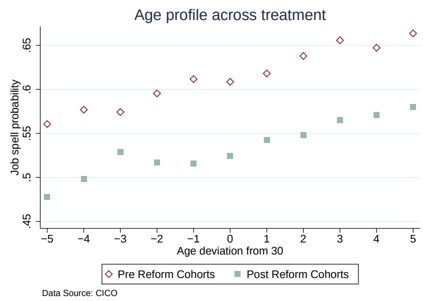
(a) Apprenticeship Probability.



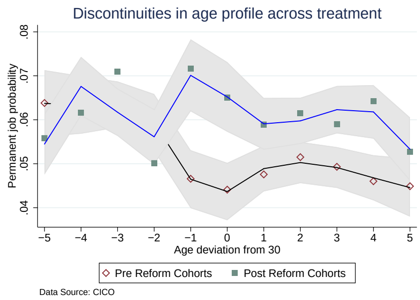
(b) Apprenticeship Probability.



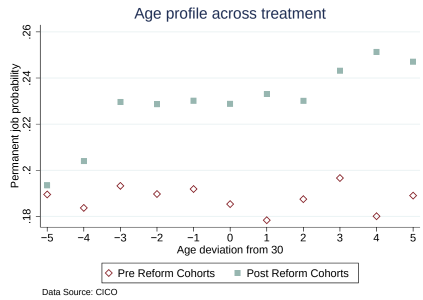
(c) Employment Probability.



(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A2. Difference in discontinuities.

Table A10. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	.00789	.00486	.0026	.0037	.0113	.00766
	.03302	.02099	.02063	.02087	.01974	.01117
Apprenticeship prob.	.0077	.00769	.00749	.00746	.00754	.00778
	.0068	.00674	.00635	.00636	.00626	.00641
Perm. Employment prob.	.00135	.00066	-.00173	-.00144	-.00061	-.00231
	.01636	.01412	.01326	.0132	.01317	.0125
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

A1.3. Trentino Alto Adige

Table A11. Apprenticeship probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	46.737	122.359	0	54.093	271.024
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		7.824	19.355		6.829	105.867
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	10.172		0.002	16.495
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	4.017		0	0.088
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A12. Employment probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	2.036	6.771	0	15.950	32.541
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		2.009	6.454		16.014	30.669
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	3.442		4.393	24.126
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	3.223		0	21.473
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A13. Permanent employment probability.

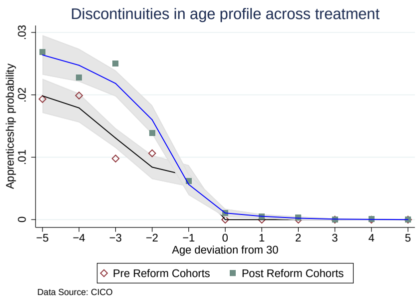
	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	69.550	73.781	0	29.087	75.970
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		44.365	73.759		12.760	75.736
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	73.750		8.003	47.407
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	47.389		0	18.491
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

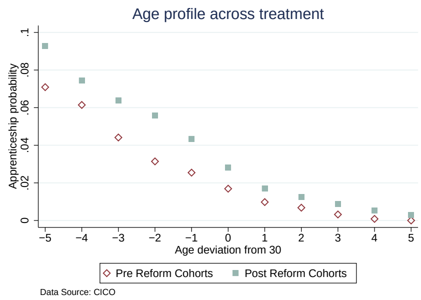
Table A14. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	−0.027***	−0.025***	−0.027	−0.016
	0.004	0.003	0.022	0.024
Region of birth	1.619***	3.100***	1.619	1.021
	0.377	0.265	2.208	2.325
Education	−0.943***	−1.132***	−0.943	−0.802
	0.201	0.141	1.182	1.295
Missing education	0.012***	0.019***	0.012	0.003
	0.004	0.003	0.022	0.025
Past experience	−93.083***	−206.196***	−93.083	−64.729
	6.127	4.286	109.357	115.170
Missing past exp.	0.005	0.019***	0.005	−0.005
	0.004	0.002	0.020	0.022
Region of work	0.127**	0.467***	0.127	0.176
	0.063	0.044	0.319	0.335
Changing sector	0.006*	0.003	0.006	0.008
	0.003	0.002	0.011	0.010
Regional mobility	0.008**	0.015***	0.008	0.003
	0.004	0.003	0.021	0.021
Higher 25 per. monthly job spells	−0.012***	0.014***	−0.012	−0.007
	0.004	0.003	0.074	0.072
Higher 25 per. monthly sep. flows	−0.001	0.000	−0.001	0.001
	0.002	0.002	0.016	0.015
Higher 25 per. monthly net job flows	−0.002	−0.005**	−0.002	−0.003
	0.003	0.002	0.006	0.005
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	−0.000	0.000	−0.000	−0.001
	0.000	0.000	0.001	0.001
Higher than 25 perc. soc. insurance benefits	0.001	0.001**	0.001	0.001
	0.000	0.000	0.003	0.003

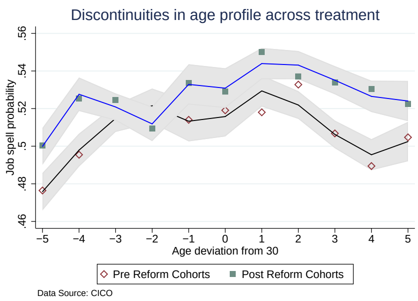
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is $\pm 1(2)$. Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



(a) Apprenticeship Probability.

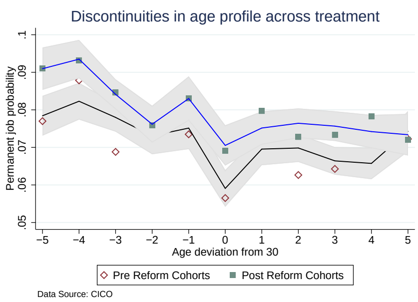


(b) Apprenticeship Probability.

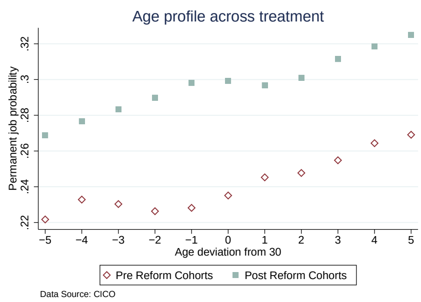


(c) Employment Probability.

(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A3. Difference in discontinuities.

Table A15. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	-.00283	.00077	.00162	.00162	.0052	-.00415
	.03469	.02027	.02039	.01968	.01879	.00921
Apprenticeship prob.	-.00016	-.00018	-.00024	-.00024	-.00027	-.0005
	.00242	.00262	.00266	.00265	.00265	.0027
Perm. Employment prob.	-.01595	-.01561	-.01465	-.01465	-.01686*	-.01593*
	.01049	.01138	.01018	.01014	.00998	.00946
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

A1.4. Calabria

Table A16. Apprenticeship probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	125.592	306.531	0	118.915	241.789
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		22.152	89.845		5.252	40.248
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	38.868		0.058	33.685
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	9.499		0	4.777
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A17. Employment probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	2.291	3.575	0	15.208	20.784
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.228	2.516		12.240	21.146
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	1.863		8.850	18.339
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.402		0	16.752
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A18. Permanent employment probability.

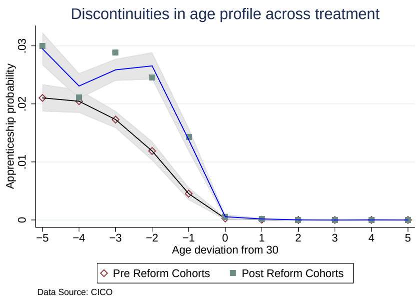
	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	3.253	39.853	0	17.381	67.796
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.782	6.644		12.379	30.270
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	1.734		1.301	14.367
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	1.714		0	8.198
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

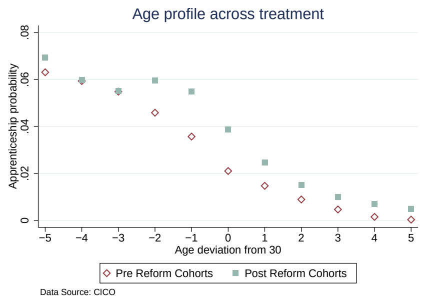
Table A19. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	−0.010***	−0.010***	−0.010	−0.015
	0.003	0.002	0.015	0.015
Region of birth	−0.998***	−1.734***	−0.998	−0.955
	0.268	0.190	1.425	1.063
Education	−0.402***	−0.310***	−0.402	−0.539
	0.142	0.100	0.606	0.521
Missing education	0.011***	0.018***	0.011	0.006
	0.003	0.002	0.011	0.010
Past experience	−81.350***	−144.379***	−81.350	−68.274
	3.304	2.305	89.716	84.300
Missing past exp.	0.001	0.011***	0.001	−0.006
	0.003	0.002	0.048	0.041
Region of work	0	0	0	0
	0	0	0	0
Changing sector	0.012***	0.003*	0.012	0.005
	0.002	0.002	0.017	0.019
Regional mobility	−0.011***	−0.017***	−0.011	−0.012
	0.003	0.002	0.016	0.012
Higher 25 per. monthly job spells	−0.006*	−0.012***	−0.006	0.000
	0.003	0.002	0.084	0.080
Higher 25 per. monthly sep. flows	−0.004**	−0.003*	−0.004	−0.003
	0.002	0.001	0.017	0.017
Higher 25 per. monthly net job flows	−0.003	−0.003*	−0.003	−0.002
	0.002	0.002	0.008	0.008
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	−0.004***	−0.003***	−0.004	−0.011
	0.001	0.001	0.020	0.020
Higher than 25 perc. soc. insurance benefits	−0.001***	−0.000***	−0.001	−0.001
	0.000	0.000	0.000	0.001

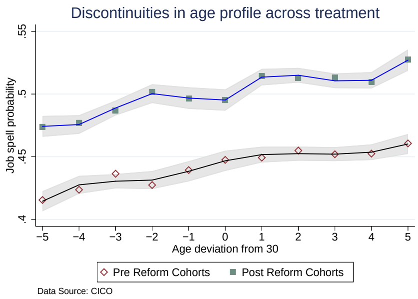
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is ±1(2). Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



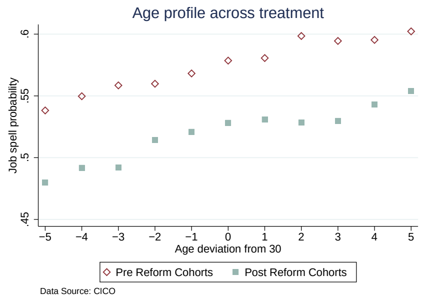
(a) Apprenticeship Probability.



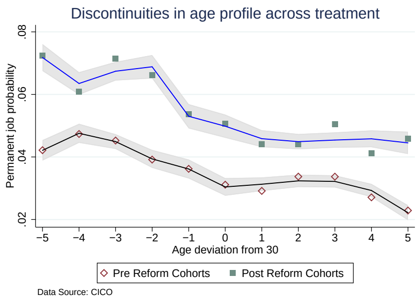
(b) Apprenticeship Probability.



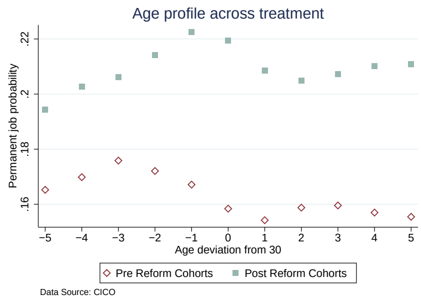
(c) Employment Probability.



(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A4. Difference in discontinuities.

Table A20. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	.03558	.0325*	.03319*	.03297*	.03421**	.00839**
	.04723	.01699	.01722	.01735	.01623	.00426
Apprenticeship prob.	.00989***	.00988***	.00972***	.00973***	.00953***	.00904***
	.00246	.00229	.00218	.00217	.00217	.00207
Perm. Employment prob.	-.00795	-.00851	-.00801	-.00806	-.00878	-.01095**
	.00707	.0061	.00561	.00573	.00558	.0043
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

A1.5. Campania

Table A21. Apprenticeship probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	315.794	645.748	0	235.961	350.340
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		109.725	368.321		12.395	139.117
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	148.543		0.675	114.207
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	55.826		0	15.818
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A22. Employment probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	6.550	15.341	0	12.862	36.755
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		2.574	4.652		7.650	26.144
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	4.446		7.670	24.783
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	2.563		0	6.272
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A23. Permanent employment probability.

