Breaking barriers to secure a training contract*

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Abstract

We study agglomeration economies and knowledge spillovers as a route to long-term jobs started with training contracts. We break down macro-areas into quartiles of the number of active firms and the PISA maths test scores. Within these areas, we compare workers aged 29, who can be hired as apprentices, with those aged 30 who cannot, before and after a 2012 reform. We find that many firms close to each other help start open-ended jobs as apprentices because of lower transfer costs from and to firms. Yet, areas with many firms do not have more advantages in long-term jobs than others. A training contract to build long-term careers needs knowledge spillovers.

Keywords: Agglomeration economies; knowledge spillovers; training contracts

JEL Codes:J24, J23, J21, R23, I20, D2

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1 Introduction

United States President Joe Biden has frequently stated that creating good jobs is a policy goal. To address this issue, we need to define a good job. For instance, one cannot stop at employment figures that treat all jobs as equal. In defining good jobs, we might look at three parts. The first could be if the job is well paid compared with equal requirements. The second could be the quality of the working environment, from the nature and content of the work to the pressure the job involves. The third is labour market security: a job that lasts long is one essential measure of its goodness. With the surge of temporary jobs, a wealth of work has studied its consequences (see for instance Dolado 2017). Yet, a few studies explain why firms might opt for fixed-term jobs as the norm (see for instance Cahuc, Charlot and Malherbet 2016). Moreover, no clear consensus is reached on the best route to a secure good job. It is even less clear if this route is viable for everyone.

In this paper, we study the conditions for a successful training contract. For us, a training contract succeeds if it is more likely than a temporary job to lead to secure employment. Under such circumstances, we dig deep into Cahuc et al. (2016)'s results. For them, firms are in the position to offer a job that is not fixed-term if they have long-term production plans. These firms are likely more productive than the ones with short-term plans whose hirings are made of temporary workers. We focus on two well-recognised drivers of firms' productivity: agglomeration economies and knowledge spillovers. With agglomeration economies, firms benefit from being close to each other. This process might help explain why some workers could be hired as apprentices if they are in the right place at the right time. However, it does not fully explain why productive firms might favour an open-ended job with a training period to screen workers. A fixed-term job of the same length as the other job's training period could achieve the same outcome. Yet, it is not the case if screening efficacy depends not only on time spent on it but also on how it is performed. Better education is essential to develop the workers' skills and knowledge that help shape this screening (Autor 2001). Hence, they become crucial for facilitating knowledge transfer from and to firms. With knowledge spillovers, the share of better-educated workers facilitate this transfer and make all workers more productive (Moretti 2011).

We focus on Italy's 2012 labour market reform to show how agglomeration economies and knowledge spillovers can be a route to a successful training contract. This policy outlined an overhaul of apprenticeships that led some firms to hire more apprentices and retain them more (Maida and Sonedda Forthcoming). When a firm hires an apprentice, it has to declare the length of the training period which ranges from six months to three years. During this time, the firm is committed to the training provision and has to pay firing costs as high as those of open-ended jobs to dismiss the worker. The training costs are shared between the employer and the apprentices, who are paid less than workers hired with other contracts. At the end of the training period, the job becomes a standard open-ended one unless the firm gives a 15 days notice to end the contract once the training period is over. Hence, the employer's choice of the training length has to be taken carefully to screen workers adequately.

We use an administrative data set *CICO* (*Comunicazioni Obbligatorie*) that has been covering about 13% of the entirety of job flows since 2009. We can construct workers' histories once they appear for the first time, after 2009, in the data. We compare the outcomes of workers in less than a year of age range before (from January 2010 to June 2012) and after (from July 2012 to December 2014) the reform. We consider three outcomes, all measured by an indicator function that is equal to 1 if the status applies or 0 otherwise. The first relates to being hired as an apprentice; the second to being hired with an open-ended job; the third to starting a job that is at least 15 days long.