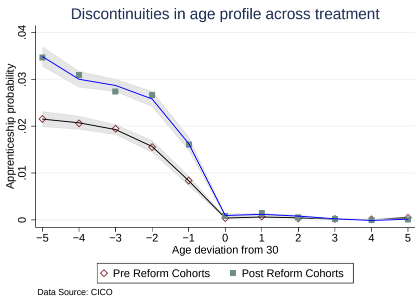
	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	16.418	35.824	0	32.007	65.857
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.008	12.282		10.454	34.960
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		−0.001	10.150		10.051	24.008
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		−0.001	0.114		0.001	9.105
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

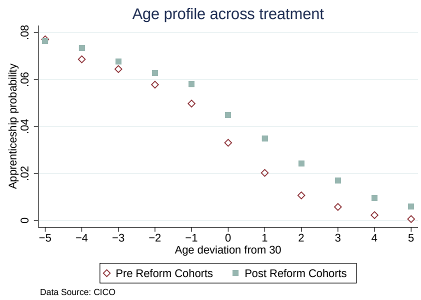
Table A24. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	−0.001	0.006***	−0.001	−0.002
	0.002	0.002	0.012	0.012
Region of birth	−0.135	0.041	−0.135	−0.536
	0.174	0.123	0.667	0.711
Education	−1.195***	−1.423***	−1.195	−1.102
	0.098	0.070	0.864	0.935
Missing education	0.004**	0.009***	0.004	0.001
	0.002	0.001	0.009	0.009
Past experience	−86.581***	−182.968***	−86.581	−72.788
	2.853	1.986	88.277	87.371
Missing past exp.	−0.011***	0.012***	−0.011	−0.016
	0.002	0.002	0.038	0.034
Region of work	0	0	0	0
	0	0	0	0
Changing sector	0.015***	0.009***	0.015	0.013
	0.002	0.001	0.014	0.014
Regional mobility	−0.003	0.004***	−0.003	−0.009
	0.002	0.001	0.008	0.009
Higher 25 per. monthly job spells	−0.003	0.004**	−0.003	−0.001
	0.002	0.002	0.072	0.068
Higher 25 per. monthly sep. flows	0.005***	0.002**	0.005	0.005
	0.001	0.001	0.011	0.011
Higher 25 per. monthly net job flows	0.003*	0.001	0.003	0.004
	0.002	0.001	0.014	0.014
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	0.004***	0.008***	0.004	0.005
	0.001	0.001	0.016	0.015
Higher than 25 perc. soc. insurance benefits	0.001***	0	0.001	0.001
	0.000	0.000	0.001	0.001

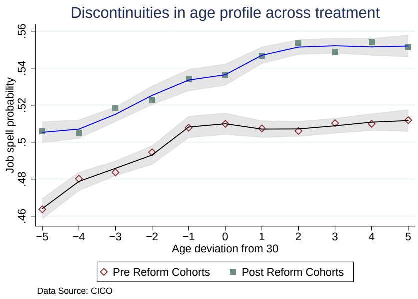
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is ±1(2). Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



(a) Apprenticeship Probability.

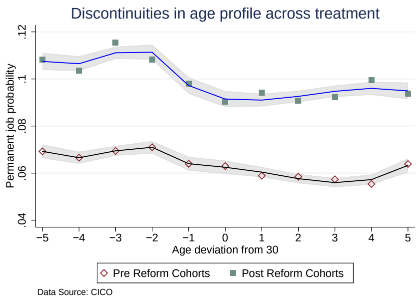


(b) Apprenticeship Probability.

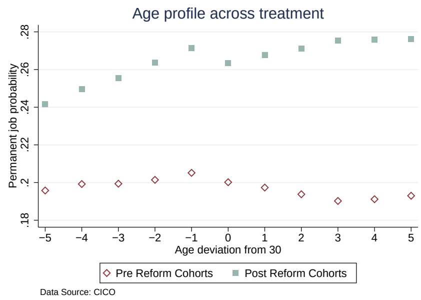


(c) Employment Probability.

(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A5. Difference in discontinuities.

Table A25. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	.00522	.00164	.00206	.00236	.00103	-.00385
	.04277	.00863	.00818	.00813	.00814	.00358
Apprenticeship prob.	.00773***	.00773***	.00738***	.00737***	.00754***	.00749***
	.00181	.00199	.00193	.00194	.00188	.00194
Perm. Employment prob.	.00863	.00778**	.00555*	.00563*	.00597**	.00674**
	.00712	.00306	.00302	.00302	.003	.00337
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

A1.6. Emilia Romagna

Table A26. Apprenticeship probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	642.993	1452.951	0	334.957	841.046
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		301.572	638.216		4.326	93.410
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	245.816		0.251	80.231
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	170.636		0	2.987
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A27. Employment probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	0.093	5.388	0	31.395	56.592
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		-0.010	4.070		30.710	55.688
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	0.101		0.546	43.811
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.112		0	28.526
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A28. Permanent employment probability.

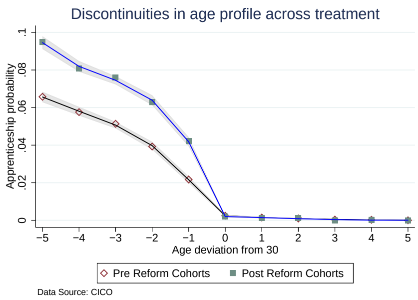
	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	35.868	154.841	0	39.497	111.039
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		3.430	70.617		2.544	41.716
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	13.074		0.224	15.910
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.262		0	3.638
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

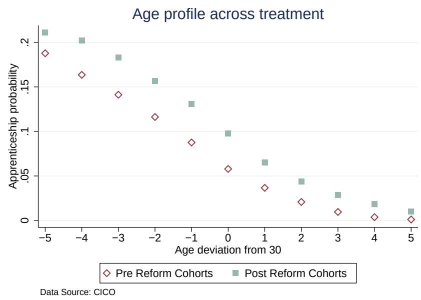
Table A29. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		**Polynomial fit**	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	−0.000	−0.006***	−0.000	−0.007
	0.002	0.002	0.015	0.015
Region of birth	−0.746***	−1.225***	−0.746	−1.645
	0.214	0.151	1.194	1.027
Education	0.025	−0.310***	0.025	−0.239
	0.111	0.078	0.597	0.568
Missing education	0.006***	0.014***	0.006	0.008
	0.002	0.002	0.010	0.009
Past experience	−136.006***	−209.704***	−136.006	−117.840
	3.436	2.380	94.721	94.576
Missing past exp.	0.001	0.007***	0.001	0.006
	0.002	0.001	0.032	0.034
Region of work	0	0	0	0
	0	0	0	0
Changing sector	−0.006***	−0.001	−0.006	−0.013*
	0.002	0.001	0.007	0.007
Regional mobility	−0.012***	−0.025***	−0.012*	−0.017***
	0.002	0.002	0.006	0.006
Higher 25 per. monthly job spells	−0.005*	−0.020***	−0.005	−0.002
	0.002	0.002	0.049	0.048
Higher 25 per. monthly sep. flows	−0.003**	−0.004***	−0.003	−0.003
	0.001	0.001	0.011	0.011
Higher 25 per. monthly net job flows	−0.003**	−0.008***	−0.003	−0.004
	0.002	0.001	0.019	0.018
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	0	0.001***	0	0.000
	0.000	0.000	0.001	0.001
Higher than 25 perc. soc. insurance benefits	−0.001***	−0.001***	−0.001	−0.001
	0.000	0.000	0.001	0.001

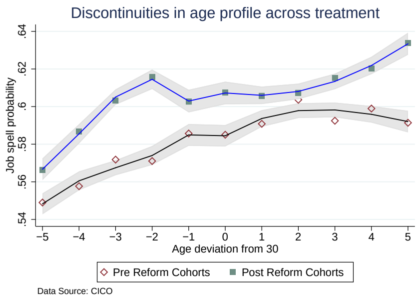
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is ±1(2). Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



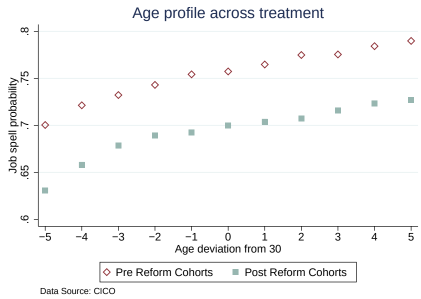
(a) Apprenticeship Probability.



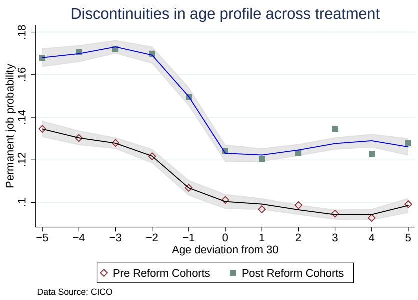
(b) Apprenticeship Probability.



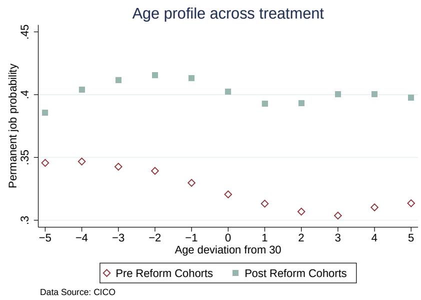
(c) Employment Probability.



(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A6. Difference in discontinuities.

Table A30. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	-.00602	-.00555	-.00599	-.00665	-.00277	.00114
	.02407	.00916	.00909	.00898	.00935	.00398
Apprenticeship prob.	.02021***	.02024***	.02032***	.02034***	.02025***	.02017***
	.00502	.00475	.00479	.00479	.00475	.00468
Perm. Employment prob.	.01589*	.01612***	.01725***	.01707***	.01666***	.01825***
	.00823	.00618	.00618	.00618	.00621	.00588
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

A1.7. Friuli Venezia Giulia

Table A31. Apprenticeship probability.

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	90.090	197.795	0	32.154	115.301
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		54.124	74.363		0.190	5.228
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	37.437		0.013	3.919
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	34.578		0	0.503
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A32. Employment probability.

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	3.530	7.993	0	5.745	13.690
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.803	7.583		3.516	11.417
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	3.339		0.288	9.334
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.324		0	6.518
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A33. Permanent employment probability.

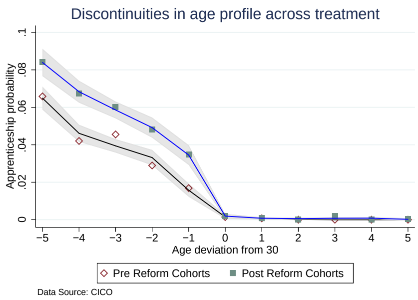
	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	23.290	45.785	0	43.138	92.749
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		5.310	31.733		15.657	82.790
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	26.333		12.965	64.952
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	8.072		0	18.100
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

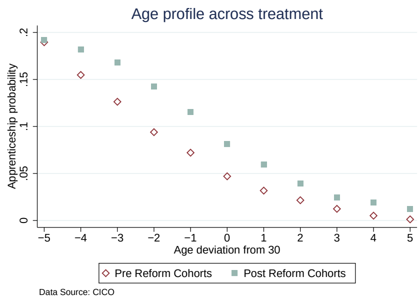
Table A34. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		**Polynomial fit**	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	-0.028^{***}	-0.012^{***}	-0.028^{*}	-0.027^{*}
	0.006	0.004	0.014	0.015
Region of birth	-3.768^{***}	-3.325^{***}	-3.768	-4.867
	0.476	0.335	3.051	3.264
Education	2.479^{***}	2.367^{***}	2.479	2.896^{*}
	0.267	0.188	1.529	1.584
Missing education	-0.030^{***}	-0.038^{***}	-0.030	-0.039
	0.004	0.003	0.024	0.025
Past experience	-116.467^{***}	-268.193^{***}	-116.467	-137.444
	8.196	5.814	106.386	109.115
Missing past exp.	-0.010^{**}	0.024^{***}	-0.010	-0.005
	0.005	0.003	0.042	0.048
Region of work	0	0	0	0
	0	0	0	0
Changing sector	-0.025^{***}	-0.023^{***}	-0.025	-0.014
	0.005	0.003	0.018	0.020
Regional mobility	-0.025^{***}	-0.023^{***}	-0.025	-0.028
	0.005	0.004	0.032	0.033
Higher 25 per. monthly job spells	-0.008	0.011^{***}	-0.008	-0.007
	0.005	0.004	0.065	0.059
Higher 25 per. monthly sep. flows	-0.000	-0.002	-0.000	0.003
	0.003	0.002	0.009	0.010
Higher 25 per. monthly net job flows	0.004	0.001	0.004	0.005
	0.004	0.003	0.017	0.014
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	-0.001^{**}	-0.001	-0.001	0.002
	0.001	0.000	0.002	0.002
Higher than 25 perc. soc. insurance benefits	0.001	0.001^{**}	0.001	0.000
	0.001	0.001	0.003	0.004

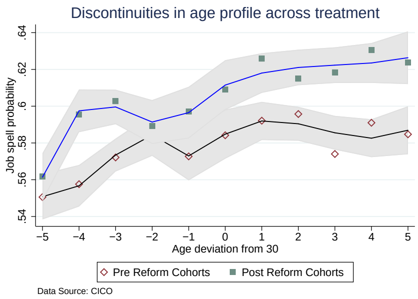
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is $\pm 1(2)$. Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



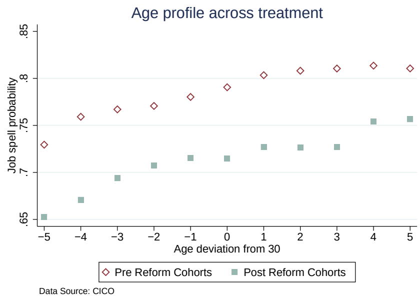
(a) Apprenticeship Probability.



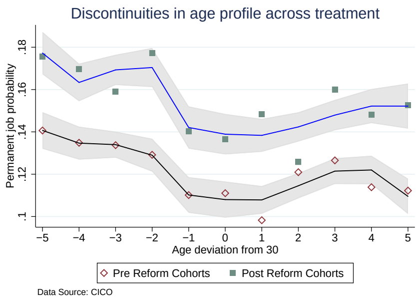
(b) Apprenticeship Probability.



(c) Employment Probability.



(d) Employment Probability.



(e) Permanent Employment Probability.

(f) Permanent Employment Probability.

Figure A7. Difference in discontinuities.

Table A35. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	.00071	.0014	.00175	.00106	-.00002	-.00263
	.03422	.02001	.01979	.02005	.01797	.00966
Apprenticeship prob.	.01757***	.01762***	.0178***	.01782***	.01766***	.01737***
	.00627	.00597	.0057	.0057	.00567	.00564
Perm. Employment prob.	.00225	.00277	.00318	.00299	.00245	.00229
	.01693	.01614	.01666	.01676	.01675	.01484
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

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Table A36. Apprenticeship probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	1039.092	2512.437	0	411.380	707.464
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		646.624	2173.233		17.588	448.833
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	575.686		1.250	261.787
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	341.371		0	11.154
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A37. Employment probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	4.211	20.961	0	6.337	42.013
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		4.017	8.616		5.337	30.239
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	3.379		4.326	30.333
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	2.774		0	7.256
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A38. Permanent employment probability.

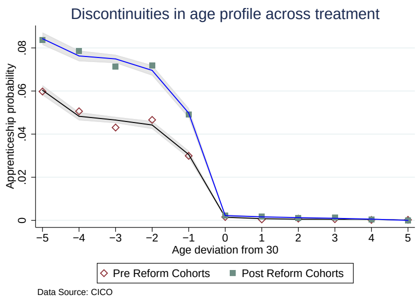
	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	141.929	344.229	0	65.534	112.533
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		76.365	347.882		1.422	110.667
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0.002	112.079		0.489	75.254
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0.002	39.302		0	0.772
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

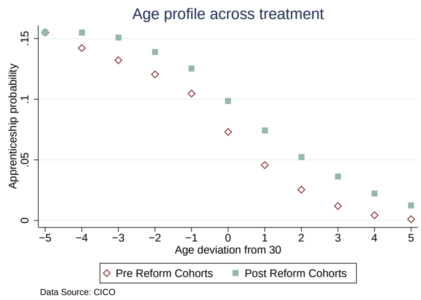
Table A39. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	0.004*	−0.012***	0.004	0.006
	0.002	0.002	0.008	0.007
Region of birth	−1.288***	0.213*	−1.288	−2.163*
	0.172	0.121	1.190	1.113
Education	0.121	−0.480***	0.121	0.280
	0.103	0.072	0.455	0.427
Missing education	−0.003*	−0.001	−0.003	−0.005
	0.002	0.001	0.010	0.010
Past experience	−107.898***	−189.427***	−107.898	−94.096
	2.710	1.870	94.828	89.808
Missing past exp.	0.010***	0.035***	0.010	0.007
	0.002	0.001	0.039	0.036
Region of work	0	0	0	0
	0	0	0	0
Changing sector	−0.017***	−0.011***	−0.017	−0.003
	0.002	0.001	0.013	0.013
Regional mobility	−0.014***	−0.004***	−0.014	−0.018*
	0.002	0.002	0.010	0.010
Higher 25 per. monthly job spells	−0.003	−0.004**	−0.003	−0.004
	0.002	0.002	0.058	0.057
Higher 25 per. monthly sep. flows	−0.003**	−0.003***	−0.003	−0.002
	0.001	0.001	0.006	0.006
Higher 25 per. monthly net job flows	−0.002	−0.005***	−0.002	−0.002
	0.001	0.001	0.017	0.015
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	−0.001*	−0.001***	−0.001	0.001
	0.001	0.000	0.003	0.003
Higher than 25 perc. soc. insurance benefits	0.002***	0.001***	0.002	0.002*
	0.000	0.000	0.001	0.001

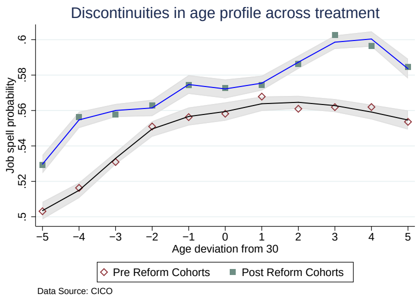
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is $\pm 1(2)$. Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



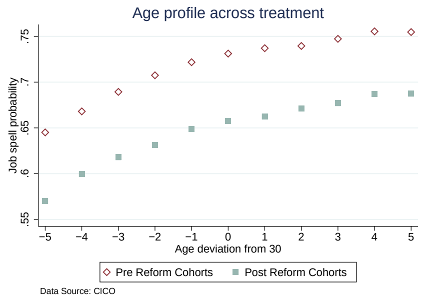
(a) Apprenticeship Probability.



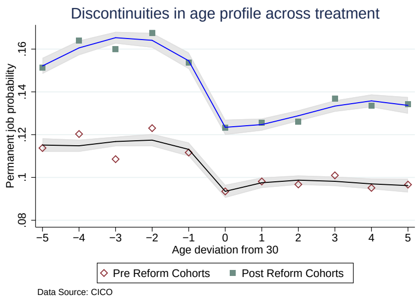
(b) Apprenticeship Probability.



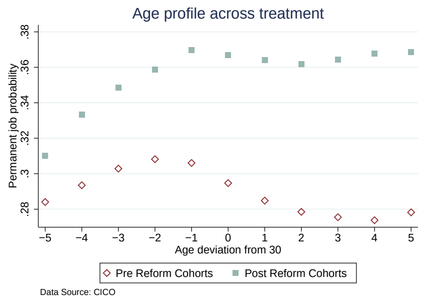
(c) Employment Probability.



(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A8. Difference in discontinuities.

Table A40. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	-.00386	-.00483	-.00539	-.00546	-.00545	.00218
	.03208	.01033	.01005	.00997	.00961	.00488
Apprenticeship prob.	.01921***	.01922***	.01945***	.01945***	.01925***	.01918***
	.00416	.00424	.00412	.00412	.00408	.0041
Perm. Employment prob.	.01595*	.01552**	.01586**	.01584**	.01588**	.01871***
	.00881	.00691	.0065	.00648	.00644	.00573
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

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Table A41. Apprenticeship probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	213.917	468.950	0	116.629	232.592
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		100.620	291.894		1.615	70.279
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	98.887		0.516	54.766
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	54.055		0	0.826
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A42. Employment probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	9.895	19.605	0	13.485	28.332
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.001	19.612		3.242	28.327
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	14.255		2.124	24.469
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.160		0	2.120
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A43. Permanent employment probability.

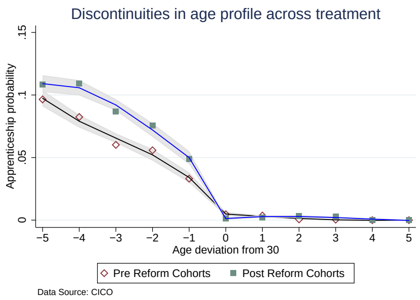
	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	36.772	77.950	0	12.411	38.190
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		25.536	42.026		1.293	6.440
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	20.557		0.325	5.727
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	18.941		0	2.505
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

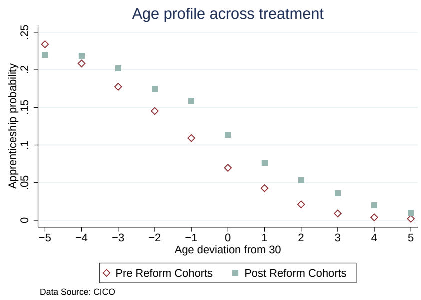
Table A44. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	−0.028***	−0.001	−0.028*	−0.017
	0.005	0.003	0.015	0.018
Region of birth	0.657	−0.957***	0.657	0.332
	0.406	0.285	3.044	2.555
Education	0.564***	0.867***	0.564	0.258
	0.214	0.150	1.170	1.350
Missing education	−0.011***	−0.031***	−0.011	−0.011
	0.004	0.003	0.021	0.024
Past experience	−111.521***	−209.635***	−111.521	−87.946
	6.181	4.269	107.455	102.052
Missing past exp.	−0.025***	0.013***	−0.025	−0.029
	0.004	0.003	0.052	0.043
Region of work	0	0	0	0
	0	0	0	0
Changing sector	0.009**	−0.014***	0.009	0.004
	0.004	0.003	0.017	0.016
Regional mobility	0.006	−0.010***	0.006	−0.006
	0.005	0.003	0.018	0.015
Higher 25 per. monthly job spells	−0.007	−0.002	−0.007	−0.005
	0.005	0.003	0.058	0.053
Higher 25 per. monthly sep. flows	−0.006***	−0.004**	−0.006	−0.006
	0.002	0.002	0.009	0.007
Higher 25 per. monthly net job flows	0.003	−0.001	0.003	0.004
	0.003	0.002	0.019	0.020
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	−0.005***	−0.004***	−0.005**	−0.006***
	0.001	0.000	0.002	0.002
Higher than 25 perc. soc. insurance benefits	0.005***	0	0.005	0.002
	0.000	0.000	0.003	0.004

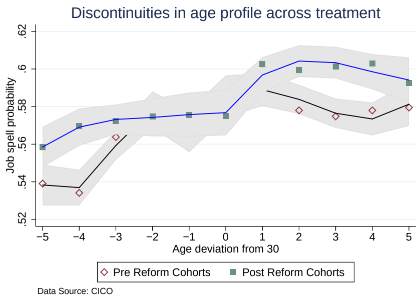
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is ±1(2). Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



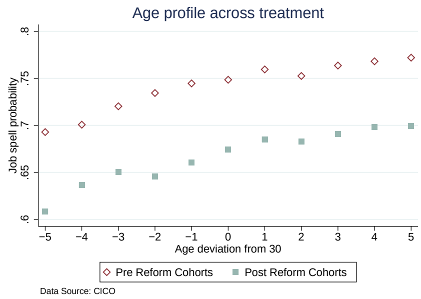
(a) Apprenticeship Probability.



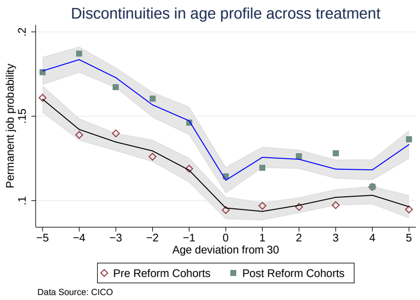
(b) Apprenticeship Probability.



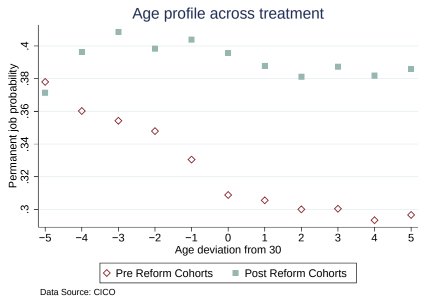
(c) Employment Probability.



(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A9. Difference in discontinuities.

Table A45. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	-.01369	-.00852	-.00658	-.00744	-.01026	-.00462
	.02999	.01688	.01677	.01661	.01645	.0068
Apprenticeship prob.	.01576**	.0157**	.01572**	.01574**	.01587**	.0159**
	.00723	.00723	.00733	.00733	.0072	.00728
Perm. Employment prob.	.00142	.00202	.00229	.00206	.00237	.00343
	.01564	.01351	.0131	.01309	.01289	.01316
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

A1.10. Lombardia

Table A46. Apprenticeship probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	766.575	1800.603	0	594.522	1691.562
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		261.812	474.462		31.109	177.655
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	230.834		2.757	104.763
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	150.035		0	11.333
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A47. Employment probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	15.637	18.326	0	10.138	21.901
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		15.712	16.994		10.113	18.472
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	15.362		6.926	15.037
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	15.169		0	13.264
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A48. Permanent employment probability.

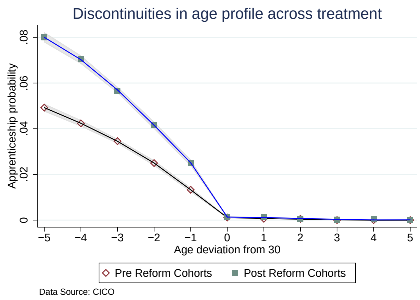
	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	−0.005	125.670	205.069	0	50.970	111.869
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		83.427	120.135		17.280	48.900
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		−0.004	80.044		12.073	32.530
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		−0.004	68.701		0	15.710
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

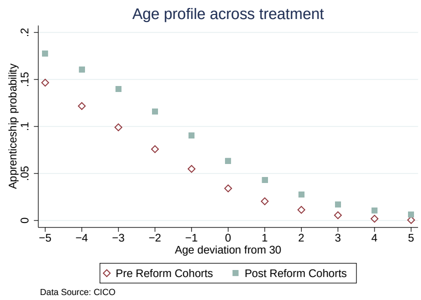
Table A49. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	−0.005***	−0.012***	−0.005	−0.008
	0.002	0.001	0.016	0.017
Region of birth	1.235***	0.725***	1.235	0.764
	0.152	0.106	1.112	1.142
Education	−0.359***	−0.173***	−0.359	−0.441
	0.090	0.063	0.614	0.596
Missing education	−0.000	0.001	−0.000	−0.001
	0.002	0.001	0.010	0.009
Past experience	−154.522***	−237.699***	−154.522	−128.363
	2.790	1.932	110.320	107.673
Missing past exp.	0.015***	0.022***	0.015	0.005
	0.002	0.001	0.033	0.033
Region of work	0	0	0	0
	0	0	0	0
Changing sector	−0.007***	−0.010***	−0.007	−0.003
	0.002	0.001	0.008	0.009
Regional mobility	0.005***	−0.011***	0.005	−0.003
	0.002	0.001	0.012	0.011
Higher 25 per. monthly job spells	−0.009***	−0.006***	−0.009	−0.003
	0.002	0.001	0.063	0.060
Higher 25 per. monthly sep. flows	−0.003***	−0.003***	−0.003	−0.002
	0.001	0.001	0.004	0.004
Higher 25 per. monthly net job flows	−0.007***	−0.006***	−0.007	−0.006
	0.001	0.001	0.016	0.016
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	0.000	−0.001***	0.000	−0.000
	0.000	0.000	0.001	0.001
Higher than 25 perc. soc. insurance benefits	0.001***	0.000***	0.001	0.001
	0.000	0.000	0.001	0.001

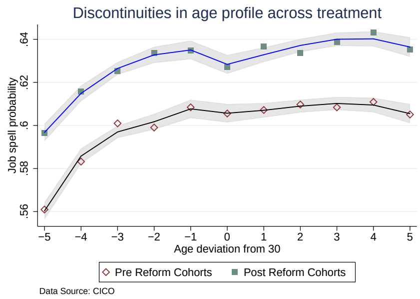
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is ±1(2). Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



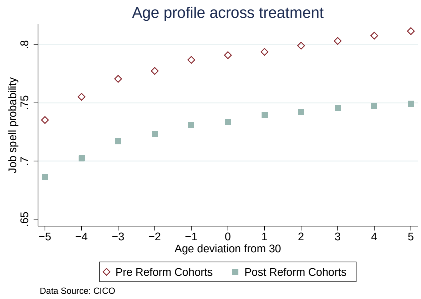
(a) Apprenticeship Probability.