The 2012 reform provided incentives to offer apprenticeships rather than fixed-term jobs to perform this screening. It set out a mentoring scheme for which hired apprentices could not outnumber other workers in the same occupation. It limited the apprentice hiring if the firm had not retained at least 30% of those hired in the previous three years under the new regime. It raised the payroll tax on fixed-term jobs and left the tax rebate on apprenticeships. Hence, the first building block of our identification strategy is a before and after reform comparison. We centre data 30 months before June 2012, when the reform kicked in, and 30 months after to make this comparison. As a second building block, we use the age limit of 30 years for hiring an apprentice. This rule has been in place since 2003 and still is. Both employer and employee can exert a certain degree of control over the probability of engaging in apprenticeships, but this control is limited. As there is no precise control on the age to hire (be hired) an apprentice, we can leverage the discontinuity in its probability. We focus on workers close to the cut-off of 30 years, selecting those aged 29 and turning 30 and those aged 30 and turning 31. These workers are similar and face the same labour market macroeconomic conditions, but those aged 30 or more cannot be hired as apprentices. As a third building block, we need a measure of agglomeration economies and knowledge spillovers for the area where people work to bring in these two factors into our analysis. Unfortunately, we can only focus on the region rather than a more disaggregated local area with our data. We use data from the Italian office for national statistics (ISTAT) on the number of active firms and the share of high-school pupils with the highest score on the PISA maths test to group regions into quartiles. The number of active firms is intended to measure agglomeration economies, and the PISA maths test scores approximate knowledge spillovers. We calculate their average value between 2010 and 2014 in each region to rule out a different grouping of regions in each quartile over time. Lower values indicate greater disadvantage, while higher values indicate greater advantage. As regions in the northern part of Italy fall into the top quartile of the PISA maths test score, regions in the south are at the bottom. Yet, the north-south divide is not so sharp when we group regions on the number of active firms. Regions from the north to the centre and south are in the top quartile (Veneto, Lombardia, Emilia Romagna (north), Lazio (centre) and Campania (south)). Behind our strategy is the assumption that how regions are broken down into quartiles is exogenous to being aged 29 rather than 30 before and after the 2012 reform. This assumption is credible because the first two building blocks are founded on a randomised source of variation. As a way to prove this argument, we show in the Online Appendix that in each quartile of each indicator, covariates of treated and untreated workers before and after the reform are balanced out. Hence, as in the tradition of regression discontinuity design, we do not need to include them in the regression model. Moreover, we can provide a graphical analysis that delivers the same results as our regression model. These are unlikely circumstances when the treatment is endogenous and correlates with observable and unobservable characteristics.

We assign workers into quartiles of the number of active firms and PISA maths test scores through their workplace region. We compare those aged 29 to 30 before and after the reform in a macro-area defined by each quartile. The treatment effect is identified within each macro-area, but we can gauge how it varies across quartiles. The extra percentage points in the outcome that workers in the top quartile benefit compared to the bottom show how agglomeration economies and knowledge spillovers affect a successful training contract route. This differences-in-difference-in-discontinuity strategy constitutes our static model. With this model, we address the issue of how agglomeration economies and knowledge spillovers facilitate the route to an open-ended job through a training contract. Yet we also estimate a dynamic model to ascertain whether these two factors are a route to building a long-term career. This dynamic model leverages the same sources of randomised variation as the static one. However, it estimates the treatment effects after 30 months from the baseline. These treatment effects depend on their past histories and are founded around job mobility. As long as workers do not change jobs, the higher the treatment status's persistence and the more successful the training contract becomes.

We have five primary results.

First, treated workers have a probability of starting an open-ended job through apprenticeships as high as the untreated ones in areas in the bottom quartile of the number of active firms. In comparison, in the top quartile, treated workers increased this probability by about one percentage point compared with the untreated ones.

Second, after 30 months, treated workers have about eight percentage points higher probability of being in the same job than the untreated ones. However, no extra percentage points are given to those in the top quartile compared with the bottom. If anything, it is the bottom quartile to gain slightly more. How many firms are close to each other help to transfer workers from less to more successful firms. Hence, it is more likely to be hired in an open-ended job through apprenticeships. Yet, this sole mechanism does not prove to be enough to build a long-term position.