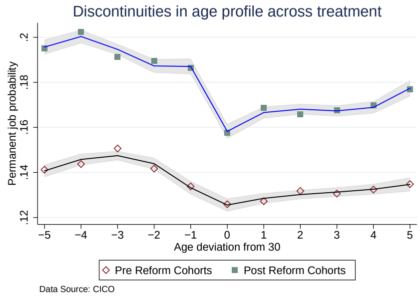
(b) Apprenticeship Probability.



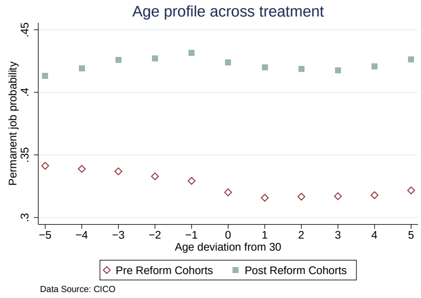
(c) Employment Probability.



(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A10. Difference in discontinuities.

Table A50. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	.00467	.00465	.00603	.00614	.00799	.00889**
	.02851	.00596	.00603	.00614	.00646	.00421
Apprenticeship prob.	.01178***	.01183***	.0117***	.0117***	.01149***	.01111***
	.0039	.00376	.00382	.00382	.00383	.00374
Perm. Employment prob.	.02701***	.02702***	.02734***	.02737***	.02673***	.02898***
	.00886	.00557	.00559	.0056	.00561	.0055
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

A1.11. Marche

Table A51. Apprenticeship probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	294.888	597.789	0	89.880	154.023
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		182.639	462.085		0.261	85.330
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	164.400		0.158	54.774
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	108.902		0	0.411
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A52. Employment probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	2.667	11.701	0	8.310	24.714
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		1.923	8.118		8.253	19.412
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	5.298		4.613	9.866
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	2.994		0	7.393
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A53. Permanent employment probability.

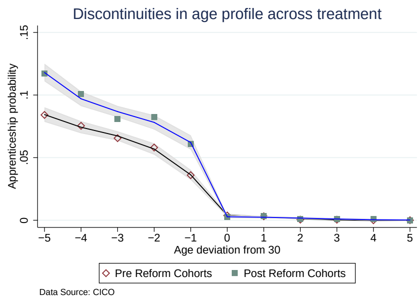
	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	1.651	57.476	0	23.188	88.116
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		1.534	36.468		23.031	73.657
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	1.357		9.517	57.884
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.051		0	35.138
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

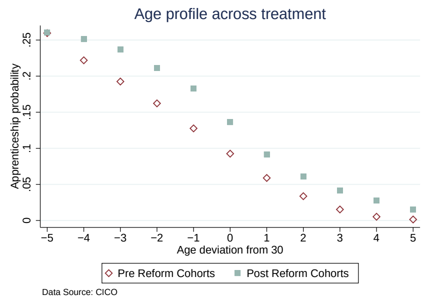
Table A54. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	−0.008*	−0.001	−0.008	−0.001
	0.004	0.003	0.025	0.021
Region of birth	2.444***	0.918***	2.444	2.927**
	0.376	0.265	2.031	1.328
Education	−1.773***	−0.593***	−1.773	−1.907
	0.217	0.152	1.224	1.405
Missing education	−0.014***	−0.022***	−0.014	−0.015
	0.004	0.003	0.017	0.020
Past experience	−121.344***	−226.785***	−121.344	−103.927
	6.777	4.754	116.204	104.532
Missing past exp.	−0.020***	0.032***	−0.020	−0.004
	0.004	0.003	0.047	0.044
Region of work	0	0	0	0
	0	0	0	0
Changing sector	−0.038***	−0.021***	−0.038**	−0.039***
	0.004	0.003	0.015	0.011
Regional mobility	0.024***	0.012***	0.024	0.033
	0.004	0.003	0.026	0.019
Higher 25 per. monthly job spells	0.022***	0.005*	0.022	0.017
	0.004	0.003	0.054	0.049
Higher 25 per. monthly sep. flows	0.006**	−0.005***	0.006	0.004
	0.002	0.002	0.010	0.010
Higher 25 per. monthly net job flows	0.006**	−0.007***	0.006	0.003
	0.003	0.002	0.016	0.017
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	0.000	0.000	0.000	0.003
	0.001	0.001	0.004	0.003
Higher than 25 perc. soc. insurance benefits	−0.001***	−0.001***	−0.001	−0.002
	0.001	0.000	0.004	0.003

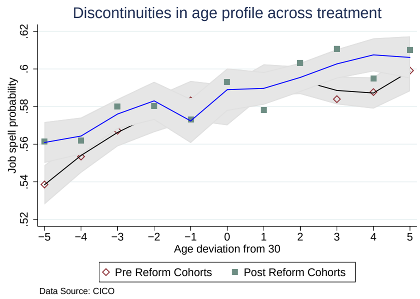
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is $\pm 1(2)$. Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



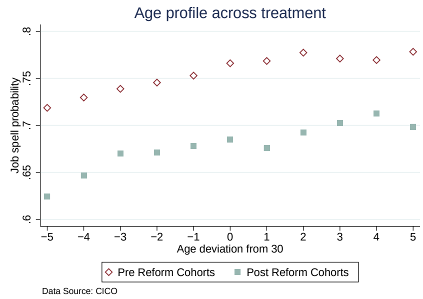
(a) Apprenticeship Probability.



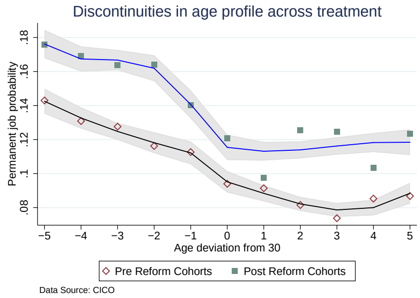
(b) Apprenticeship Probability.



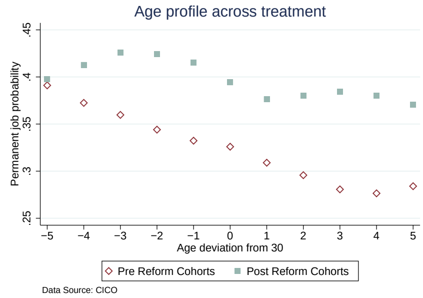
(c) Employment Probability.



(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A11. Difference in discontinuities.

Table A55. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	-.03192	-.03293**	-.03237**	-.03185**	-.03322**	-.00636
	.02991	.01382	.0138	.01391	.01435	.00464
Apprenticeship prob.	.02493**	.02501**	.02522**	.02521**	.02493**	.0259**
	.01124	.01108	.01105	.01105	.01096	.01099
Perm. Employment prob.	.00145	.00199	.00324	.00338	.0029	.00841
	.01291	.01108	.01227	.01222	.01222	.01242
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

A1.12. Molise

Table A56. Apprenticeship probability.

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	11.333	59.292	0	23.056	84.122
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.010	6.506		6.268	9.472
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	0.402		0.154	3.769
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.284		0	3.651
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A57. Employment probability.

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	14.066	34.346	0	1.130	36.165
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		13.152	25.427		0.373	27.195
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	20.531		0.207	5.494
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	17.269		0	0.523
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A58. Permanent employment probability.

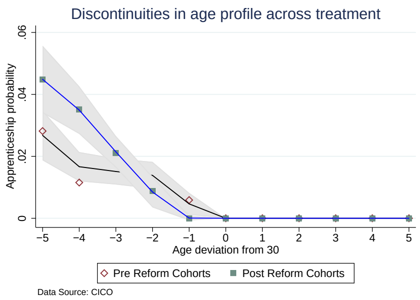
	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	10.223	15.969	0	7.896	13.703
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		4.232	16.068		2.670	13.704
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	10.097		1.963	9.894
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	2.765		0	2.036
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

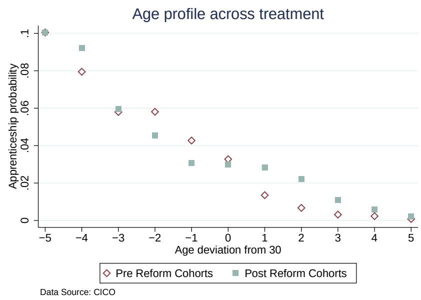
Table A59. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		**Polynomial fit**	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	-0.065^{***}	0.012^{*}	-0.065	0.016
	0.010	0.007	0.061	0.066
Region of birth	-6.225^{***}	-3.209^{***}	-6.225^{*}	-5.233
	0.727	0.519	3.026	3.231
Education	2.853^{***}	0.386	2.853	0.870
	0.451	0.321	2.022	1.694
Missing education	-0.073^{***}	-0.025^{***}	-0.073^{*}	-0.061^{**}
	0.007	0.005	0.038	0.027
Past experience	-101.553^{***}	-216.169^{***}	-101.553	-121.723
	11.780	8.642	101.166	88.056
Missing past exp.	0.002	-0.035^{***}	0.002	-0.006
	0.008	0.006	0.077	0.059
Region of work	0	0	0	0
	0	0	0	0
Changing sector	0.065^{***}	0.036^{***}	0.065	0.068^{*}
	0.008	0.006	0.038	0.035
Regional mobility	-0.062^{***}	-0.049^{***}	-0.062	-0.073^{*}
	0.010	0.007	0.043	0.042
Higher 25 per. monthly job spells	0.038^{***}	0.050^{***}	0.038	0.043
	0.010	0.007	0.081	0.084
Higher 25 per. monthly sep. flows	-0.011^{**}	0.002	-0.011	-0.003
	0.005	0.004	0.012	0.011
Higher 25 per. monthly net job flows	-0.008	-0.002	-0.008	-0.001
	0.006	0.004	0.014	0.012
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	-0.001	-0.011^{***}	-0.001	-0.009
	0.005	0.003	0.019	0.018
Higher than 25 perc. soc. insurance benefits	0.002^{**}	-0.002^{***}	0.002	0.000
	0.001	0.001	0.004	0.004

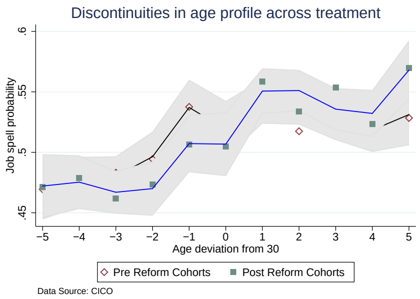
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is $\pm 1(2)$. Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



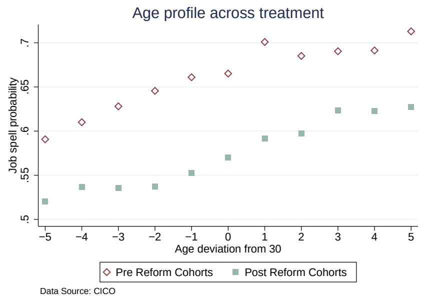
(a) Apprenticeship Probability.



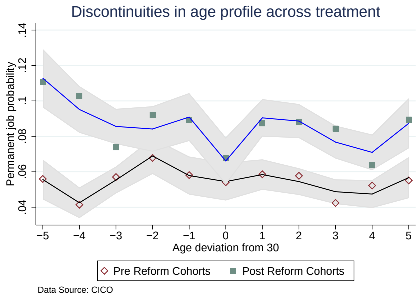
(b) Apprenticeship Probability.



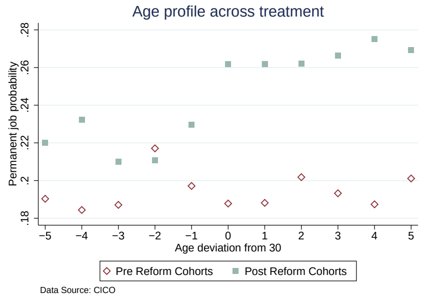
(c) Employment Probability.



(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A12. Difference in discontinuities.

Table A60. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	-.0519	-.04707	-.04719	-.04631	-.05313*	-.01641
	.05443	.02973	.02977	.03043	.02954	.01212
Apprenticeship prob.	-.00565	-.00557	-.00512	-.00514	-.00573	-.00441
	.00411	.00419	.00436	.00434	.00432	.00432
Perm. Employment prob.	.00543	.00626	.01296	.0132	.01241	.02003
	.01819	.01827	.01704	.01715	.01784	.01803
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

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Table A61. Apprenticeship probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	455.289	1055.175	0	251.113	445.371
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		206.922	703.106		5.884	179.070
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	212.943		3.492	118.946
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	103.663		0	7.251
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A62. Employment probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	5.358	19.554	0	6.030	26.311
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		4.546	10.545		3.882	9.192
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	2.953		1.824	8.701
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	2.960		0	4.993
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A63. Permanent employment probability.