Third, open-ended jobs are made twice as likely by being at the top rather than the bottom quartile of the PISA maths test scores. As treated workers in the former are half a percentage point more likely than untreated ones, those at the top have a 1.2 percentage point advantage.

Fourth, after 30 months, treated workers at the top quartile capitalise on their advantage and are eight percentage points more likely to be in the same job than untreated ones. This advantage is halved at the bottom quartile. Areas with better-educated workers are more likely to have successful training contracts. Knowledge spillovers are an essential part of the route to it.

Fifth, areas with a large number of firms close to each other that hire better-educated workers have an advantage over other areas. Compared with the untreated, treated workers in areas in the top quartiles of the number of active firms and PISA maths test scores are twice as likely as treated workers in other areas to start an open-ended job through apprenticeships.

In the last part of the paper, we follow two different strategies to show that our results do not depend on how we group regions into quartiles. First, we estimate worker fixed effects in a two-way fixed-effects linear model for the probability of being hired as an apprentice. We define *good* workers as those who fall within the top one-third of the distribution of these fixed effects. For these good workers, we compare at the same quantile areas in the top quartile of the PISA maths test scores with other areas. We show that more good workers are found in areas in the top quartile of the PISA maths test scores. Second, we focus on agglomeration economies within one region in the northern part of Italy, Piedmont. The data structure is the same as the National representative sample, but we have the universe of all job flows in the region. However, we cannot reconstruct the entire working histories of those who migrate and don't keep the domicile in the region. This drawback prevents us from estimating the dynamic model, but we can estimate our static model. We separate local labour markets in quartiles of the number of active firms. We consider two groups: one made by the top quartile (Turin's district) and all the other labour markets. We find that treated workers in the Turin district are about a one percentage point more likely to start an open-ended job through apprenticeships than the untreated ones. This result aligns with what we estimate when we use the national data.

In our paper, we introduce some features of the literature on agglomeration economies and knowledge spillovers (see for instance Moretti 2011) into the one on the best contract to access an open-ended job. For a review of temporary jobs as stepping stones or dead end jobs, see Picchio and Filomena (Forthcoming). It is the first paper to do that to add a new channel on the best route to successful training contracts. Previous works focused on binding commitments to training provision (Dustmann and Schönberg 2012) or the degree of unionisation (Dustmann and Schönberg 2009). Our analysis complements the understanding of this issue in a novel way.

The rest of the paper is organised as follows. Section 2 outlines the context. Section 3 describes the institutional framework. Section 4 illustrates the data, and Section 5 discusses the empirical model. We report our results in Section 6. Section 7 concludes.

2 The economic setting through the lens of the literature

The surge of fixed-term contracts hails a debate on firms' choices about the type of contract offered. As temporary jobs are nearly the norm for workers when they start their careers, understanding the best route to a secure job for them is needed. Temporary workers are worse off in terms of many aspects of job quality. They tend to receive less training (see for instance Cabrales, Dolado and Mora Villarrubia 2017), earn less (see for instance Blanchard and Landier 2002) and have worse career prospects than workers in open-ended positions (García-Pérez, Marinescu and Vall Castello 2019). Yet, only a few papers tackle the issue of when and why firms opt for fixed-term rather than open-ended jobs (Caggese and Cuñat 2008, Berton and Garibaldi 2012, Cahuc et al. 2016, Guglielminetti and Nur 2017, Fialho 2017, Tealdi 2019). One reason for temporary jobs is to fill short-term production (Cahuc et al. 2016). As employers deem their economic horizon to be long-term, they are more willing to make a worker start an open-ended job. They could be even keener to pursue these jobs if this is the route to increase the chance to find the right worker for the vacancy to be filled. A training contract can help screen workers (Autor 2001) and cannot be for everyone for at least two reasons in such a setting. First, firms will select those who will be offered this job to increase the probability to minimise the screening costs. Second, not all firms will offer it, but only those with a long-term horizon—and these firms are likely to be more productive. We focus on the latter and look at two different building blocks of the literature that explain why firms are more productive in some local labour markets.