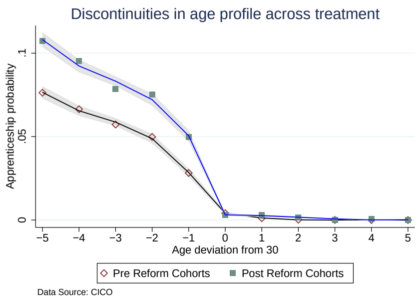
	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	119.052	168.649	0	48.324	71.515
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		68.618	124.185		2.942	47.266
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	82.173		2.848	35.670
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	54.284		0	3.438
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

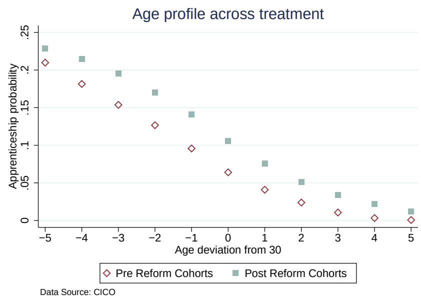
Table A64. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	−0.019***	−0.016***	−0.019	−0.008
	0.003	0.002	0.016	0.015
Region of birth	−0.191	0.556***	−0.191	−1.181
	0.248	0.174	0.545	0.684
Education	0.253*	0.431***	0.253	0.442
	0.143	0.101	0.671	0.836
Missing education	−0.005*	−0.002	−0.005	−0.003
	0.002	0.002	0.012	0.012
Past experience	−143.608***	−242.960***	−143.608	−119.411
	4.685	3.283	119.234	116.914
Missing past exp.	0.041***	0.041***	0.041	0.037
	0.003	0.002	0.048	0.035
Region of work	0	0	0	0
	0	0	0	0
Changing sector	−0.017***	−0.006***	−0.017	−0.010
	0.003	0.002	0.015	0.012
Regional mobility	0.001	0.013***	0.001	−0.009
	0.003	0.002	0.018	0.017
Higher 25 per. monthly job spells	−0.003	0.000	−0.003	−0.001
	0.003	0.002	0.055	0.053
Higher 25 per. monthly sep. flows	−0.005***	−0.005***	−0.005	−0.004
	0.001	0.001	0.008	0.008
Higher 25 per. monthly net job flows	−0.008***	−0.008***	−0.008	−0.006
	0.002	0.001	0.014	0.014
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	0.003***	0.001***	0.003***	0.001
	0.000	0.000	0.001	0.001
Higher than 25 perc. soc. insurance benefits	−0.001***	−0.002***	−0.001	−0.002
	0.000	0.000	0.002	0.002

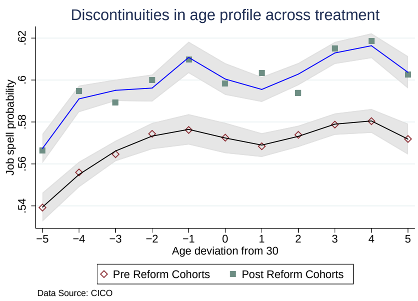
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is ±1(2). Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



(a) Apprenticeship Probability.

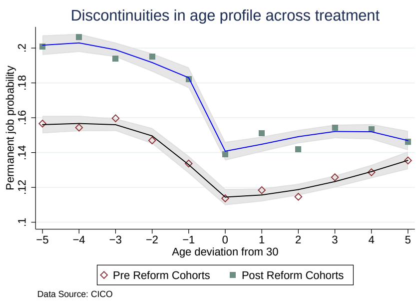


(b) Apprenticeship Probability.

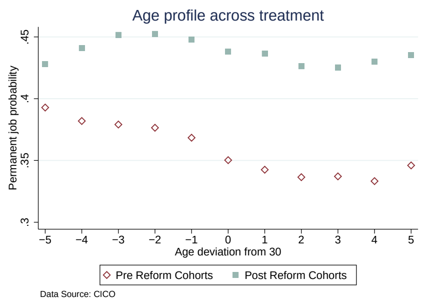


(c) Employment Probability.

(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A13. Difference in discontinuities.

Table A65. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	.01128	.01039	.01031	.00964	.0157	.01335**
	.02671	.01177	.01166	.01154	.01132	.00532
Apprenticeship prob.	.02138***	.02142***	.02149***	.0215***	.02138***	.0208***
	.00544	.00528	.00519	.0052	.00513	.00497
Perm. Employment prob.	.02193	.02226	.02309*	.02292*	.02314*	.02433*
	.01585	.01371	.01307	.01302	.01309	.01255
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

Notes: Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

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Table A66. Apprenticeship probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	211.571	433.528	0	85.199	287.571
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		122.893	177.875		27.702	42.751
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	90.341		0.413	42.173
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	78.715		0	31.098
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A67. Employment probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	5.178	25.992	0	9.744	31.222
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.958	7.796		5.057	14.015
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	3.350		4.869	7.040
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	2.006		0	5.108
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A68. Permanent employment probability.

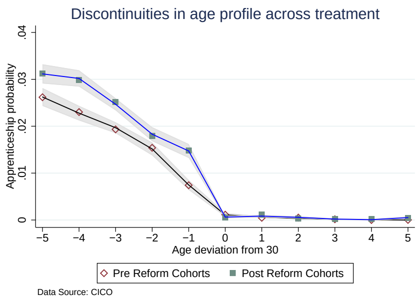
	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0.001	39.825	66.661	0	35.881	64.795
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		17.122	64.716		6.087	56.895
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0.001	46.033		5.045	50.382
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0.001	12.834		−0.001	10.758
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

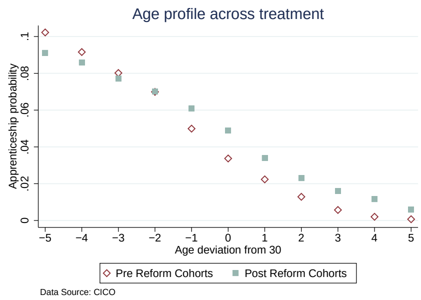
Table A69. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	−0.023***	−0.013***	−0.023	−0.031*
	0.002	0.002	0.020	0.017
Region of birth	0.841***	0.068	0.841	−0.318
	0.173	0.123	0.948	1.145
Education	−1.570***	−0.780***	−1.570*	−1.314
	0.097	0.069	0.714	0.767
Missing education	0.015***	0.015***	0.015	0.012
	0.002	0.001	0.011	0.011
Past experience	−113.259***	−184.737***	−113.259	−83.919
	2.937	2.043	112.449	105.271
Missing past exp.	0.001	0.006***	0.001	−0.005
	0.002	0.001	0.062	0.057
Region of work	0	0	0	0
	0	0	0	0
Changing sector	−0.006***	−0.002	−0.006	−0.004
	0.002	0.001	0.017	0.019
Regional mobility	0.011***	0.006***	0.011	−0.001
	0.002	0.002	0.013	0.016
Higher 25 per. monthly job spells	0.005*	0.010***	0.005	0.011
	0.002	0.002	0.058	0.056
Higher 25 per. monthly sep. flows	−0.001	0.002*	−0.001	0.000
	0.001	0.001	0.013	0.012
Higher 25 per. monthly net job flows	0.002	−0.003**	0.002	0.004
	0.002	0.001	0.015	0.014
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	−0.001	−0.002**	−0.001	−0.002
	0.001	0.001	0.013	0.012
Higher than 25 perc. soc. insurance benefits	0.001***	0.000	0.001	0.002*
	0.000	0.000	0.001	0.001

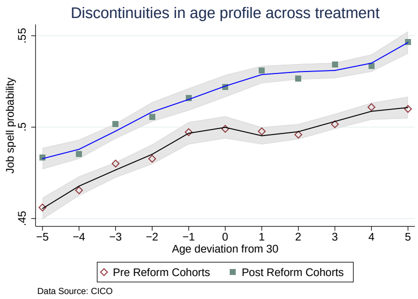
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is $\pm 1(2)$. Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



(a) Apprenticeship Probability.

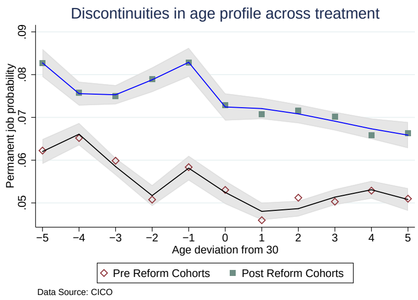


(b) Apprenticeship Probability.

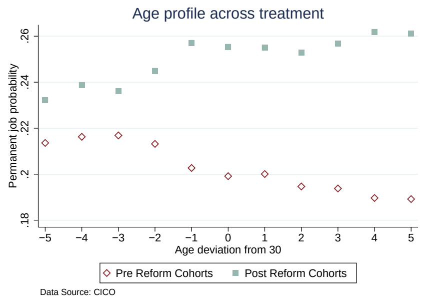


(c) Employment Probability.

(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A14. Difference in discontinuities.

Table A70. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	-.00264	-.0034	-.00281	-.00303	-.00435	.00318
	.03713	.00932	.00938	.00966	.01037	.00558
Apprenticeship prob.	.00751***	.00746***	.00715***	.00715***	.00756***	.00809***
	.0025	.00241	.00223	.00223	.00217	.00214
Perm. Employment prob.	-.00075	-.00104	-.00232	-.00238	-.00197	-.00021
	.0087	.00533	.00397	.00402	.00412	.00364
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

A1.15. Sardegna

Table A71. Apprenticeship probability.

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	68.461	161.636	0	51.195	159.713
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		36.524	45.702		14.202	26.584
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	25.439		0.319	11.859
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	23.413		0	8.742
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A72. Employment probability.

	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	3.184	5.057	0	4.150	14.410
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.098	5.008		0.626	14.463
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	4.150		0.571	7.254
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.020		0	1.201
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A73. Permanent employment probability.

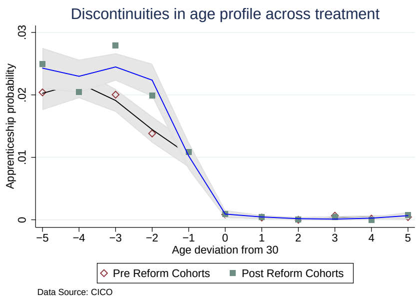
	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	18.897	58.930	0	22.348	53.340
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.099	23.960		2.236	24.616
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	10.231		1.921	14.953
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.143		0	2.129
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

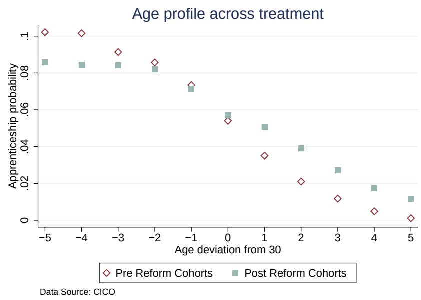
Table A74. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	0.032***	0.026***	0.032*	0.044***
	0.004	0.003	0.016	0.013
Region of birth	0.074	0.126	0.074	−0.817
	0.208	0.147	1.353	1.365
Education	0.539***	0.022	0.539	0.823
	0.169	0.119	1.118	1.193
Missing education	0.004	0.010***	0.004	0.001
	0.003	0.002	0.013	0.013
Past experience	−76.794***	−160.479***	−76.794	−29.323
	4.861	3.409	113.574	109.480
Missing past exp.	−0.018***	−0.012***	−0.018	−0.042
	0.003	0.002	0.067	0.068
Region of work	0	0	0	0
	0	0	0	0
Changing sector	0.018***	0.030***	0.018	0.024
	0.003	0.002	0.016	0.014
Regional mobility	−0.025***	−0.015***	−0.025*	−0.037**
	0.003	0.002	0.013	0.015
Higher 25 per. monthly job spells	−0.001	−0.005*	−0.001	−0.008
	0.004	0.003	0.065	0.063
Higher 25 per. monthly sep. flows	−0.004*	−0.002	−0.004	−0.004
	0.002	0.002	0.017	0.016
Higher 25 per. monthly net job flows	0.001	−0.000	0.001	0.000
	0.003	0.002	0.017	0.016
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	−0.007***	−0.009***	−0.007	−0.002
	0.002	0.001	0.014	0.014
Higher than 25 perc. soc. insurance benefits	−0.002***	−0.001***	−0.002	−0.002
	0.000	0.000	0.002	0.002

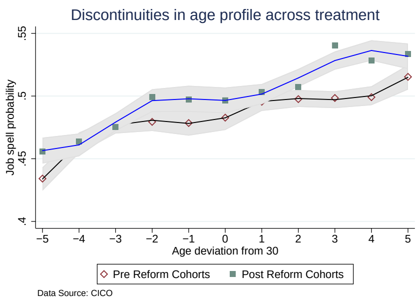
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is $\pm 1(2)$. Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



(a) Apprenticeship Probability.

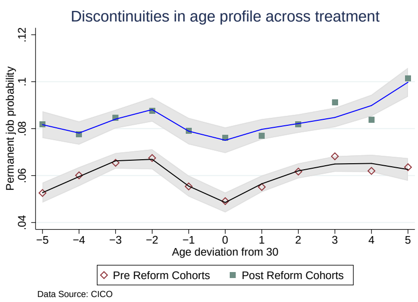


(b) Apprenticeship Probability.

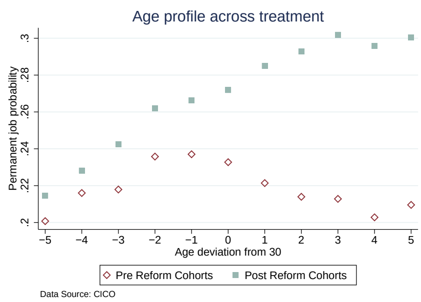


(c) Employment Probability.

(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A15. Difference in discontinuities.

Table A75. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	-.0031	-.00165	-.00047	-.00031	-.00615	-.00697*
	.04194	.00866	.00824	.00834	.01041	.00397
Apprenticeship prob.	.00036	.00036	.00017	.00017	-.00036	-.00057
	.00216	.00254	.00255	.00255	.00256	.00259
Perm. Employment prob.	-.00157	-.00119	-.00061	-.00057	-.0022	-.00288
	.00908	.00644	.00662	.00658	.00668	.00569
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

A1.16. Sicilia

Table A76. Apprenticeship probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	324.424	619.238	0	128.471	279.055
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		177.340	322.165		0.006	44.250
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	147.081		−0.007	39.246
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	108.608		−0.001	0.095
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A77. Employment probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	6.381	24.772	0	33.846	47.650
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.026	25.216		21.369	45.982
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	7.219		11.829	30.732
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.286		0	22.383
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A78. Permanent employment probability.

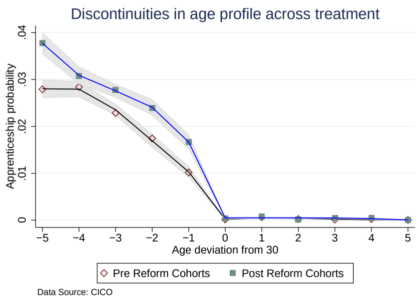
	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	26.585	122.292	0	24.228	105.024
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		27.063	63.689		22.442	46.455
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	32.497		19.030	45.806
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	19.094		−0.001	23.784
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

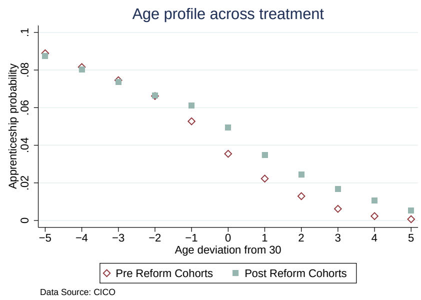
Table A79. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		**Polynomial fit**	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	0.004	0.011***	0.004	0.002
	0.002	0.002	0.015	0.014
Region of birth	0.003	−0.426***	0.003	−0.296
	0.157	0.111	1.248	0.962
Education	−0.155	−0.102	−0.155	−0.596
	0.097	0.068	0.771	0.791
Missing education	−0.005***	−0.004***	−0.005	−0.001
	0.002	0.001	0.011	0.011
Past experience	−129.579***	−198.968***	−129.579	−100.850
	2.900	2.039	104.744	96.112
Missing past exp.	0.015***	0.025***	0.015	0.008
	0.002	0.002	0.038	0.035
Region of work	0	0	0	0
	0	0	0	0
Changing sector	0.011***	0.002	0.011	0.011
	0.002	0.001	0.018	0.018
Regional mobility	0.005**	−0.000	0.005	−0.001
	0.002	0.001	0.016	0.015
Higher 25 per. monthly job spells	−0.000	0.003*	−0.000	−0.008
	0.002	0.002	0.063	0.062
Higher 25 per. monthly sep. flows	−0.001	0.001	−0.001	−0.001
	0.001	0.001	0.014	0.014
Higher 25 per. monthly net job flows	−0.000	0.001	−0.000	0.001
	0.002	0.001	0.013	0.012
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	0.005***	0.002**	0.005	0.008
	0.001	0.001	0.018	0.018
Higher than 25 perc. soc. insurance benefits	0.001***	−0.000	0.001	0.000
	0.000	0.000	0.001	0.001

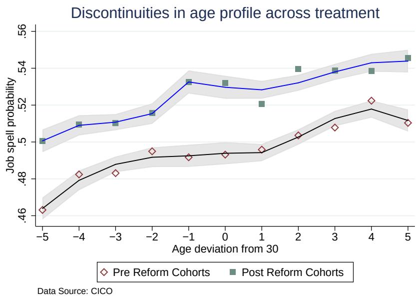
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is $\pm 1(2)$. Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



(a) Apprenticeship Probability.

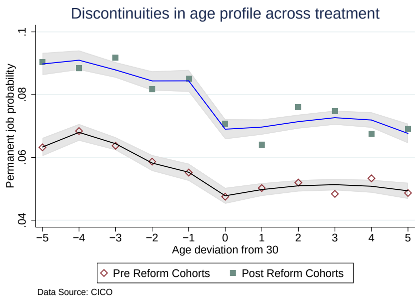


(b) Apprenticeship Probability.

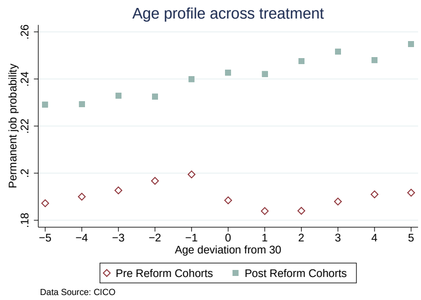


(c) Employment Probability.

(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A16. Difference in discontinuities.

Table A80. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	.01961	.01748***	.0185***	.01801***	.01705**	.00143
	.03979	.00644	.00639	.00648	.0074	.00537
Apprenticeship prob.	.00666***	.00667**	.0064**	.00641**	.00624**	.00613**
	.00243	.00263	.00257	.00257	.00264	.00261
Perm. Employment prob.	.00485	.00447	.00536	.00523	.00433	.00262
	.00774	.00616	.00559	.00563	.00547	.00592
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

A1.17. Toscana

Table A81. Apprenticeship probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	425.812	1058.264	0	267.449	653.391
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		176.113	399.817		10.428	91.667
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	145.688		0.119	70.363
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	96.496		0	15.947
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A82. Employment probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	22.559	29.879	0	8.756	13.171
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		15.876	29.284		5.052	13.032
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	18.437		1.455	11.853
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	12.462		0	5.568
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A83. Permanent employment probability.

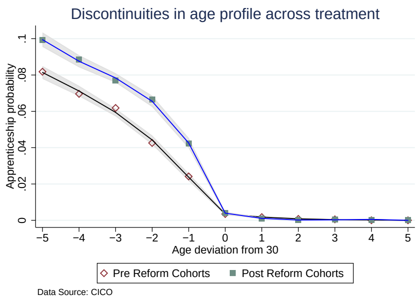
	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	60.657	162.523	0	35.676	77.273
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		26.090	98.483		1.440	34.229
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	28.699		0.643	18.599
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	13.868		0	2.963
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

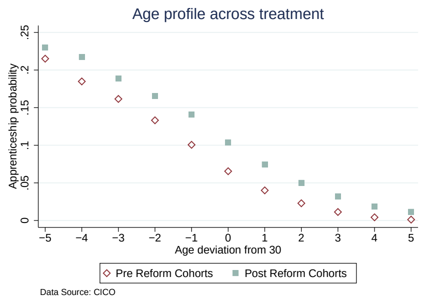
Table A84. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	−0.005**	−0.009***	−0.005	−0.003
	0.003	0.002	0.020	0.023
Region of birth	−1.689***	−0.920***	−1.689	−2.509**
	0.223	0.158	1.376	1.192
Education	−0.296**	−0.059	−0.296	−0.303
	0.125	0.088	0.683	0.679
Missing education	−0.003	0.005***	−0.003	0.003
	0.002	0.002	0.012	0.013
Past experience	−126.220***	−226.702***	−126.220	−117.887
	3.913	2.743	102.074	101.511
Missing past exp.	0.018***	0.027***	0.018	0.018
	0.002	0.002	0.028	0.027
Region of work	0	0	0	0
	0	0	0	0
Changing sector	−0.008***	−0.011***	−0.008	−0.004
	0.002	0.002	0.008	0.007
Regional mobility	−0.022***	−0.012***	−0.022*	−0.030**
	0.003	0.002	0.011	0.012
Higher 25 per. monthly job spells	−0.017***	−0.011***	−0.017	−0.015
	0.003	0.002	0.055	0.051
Higher 25 per. monthly sep. flows	−0.006***	−0.006***	−0.006	−0.007
	0.001	0.001	0.012	0.012
Higher 25 per. monthly net job flows	−0.000	−0.006***	−0.000	−0.002
	0.002	0.001	0.014	0.014
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	0.002***	0.002***	0.002	0.001
	0.000	0.000	0.002	0.002
Higher than 25 perc. soc. insurance benefits	0.001**	0.000	0.001	0.000
	0.000	0.000	0.002	0.002

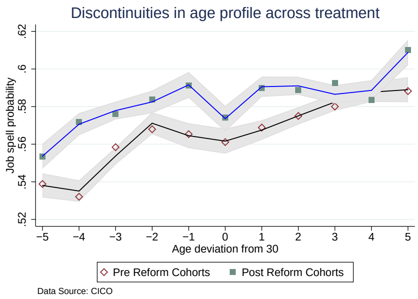
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is $\pm 1(2)$. Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



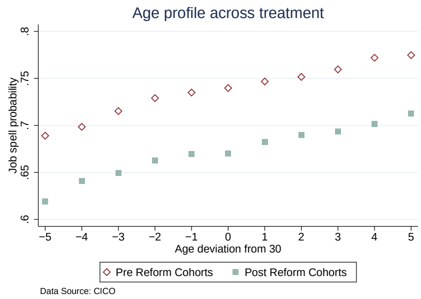
(a) Apprenticeship Probability.



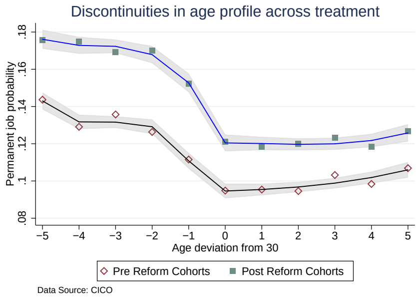
(b) Apprenticeship Probability.



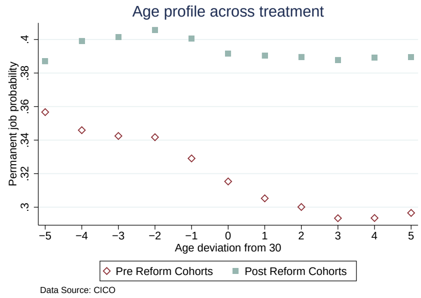
(c) Employment Probability.



(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

Figure A17. Difference in discontinuities.

Table A85. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	.00396	.00698	.00707	.00708	.01311*	.00698
	.02611	.00739	.00716	.0073	.00789	.00432
Apprenticeship prob.	.01801***	.01793***	.01783***	.01783***	.01762***	.01707***
	.00545	.00529	.00535	.00536	.00524	.00512
Perm. Employment prob.	.01417	.01441	.01417	.01417	.01311	.01393
	.01173	.01021	.01028	.01025	.01031	.00994
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

A1.18. Umbria

Table A86. Apprenticeship probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	227.367	430.196	0	74.467	122.824
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		166.139	320.540		14.810	59.745
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	121.152		0.245	46.734
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	103.643		0	24.152
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A87. Employment probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	8.451	11.585	0	14.691	41.037
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.282	9.754		3.622	39.649
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	9.057		0.879	36.708
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.134		0	9.069
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A88. Permanent employment probability.

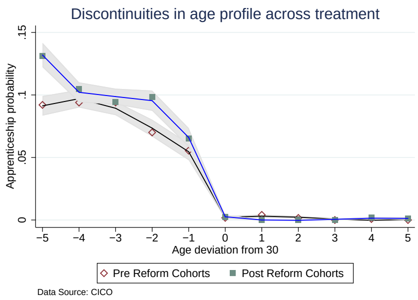
	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	101.901	163.001	0	41.070	82.096
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		57.797	95.057		2.099	33.752
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	61.006		2.070	24.365
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	44.620		0	1.706
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

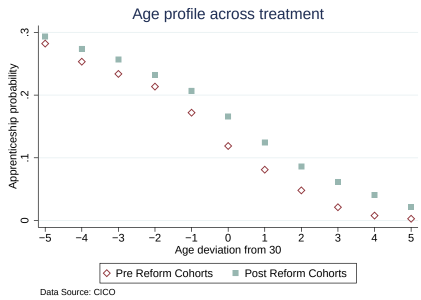
Table A89. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	0.008	−0.000	0.008	0.042
	0.006	0.004	0.032	0.033
Region of birth	−0.536	−0.906***	−0.536	−1.654
	0.471	0.335	2.407	2.427
Education	1.718***	1.086***	1.718	2.219
	0.289	0.206	1.538	1.831
Missing education	−0.069***	−0.067***	−0.069**	−0.077**
	0.005	0.004	0.027	0.029
Past experience	−117.600***	−195.876***	−117.600	−84.037
	8.580	6.060	114.083	116.975
Missing past exp.	0.005	−0.010***	0.005	−0.012
	0.005	0.004	0.042	0.040
Region of work	0	0	0	0
	0	0	0	0
Changing sector	−0.009*	−0.003	−0.009	−0.031
	0.005	0.004	0.040	0.042
Regional mobility	−0.004	−0.003	−0.004	−0.011
	0.006	0.004	0.036	0.033
Higher 25 per. monthly job spells	−0.008	−0.029***	−0.008	−0.006
	0.006	0.004	0.061	0.054
Higher 25 per. monthly sep. flows	−0.009***	−0.008***	−0.009	−0.004
	0.003	0.002	0.009	0.009
Higher 25 per. monthly net job flows	−0.002	−0.007**	−0.002	−0.002
	0.004	0.003	0.020	0.018
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	0.010***	0.009***	0.010	0.004
	0.001	0.001	0.006	0.006
Higher than 25 perc. soc. insurance benefits	−0.001	0.001	−0.001	−0.001
	0.001	0.001	0.003	0.003

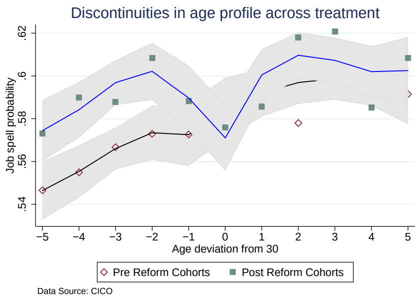
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is ±1(2). Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



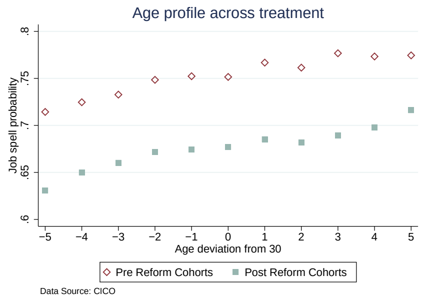
(a) Apprenticeship Probability.