Location is an important factor in starting and growing a firm. It was more than a century ago when Marshall (1890) discussed it, and it still is. Each country has its hotspots of growth for businesses and areas where firms want to be close to each other despite having to pay higher wages and prices. As Marshall (1890) suggested, these locational preferences can be due to higher productivity or lower costs generated by firms' proximity. Cheaper and faster provision of services and goods lower employers' costs when the input-output chain is the primary reason for their locational preferences. Yet, this mechanism makes firms' total factor productivity unchanged even when agglomeration costs vary. Hence, the input-output chain cannot explain why some firms might offer training contracts rather than fixed-term jobs.

Labour market's thickness can be a reason for firms' preferences to be close to each other (Serafinelli 2019, Greenstone, Hornbeck and Moretti 2010, Combes, Duranton, Gobillon, Puga and Roux 2012, Gathmann, Helm and Schönberg 2020). With search frictions and heterogeneous firms and workers, the probability of better worker-firm matches increases with the number of job offers and workers keen to accept them (Abowd and Kramarz 2003, Blatter, Muehlemann, Schenker and Wolter 2016, Helsley and Strange 1990). As the number of firms and workers in the same labour market is large, the costs of moving workers from unsuccessful to successful firms reduce (Moretti 2011). These more successful firms could be willing to offer them a different job compared with the firm of origin.

A second reason is knowledge spillovers and human capital externalities. Formal and informal workers' networks spread shared knowledge and speed learning in and across workplaces (Glaeser 1999, Serafinelli 2019). The higher the knowledge and competencies in the area, the faster and more effective this process is. As different measures of this higher knowledge can be used, Moretti (2004) opts for the share of college graduates in the local labour market.

In the next section, we discuss how a reform led some firms to offer a training contract rather than a fixed-term job. We then focus on agglomeration economies and knowledge spillovers to show how these two factors help shape this job offer.

3 Institutional framework

As Law No. 30/2003 and Legislative Decree No. 276/2003 passed a sweeping overhaul of the apprenticeship rules, regions had the power to oversee and steer it. Not all of them moved at pace to address this issue. Cappellari, Dell'Aringa and Leonardi (2012) exploit this different pace to show that the policy increased firms' productivity.[1] After eight years, Legislative Decree No. 167/2011 introduced a national regulation for this contract, which all regions must follow. These two laws set out the rules of the pre-reform regime. We report those essential to our analysis that were kept in the post-reform regime.

A hiring age limit for vocational apprenticeships of 29 years and 364 days was settled to underline its role as an entry job position. Some features of this contract make it unique. It is an open-ended labour contract that commits employees and firms to an initial fixed training period.[2] The training is primarily on-the-job. However, workers could be asked to attend some external courses if their training programme takes them in. The training programme is written and agreed upon by firms and workers as soon as the job starts. While we cannot verify if this training programme takes place, other works rule out evidence of the misuse of this contract (Citino and Fenizia 2022, Maida and Sonedda Forthcoming)

The firm can withdraw from the contract when the training period expires. If the employer does not notice the worker, the contract automatically follows the rules of a standard open-ended contract. If the firm terminates the job before the end of the training period, it has to pay the open-ended contracts' firing costs. Law No. 92/2012 kicked in in this context. The law explicitly encouraged firms to substitute temporary with apprenticeship contracts. The reform set the minimum length of the training period to six months and the maximum length to three years (before this, it was six years), although there are some exceptions. Hence, people older than 30 can work as apprentices but cannot enter new positions as apprentices. The law enforced a mentoring scheme, imposing a ratio between apprentices and other workers in the same firm. The law sanctioned firms that do not adhere to the contract's open-ended nature. Violating firms cannot hire more than one apprentice for three years after the previous worker entries if they still employ less than 30% of them. As a final move against the preference for fixed-term contracts, the law increased their social security contributions and did not remove the tax rebate on the apprenticeship contract. All these changes favoured the route to a training contract.

[1] Regions' response was not the only dimension considered by the authors. The staggered law's implementation was also due to the timeline of the renewals of collective agreements.

[2] In Italy, there are three kinds of apprenticeships. One is a vocational and education training VET scheme. However, this contract's age limit is 24 years and 364 days, below the age range considered in our analysis. In the light of this consideration, we are focusing on a training contract.

4 Data

We use data on job flows from an administrative data set provided by the Ministry of Labour and Social Policies, CICO (Comunicazioni Obbligatorie). Since 2009, these data have included each date (day, month, and year) and detailed information of all job flows of dependent workers and self-employed ones (individuals with a VAT number). This detailed information ranges from the type of labour contract to an anonymous identifier for both the firm and the worker, the gender, birth year, the region of birth and work, citizenship, and education for each worker. It is a random draw of the entirety of these job flows. All individuals born on the 1st, 9th, 10th, or 11th of each month for each birth cohort are gathered in these data. The coverage is about 13% of the universe.

We can construct the working histories in a panel structure and select those who started a job in a 30 months interval around June 2012, when the reform kicked in. Hence, as untreated workers reached the cut-off age of 30 between January 2010 and June 2012, treated ones did it between July 2012 and December 2014. We restrict the cut-off age to compare those who are 29 and are turning 30 to those who are 30 and are turning 31. With information on the birth year, we measure age as of 31 December of the previous year to minimise measurement error.[3] Our sample contains 2,132,899 observations with 168,542 workers and 152,225 firms.

We use the Italian Office for National Statistics (ISTAT) data on features of the labour demand and supply at the regional level. Regions were divided into quartiles based on their firms' turnover rates, high-tech firms' share, employees' share in high-tech occupations, and the number of active firms. As we primarily focus on the number of active firms, labour demand forces might feed in all of them. The number of active firms was also divided by population size to get this number per capita. We also separate regions into quartiles based on labour supply features. These features are the percentage of those with the maximum (minimum) level on the PISA test in maths and reading; the share of those repeating the schooling year; the number of enrollees per class and per school; and the drop-out rate in high school.[4] All these quantities are averaged over time (2010-2014 for the firms' features and 2006-2015 for all the others) and therefore constant.[5]

[3] For example, in 2012, an individual is 29 years old if she belongs to the 1982 cohort and she is turning 30 during the year.

[4] We calculate the share of those repeating the schooling year as the number of those who repeated the school year over the total number of enrollees at upper secondary school. The average number of enrollees per class equals the total number of enrollees over the total number of school classes. The average number of enrollees corresponds to the total number of enrollees over all schools' total number. The drop-out rate is the total number of students who dropped out over the total number enrolled in high school.

[5] Students involved in these PISA tests are younger than those considered in our analysis. Yet this fact might not be an issue. What is essential is a stable grouping of regions into quartiles.

[Figure 1 about here]

Figure 1 displays the number of active firms (panel a) and the share of those with high scores on the PISA maths test (panel b) broken down by quartiles. A different colour refers to each quartile, ranging from the lightest to the darkest red. The lowest number of active firms is found in small regions in Italy's northern (Trentino and Valle d'Aosta), central (Umbria) and southern parts (Molise and Basilicata). The highest number is also spread across Italy as Veneto, Lombardia, Emilia Romagna (north), Lazio (centre) and Campania (south) are in the top quartile.[6] As we want to identify an effect that cannot be confused with the rich (north)-poor (south) divide, we refer to this measure rather than the per capita one. In Online Appendix C1, we show that the number of active firms per capita reflects this north-south divide. Moreover, the per capita measure mixes factors from the demand and the supply side. Population size changes the labour supply and this ratio for a given number of active firms. In Online Appendix E1, we break down these quartiles of active firms by sectors and firm size. We also report the distribution of the sectoral share of regional value-added. The division of regions displayed in panel (a) of Figure 1 is quite similar to the ones in the Online Appendix. Hence, it appears that the sectors or the firm size do not change how we group regions. In contrast, stark differences between the north and the south are apparent in panel (b) of Figure 1. Those with the highest score in the maths PISA test are in the northern part of Italy. In contrast, the entire southern part of Italy, including the main islands, exhibits percentages below the median value.[7]

As a final step to build our working data, we link the CICO dataset to each of these quartiles through the information on the worker's region of work. We do not have information at a more local level, and we do not know when workers migrated if they did. In Online Appendix D1, we discuss under which circumstances using the region of work to merge the data is equivalent to using the region of birth.[8]

5 Empirical model

5.1 Differences-in-difference-in-discontinuity

Our analysis feeds in three sources of randomised variations. First, since 2003 the age limit to hire apprentices has been 29 years and 364 days. As apprenticeships are open-ended contracts,

[6]We use the number of active firms in Bureau Van Dijk (AIDA) data as an alternative measure. This analysis can be found in Online Appendix C1. We follow the same procedure applied to ISTAT data because CICO's firm identification code is anonymous.