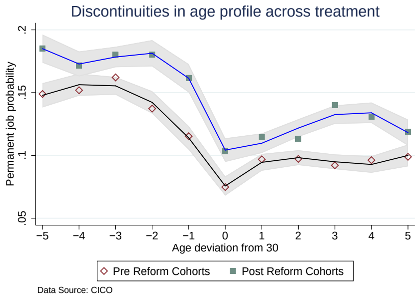
(b) Apprenticeship Probability.



(c) Employment Probability.



(d) Employment Probability.



(e) Permanent Employment Probability.

(f) Permanent Employment Probability.

Figure A18. Difference in discontinuities.

Table A90. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	-.00939	-.01274	-.01547	-.01551	-.01548	.01366*
	.03141	.01967	.01951	.01966	.01874	.00779
Apprenticeship prob.	.00903	.00908	.0089	.0089	.00832	.00893
	.01372	.0136	.01349	.01347	.01346	.01324
Perm. Employment prob.	.01679	.01688	.01352	.01351	.01372	.01918
	.01782	.01532	.01502	.01514	.01529	.01342
Self employment	.00163	.00154	.00191	.00192	.0024	-.00051
	.0105	.0106	.01037	.01037	.00994	.00956
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

A1.19. Valle d'Aosta

Table A91. Apprenticeship probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	28.658	65.313	0	35.723	104.578
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		1.827	14.750		2.969	34.809
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	7.965		0.078	10.992
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.532		0	0.178
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A92. Employment probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	2.590	6.313	0	1.931	26.591
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		2.068	6.448		1.380	25.629
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	5.140		0.260	20.667
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	2.974		0	3.333
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A93. Permanent employment probability.

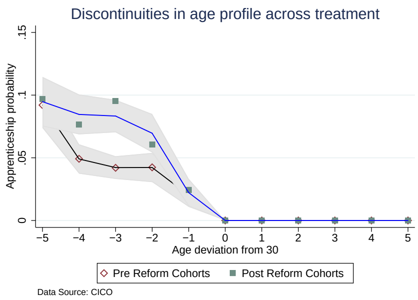
	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	12.700	17.320	0	18.063	39.366
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.612	13.547		2.257	30.331
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	11.847		0.134	11.667
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	1.039		0	0.417
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

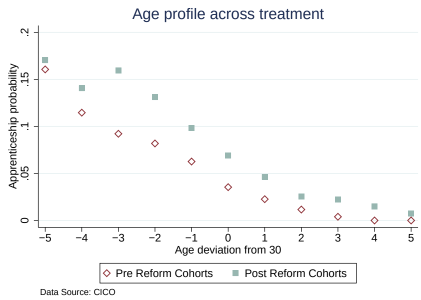
Table A94. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		Polynomial fit	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	−0.120***	−0.109***	−0.120*	−0.055
	0.013	0.009	0.061	0.065
Region of birth	−1.803*	−0.141	−1.803	−2.859
	1.090	0.767	7.065	5.819
Education	−1.349**	−3.266***	−1.349	−0.367
	0.580	0.409	3.245	3.371
Missing education	−0.050***	0.005	−0.050	−0.044
	0.012	0.008	0.083	0.068
Past experience	−58.338***	−139.698***	−58.338	−32.652
	18.449	12.990	149.170	128.516
Missing past exp.	−0.000	0.002	−0.000	0.010
	0.010	0.007	0.016	0.030
Region of work	0	0	0	0
	0	0	0	0
Changing sector	−0.135***	−0.092***	−0.135**	−0.135***
	0.011	0.008	0.042	0.042
Regional mobility	−0.014	0.018**	−0.014	−0.033
	0.012	0.009	0.067	0.047
Higher 25 per. monthly job spells	−0.058***	−0.069***	−0.058	−0.052
	0.013	0.009	0.081	0.083
Higher 25 per. monthly sep. flows	0.008	−0.007	0.008	0.012
	0.008	0.005	0.018	0.019
Higher 25 per. monthly net job flows	−0.016	−0.015**	−0.016	−0.003
	0.010	0.007	0.010	0.014
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	0.014***	0.007***	0.014**	0.003
	0.002	0.002	0.005	0.006
Higher than 25 perc. soc. insurance benefits	0.001	0.000	0.001	0.001
	0.001	0.000	0.001	0.001

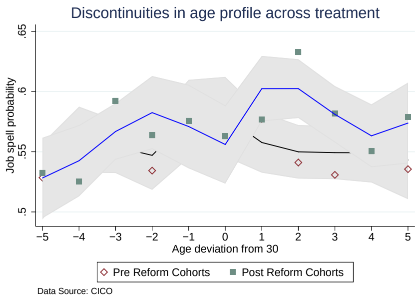
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is ±1(2). Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



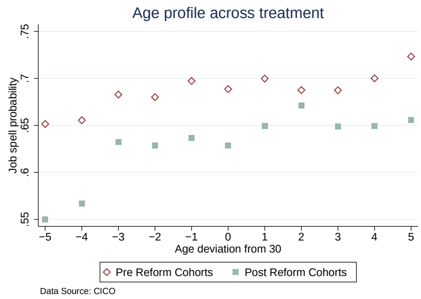
(a) Apprenticeship Probability.



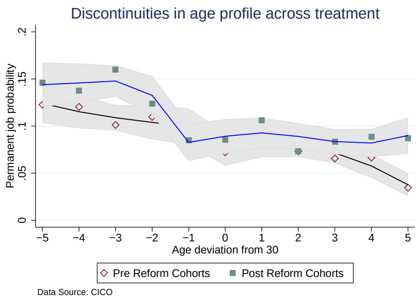
(b) Apprenticeship Probability.



(c) Employment Probability.



(d) Employment Probability.



(e) Permanent Employment Probability.

(f) Permanent Employment Probability.

Figure A19. Difference in discontinuities.

Table A95. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	-.02734	-.02337	-.02411	-.02395	-.01586	-.03063*
	.046	.0327	.03296	.03339	.03399	.01713
Apprenticeship prob.	.00395	.00411	.00522	.00521	.00419	.00444
	.01328	.01335	.0133	.01332	.01318	.01315
Perm. Employment prob.	-.04089**	-.04035**	-.03454*	-.0345*	-.03708*	-.03392*
	.01908	.01905	.01909	.0189	.01948	.01957
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

A1.20. Veneto

Table A96. Apprenticeship probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	602.309	1431.328	0	581.987	1180.089
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		104.167	408.888		18.490	192.984
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	188.550		0.051	166.068
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	46.773		0	18.885
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A97. Employment probability.

	Without DiD specification			DiD Model specification		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	4.951	18.800	0	17.114	36.749
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		0.082	2.465		11.147	17.675
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		0	1.081		11.094	15.963
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		0	0.245		0	12.053
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

Table A98. Permanent employment probability.

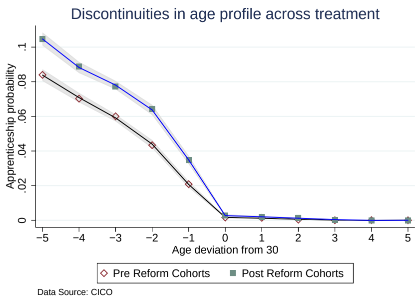
	Without DiD specification			**DiD Model specification**		
	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
First Order Polynomial						
LM	0	34.689	63.362	0	28.840	48.487
CV	6.635	11.345	15.086	11.345	18.475	24.725
Second Order Polynomial						
LM		21.883	40.160		18.734	31.199
CV		11.345	15.086		18.475	24.725
Third Order Polynomial						
LM		−0.002	20.793		18.564	30.109
CV		11.345	15.086		18.475	24.725
Fourth Order Polynomial						
LM		−0.002	16.308		0	17.289
CV		11.345	15.086		18.475	24.725

Notes: The null hypothesis of the test Lagrange Multiplier, LM, is that the functional form adopted is statistically equal to an unrestricted regression of the outcome on the full set of dummy variables for the J possible values of age which define the age range reported in brackets. If the statistic exceeds the critical values CV, the null is rejected. Standard error are clustered at the age and year of birth level.

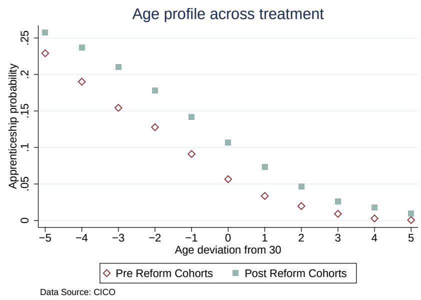
Table A99. Balancing out covariates at the threshold.

	Main Sample			
	Raw data		**Polynomial fit**	
	[-1,1]	[-2,2]	[-1,1]	[-2,2]
	DiD (Std. Dev.)	DiD (Std. Dev.)	DiD (Std. Err.)	DiD (Std. Err.)
Gender	0.010***	−0.007***	0.010	0.015
	0.003	0.002	0.011	0.013
Region of birth	−3.502***	−2.321***	−3.502***	−3.957***
	0.208	0.147	0.990	0.997
Education	0.611***	0.025	0.611	0.806
	0.124	0.088	0.853	0.787
Missing education	−0.017***	−0.002	−0.017	−0.022*
	0.002	0.002	0.011	0.011
Past experience	−124.362***	−240.013***	−124.362	−88.283
	4.192	2.939	140.816	142.075
Missing past exp.	−0.020***	0.005***	−0.020	−0.024
	0.002	0.002	0.038	0.038
Region of work	0	0	0	0
	0	0	0	0
Changing sector	0.004*	0.003*	0.004	0.007
	0.002	0.002	0.014	0.012
Regional mobility	−0.027***	−0.020***	−0.027*	−0.032*
	0.003	0.002	0.014	0.016
Higher 25 per. monthly job spells	−0.009***	−0.013***	−0.009	−0.015
	0.003	0.002	0.051	0.051
Higher 25 per. monthly sep. flows	−0.001	−0.001	−0.001	−0.000
	0.001	0.001	0.010	0.010
Higher 25 per. monthly net job flows	−0.004**	−0.004***	−0.004	−0.004
	0.002	0.001	0.018	0.017
Higher 25 perc. hiring incentive	0	0	0	0
	0	0	0	0
Higher than 25 perc. costs reduction	0	0.000	0	−0.000
	0.000	0.000	0.001	0.001
Higher than 25 perc. soc. insurance benefits	−0.000	−0.000	−0.000	−0.000
	0.000	0.000	0.002	0.002

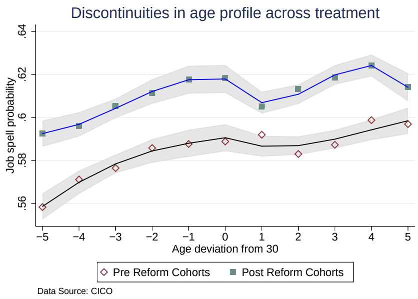
Notes: The polynomial fit corresponds to a first (third) order polynomial in age when the age range is $\pm 1(2)$. Each variable defined as higher than the 25th percentile is a dummy variable which is equal to 1 if the job episode sits in a percentile higher than the 25th of the age specific distribution of the covariate of interest, for instance the number of job spells in a given month and year.



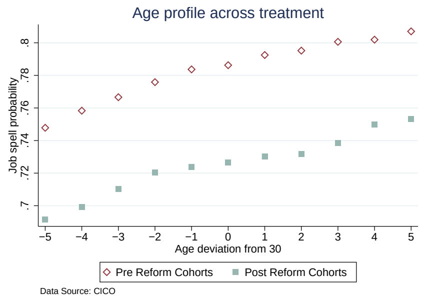
(a) Apprenticeship Probability.



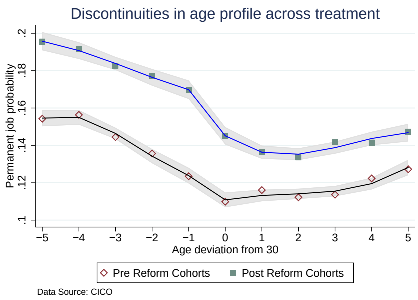
(b) Apprenticeship Probability.



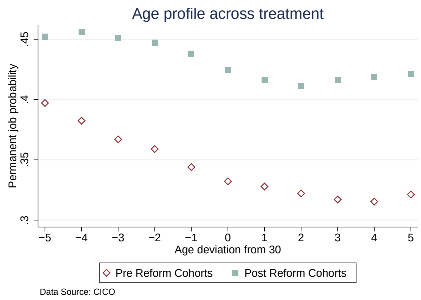
(c) Employment Probability.