[7]We can provide similar pictures for the PISA reading test.

[8]We can show that these circumstances hold in our analysis. These results are available upon request from the author.

the probability of starting an open-ended job is also discontinuous around the age cut-off of 30. We can compare those aged 30 and turning 31 with those aged 29 and turning 30. While these workers are similar, some can be hired as apprentices, and some cannot because of the policy rule. This source of variation is random if workers cannot manipulate their access to this labour contract. Second, we use the 2012 reform to compare those aged 30 and turning 31 with those aged 29 and turning 30 before and after the policy change. With this research design, consecutive birth cohorts are compared. Moreover, as the reform kicked in in June, some treated and untreated workers were born in the same year. With policy changes that could not be anticipated, they are exogenous. Third, the division of regions into quartiles is independent of being below/above 30 years before/after the reform. Another potential threat could be migration influx from and to different groups of regions. Yet, this threat is not a matter of concern in our setting for two reasons. First, we compare workers in the same area with less than one year of difference in age both in the pre-and post-reform period. It is pretty unlikely that migration flows differ in such a short time between workers of nearly the same age. Second, we can show that results do not change if we link the workers to the quartiles using the information on where these people were born rather than where they work (see Online Appendix $D1$).

We have several arguments to support the above claims. First, we report that workers and firms have limited control over the hiring age of apprentices. Second, treated and untreated workers are proved to be observationally similar. Third, we show that we do not need covariates to achieve identification. Fourth, we can reproduce our static estimates with a graph that uses a weighted average of the raw data. This evidence holds for each quartile and for each indicator that breaks down a different grouping of regions. Hence, we can rule out the correlation between our treatment and the separation of regions into quartiles.

Equation 1 reports our regression model:

$$y_{i,t} = \alpha_{1v} + \alpha_1 k_{it} + \gamma_1 d_{it} k_{it} + \gamma_0 d_{it} + v_i + \sum_{v=2}^{v=4} \beta_{1v} d_{it} v_i + \sum_{v=2}^{v=4} \alpha_{1v} k_{it} v_i + \sum_{v=2}^{v=4} \gamma_v d_{it} k_{it} v_i + \epsilon_{i,t} \quad (1)$$

We denote $y_{i,t}$ as the outcome for individual i at the time (year, month) t. We consider three outcomes, all measured at the monthly level. The first is the apprenticeship probability, which takes the value of 1 if the worker starts this job or 0 otherwise. The second is the probability of an open-ended job, which is equal to 1 for those hired with this contract or 0 if they do not. Finally, the probability of being employed is measured by an indicator function which is equal to 1 if the employee works at least 15 days in the month. The indicator function k_{it} takes a value of 1 if the worker is subject to Law No. 92/2012 and 0 otherwise. The indicator function d_{it} assumes the value of 1 if the person is less than 30 years old and 0 otherwise. Each dummy variable v_i refers to a quartile for each labour demand and supply factor.[9]

Our outcomes y are different definitions of the employment probability: starting a job that lasts at least 15 days, an open-ended or an apprenticeship contract.

We focus on the coefficients of the triple interaction, γ_v. For each quartile, this coefficient compares the outcomes of workers aged 29 with the outcomes of those aged 30 before/after the reform. It measures a static intent to treat (ITT) parameter. Hence, while the effect is identified for each quartile, we can appreciate how it varies over them to gauge the saliency of each factor to start an open-ended contract through apprenticeships. However, even with an open-ended contract, the job can end. We use a dynamic model to ascertain if these factors help shape the probability of stable jobs.