(d) Employment Probability.



(e) Permanent Employment Probability.



(f) Permanent Employment Probability.

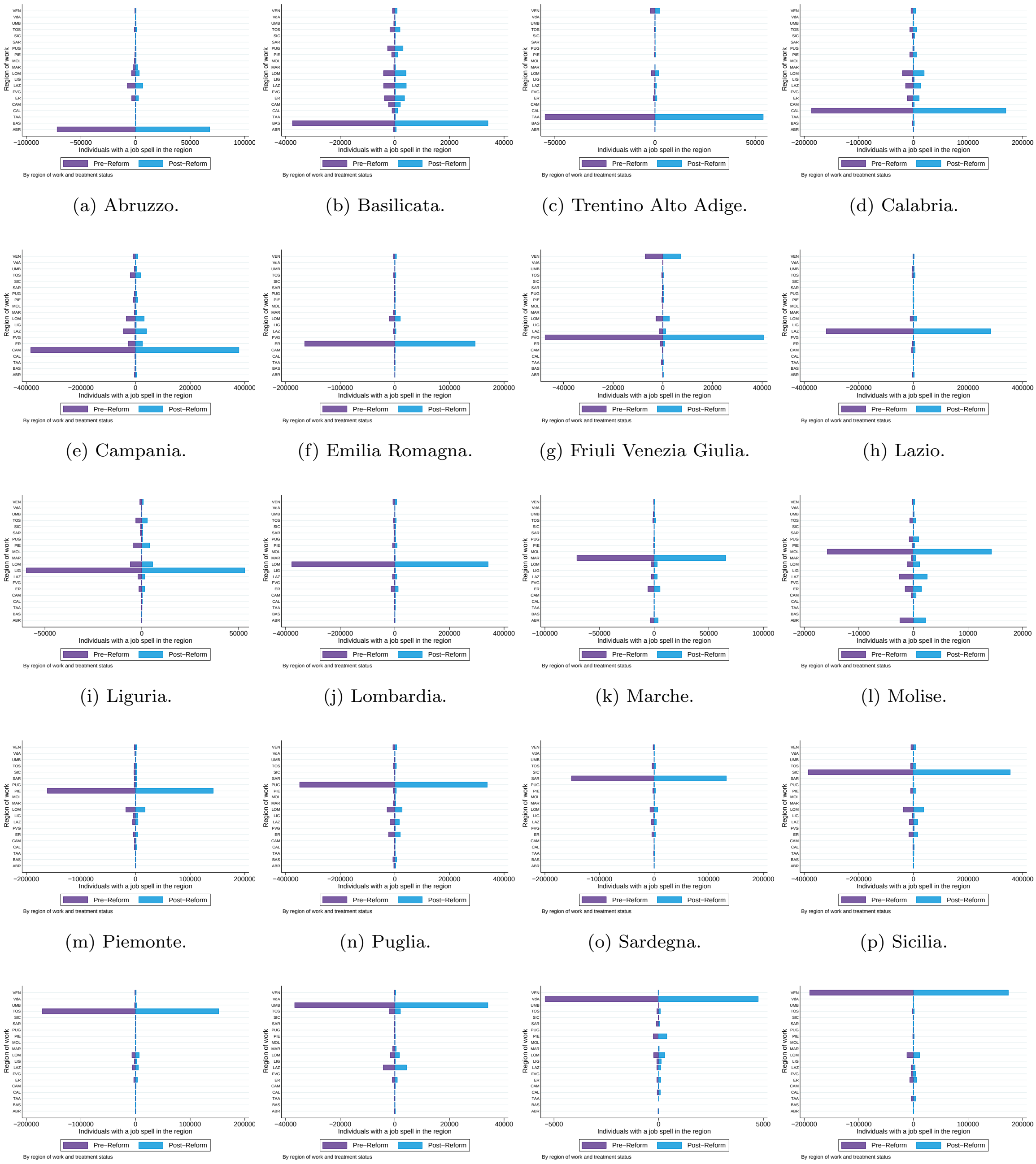
Figure A20. Difference in discontinuities.

Table A100. Static model estimates.

	Working sample at the baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
Employment prob.	.00411	.00588	.00621	.0061	.00604	-.00073
	.02804	.00822	.00793	.00809	.00773	.00444
Apprenticeship prob.	.01324**	.01324**	.01321**	.01321**	.01316**	.01268**
	.00603	.00585	.00581	.00581	.00571	.00562
Perm. Employment prob.	.0166	.017*	.01692*	.0169*	.01696*	.01726*
	.01164	.00969	.00935	.00935	.00921	.00908
Region of birth fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	NO	YES	YES	YES	YES	YES
Sector fixed effect	NO	NO	YES	YES	YES	YES
Firm fixed effect	NO	NO	NO	YES	YES	YES
Time invariant covariates	NO	NO	NO	NO	YES	YES
Time varying covariates	NO	NO	NO	NO	NO	YES

*Notes:*Time invariant characteristics correspond to the real monthly earnings at the time of recruitment, gender, a dummy for missing information on education, past experience. Time-varying baseline characteristics include a dummy if the worker's educational level is higher than the 25th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's educational level is higher than the 75th percentile of the education distribution at a given age in a given month and year; a dummy if the worker's past experience is higher than the 75th percentile of the past experience distribution at a given age in a given month and year; a dummy for changing sector; a dummy if the worker's number of multiple job spells is higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode is associated to a number of job separations higher than the 25th percentile of the corresponding distribution at a given age; a dummy equal to 1 if the job episode is associated to a number of net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution at a given age; a dummy if the job episode benefitted of hiring incentives higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, a dummy if the job episode benefitted of a labour costs reduction higher than the 25th percentile of the corresponding distribution at a given age in a given month and year, and finally a dummy if the job episode benefitted of social insurance higher than the 25th percentile of the corresponding distribution at a given age in a given month and year.

Appendix B1. Additional figures



(a) Abruzzo. (b) Basilicata. (c) Trentino Alto Adige. (d) Calabria.

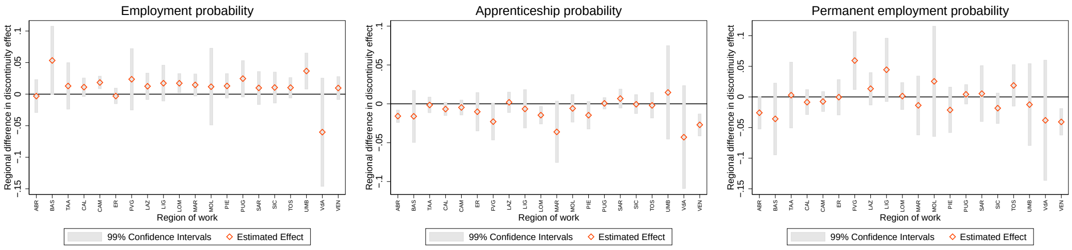
(e) Campania. (f) Emilia Romagna. (g) Friuli Venezia Giulia. (h) Lazio.

(i) Liguria. (j) Lombardia. (k) Marche. (l) Molise.

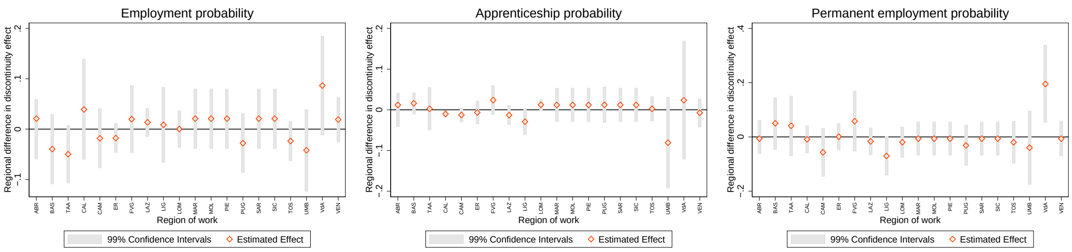
(m) Piemonte. (n) Puglia. (o) Sardegna. (p) Sicilia.

(q) Toscana. (r) Umbria. (s) Valle d'Aosta. (t) Veneto.

Figure B1. Regional distribution of workers by region of birth.

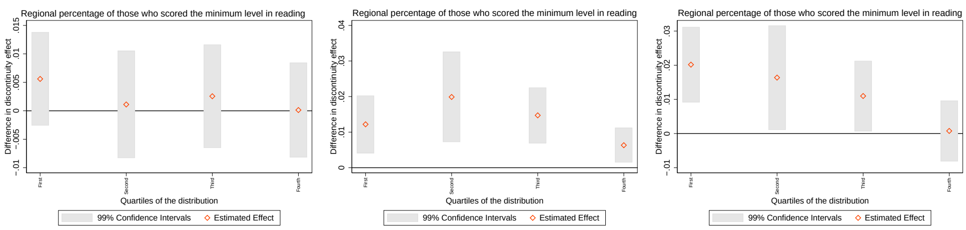


(a) Born neighbouring regions. (b) Born neighbouring regions. (c) Born neighbouring regions.

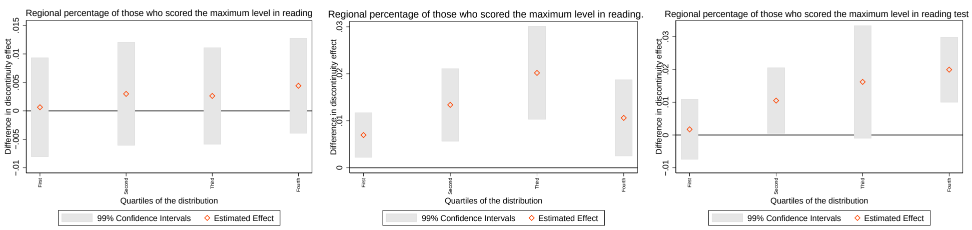


(d) Born outside. (e) Born outside. (f) Born outside.

Figure B2. Difference in discontinuities: differential impact across those born in neighbouring regions and those born outside



(a) Employment. (b) Apprenticeship. (c) Permanent employment.



(d) Employment. (e) Apprenticeship. (f) Permanent employment.

Figure B3. Difference in discontinuities: differential impact across regional level of reading PISA test scores

Appendix B2. The difference in discontinuity regression design.

Following Maida and Sonedda (2019) let's define n the fraction in the population at a given age a of those who start either working or a self-employment activity in a given year. The residual fraction $1 - n$ is made of those, aged a, who have started working in the previous year(s) and those who were unable to have a job spell (even of one day) in the given year. Law no. 30/2003 fixed the maximum age at which an apprenticeship labour contract can be signed at 29 years and 364 days. Consider then an outcome y (apprenticeship, employment and permanent employment probability) and let's express quantities in terms of expected potential outcomes for this fraction n in the population:

$$E[y_{1ib}|a_i] = \mu_{1b}$$
$$E[y_{0ib}|a_i] = \mu_{0b}$$

where b indicates before the introduction of law no.92/2012; 1 and 0 refer to the left and right side of the age threshold.

That is, $\mu_{0b} = \alpha_0 + \beta_0 a_i$ and $\mu_{1b} = \mu_{0b} + \gamma_0$.

Other covariates are not included for the sake of simplicity. The two sides of the cutoff identify the treatment and control states since the intention to assignment into treatment (i.e. job entry as apprentice) is based on the following selection rule:

$$d_i = \begin{cases} 1 & \text{if } a_i < a_m \\ 0 & \text{if } a_i \geq a_m \end{cases}$$

where a_m is the age threshold level (i.e. 30).

I start from the usual definition of the observed outcome for the n fraction in the population whose age is close to the threshold. I then take expectations under the assumption that the intention to assignment into treatment is locally randomised (i.e. independence assumption: $y_{1ib} \perp d_i$ and $y_{0ib} \perp d_i$, i.e. the law could have established another age threshold.)

$$\begin{aligned} y_{ib} &= y_{1ib}d_i + y_{0ib}(1 - d_i) \\ E[y_{ib}|d_i, a_i] = E[y_{ib}|a_i] &= E[y_{0ib}|a_i] + (E[y_{1ib}|a_i] - E[y_{0ib}|a_i])d_i \\ E[y_{ib}|a_i] &= \mu_{0b} + [\mu_{1b} - \mu_{0b}]d_i \end{aligned}$$

Assume that after the introduction of law no.92/2012, for the fraction n in the population, the potential outcomes are equal to:

$$E[y_{1ip}|a_i] = \mu_{1p}$$
$$E[y_{0ip}|a_i] = \mu_{0p}$$

where p indicates post; 1 and 0 refer to the left and right side of the age threshold.

That is, $\mu_{0post} = \alpha_0 + \alpha_1 + \beta_0 a_i$ and $\mu_{1post} = \mu_{0post} + \gamma_1$.

I wrap up here the time dimension into the before (0) and post (1) categories considering the treatment status $k = 0, 1$ with respect to the introduction of law no.

92/2012. Under the crucial hypothesis that the fraction n in the population around the age threshold is constant across the before and after reform periods, it is possible to identify a difference in discontinuity parameter by estimating the following regression model:

$$y_{it} = \alpha_0 + \alpha_1 k_{it} + \beta_0 a_{it} + \gamma_1 d_{it} k_{it} + \gamma_0 d_{it} + \epsilon_{it} \tag{B4}$$

This parameter corresponds to: $(\mu_{11} - \mu_{01}) - (\mu_{10} - \mu_{00})$.

References

Lee, D. S., & Card, D. (2008). Regression discontinuity inference with specification error. *Journal of Econometrics*, *142*(2), 655-674.

Maida, A., & Sonedda, D. (2019). *Getting out of the starting gate on the right foot: employment effects of investment in human capital.* (Mimeo)