Equation 2 considers the persistence in outcomes generated by the reform at the age cut-off for each quartile.

$$
\begin{aligned}
y_{i,t} = {} & \alpha_{1v} + \alpha_1 k_{it} + \gamma_1 d_{it} k_{it} + \gamma_0 d_{it} + v_i + \sum_{v=2}^{v=4} \beta_{1v} d_{it} v_i + \sum_{v=2}^{v=4} \alpha_{1v} k_{it} v_i + \sum_{v=2}^{v=4} \gamma_{1v} d_{it} k_{it} v_i \\
& + \phi_\tau \sum_{\tau=1}^{\tilde{\tau}} (\alpha_1 k_{i,t-\tau} + \gamma_\tau^{TOT} d_{i,t-\tau} k_{i,t-\tau} + \gamma_0 d_{i,t-\tau} + \sum_{v=2}^{v=4} \alpha_{1v} k_{i,t-\tau} v_i + \sum_{v=2}^{v=4} \gamma_{\tau v}^{TOT} d_{i,t-\tau} k_{i,t-\tau} v_i \\
& + \sum_{v=2}^{v=4} \gamma_{0v} d_{i,t-\tau} v_i) + \epsilon_{i,t}
\end{aligned} \tag{2}
$$

where $\gamma_{\tau v}^{ITT} = \gamma_{\tau v}^{TOT} + \sum_{h=1}^{\tau v} \gamma_{\tau - hv}^{TOT} \phi_h$ estimates the dynamic ITT effect for each quartile.

We can estimate these coefficients because some workers change jobs. Our effects measure if the probability of ending an open-ended contract is lower after the reform for those who started the job aged less than 30 for each quartile. We can provide these quantities for each of the following τ months from the first to the 30th. We cannot go beyond this 30 months limit as another policy kicked in.

We estimate our static and dynamic models in the range of ± 1 year of age around the cut-off. In this age interval, in Equation 1, the running variable (measured as deviation from 30) is perfectly collinear with the indicator function d_{it} due to its discrete character. The regression model requires functional form assumptions that can be tested. A battery of graphical analyses for each quartile shows the harmlessness of these functional form hypotheses. It comes as the

[9]For instance, when we separate regions into quartiles using the number of active firms, the top quartile dummy is equal to 1 for workers in Campania, Veneto, Lombardia, Emilia Romagna, and Lazio, and 0 for all the others.

sources of variation are randomised. Under such circumstances, covariates are not needed to estimate the static effects. That is to say that the difference at the cut-off between the outcomes of treated and untreated workers as measured in raw data coincide with these estimated effects. For further details on the methodology, see Maida and Sonedda (Forthcoming).

6 Empirical analysis

6.1 Graphical analysis and model validation

As proof of the validity of our model, we present here a graphical analysis for regions grouped by the top quartile of the share of students with the highest scores on the PISA maths test. Hence, we refer to workers in Trentino, Friuli Venezia Giulia, Veneto and Emilia Romagna. We report all the other graphs in Online Appendix $A1$.

The probability of being hired as apprentices decreases as workers approach the age limit of 30 (0). This trend is common to treated and untreated workers aged 25 (-5) to 35 (5). Yet, treated workers are slightly more than one percentage point likely to start this job compared with the untreated ones when they are 29 and are turning 30 (-1). This difference amounts to 3% minus 1.7% and can be read on the vertical axis of Figure 2 (panel a). Treated workers are also slightly more than one percentage point likely to find an open-ended job compared with the untreated ones at the age cut-off. We can work this out by subtracting four percentage points (15% minus 11% that can be read on the vertical axis of panel (b) for age -1) to 2.8 (13.8% minus 11% for age 0).[10]

[Figure 2 about here]

We superimpose the third-order polynomial fit in age (99% confidence intervals). As both panels indicate, the fit is pretty good. Moreover, at the age cut-off, the linear model assumption proves accurate. All the other evidence on the model's validity can be found in Online Appendix $A1$. Here we emphasise three findings. First, we follow Lee and Lemieux (2010) to show that workers do not manipulate the apprenticeship hiring age. Second, our tests confirm that covariates are balanced out at the age cut-off before and after the reform. Third, we carry out the Lee and Card (2008) test to support our hypotheses on the functional form of the regression model. All these features hold for each quartile of each indicator.

[10]This drop at the age cut-off cannot be observed for the probability of starting a job of at least 15 days. These figures are available upon request from the author.

6.2 Estimation results

We start by estimating Equation 1 when we divide regions into quartiles of the share of students with the highest score on PISA maths tests.[11] As the level of the score increases, we assume that so does the quality of education. Hence, firms in the northern regions of Lombardia, Veneto, Emilia Romagna, Trentino e Friuli Venezia Giulia can hire better-educated workers than firms in other areas. Panel (b) of Figure (3) ascertains if the 2012 reform was more or less effective because of that. In the top quartile, treated workers are about 1.3 percentage points more likely to be hired as apprentices compared with the untreated ones. This quantity coincides with what can be read in Figure (2). However, in the same quartile, the treated workers' probability of being hired with an open-ended contract is 1.9 as high as the untreated ones (panel (c)). We look at the impact on the probability of starting a new job to explain their divergence. Yet, this effect is not statistically different from zero (panel (a).[12]

[Figure 3 about here]

In the bottom quartile, treated workers were just 0.6 points more likely to be hired as apprentices than the untreated ones. Hence, in the top quartile, treated workers were 0.7 percentage points more likely to be hired as apprentices than those treated at the bottom. In this bottom quartile, we find all southern regions (Basilicata, Calabria, Campania, Molise, Sardegna and Sicilia). At first glance, one could expect that it comes because of inequalities between the north and south of Italy. However, the argument of developed versus under-developed areas is at odds with panel (a). It is more likely to find a job in a prosperous labour market. As we compare workers in the same areas with an age gap of less than a year, there is no reason to expect that being or not in a flourished economy matters.[13] Yet, it matters to use one labour contract rather than another. When firms have more long-term production opportunities, they use less fixed-term contracts (Cahuc et al. 2016). Hence, they are more likely to substitute temporary with training contracts if it is deemed to be profitable. Behind this higher profitability can be agglomeration spillovers, human capital externalities, or both. Education inequalities could deepen old geographical divisions. Firms are more productive if workers are more productive. Moretti (2004) shows that a larger fraction of educated workers makes all workers more productive because of human capital externalities. He reports that firms

[11]In Online Appendix $C1$, we report our results when regions are separated into quartiles by the share of students with the minimum score on this test. We also consider the PISA reading test.

[12]Table $A4$ in the Online Appendix $A1$ reports these coefficients. They are pretty stable to the inclusion of covariates.

[13]In Online Appendix A1, we provide support for this statement. With balanced-out covariates at the age cut-off before and after the reform, little room is left for picking up spurious correlations.

in cities with a larger share of college graduates are more productive than similar firms in areas with a smaller share. While we cannot rule out that higher education can complement a training contract, we focus on high school education for two reasons. First, higher educated workers are less likely to accept a training contract if offered because of its wage penalty. Second, high school graduates have an intermediate level of education that could complement on-the-job training.

The grouping of regions by quartiles of the PISA maths test would be mirrored by quartiles of the share of high school achievers. Southern workers are lower educated than average, with 38% having an education lower than high school in our sample, compared with 31% across Italy in our data. Hence, high school access and quality could make a difference for the firms.

Panel (d) of Figure (3) shows that treated workers in the top quartile are four percentage points more likely to have an open-ended contract than treated workers in the bottom after 30 months from the baseline. With treated workers in the bottom quartile four percentage points as high as untreated, this advantage doubles at the top.

Before drawing conclusions on the sole basis of the PISA maths test, we use a few other indicators for two reasons. First, behind these indicators are different measures of education quality. We test how robust the results are when we bring in these differences. Second, the grouping of regions varies with these indicators. With the southern regions being in the top quartile of the high school drop-out rate, there are both northern and southern regions in the top quartiles of the share of those who repeat the schooling year, class and school size. Results are robust. Treated workers (compared with the untreated) in the quartile with the lowest education quality never perform better than treated workers (compared with the untreated) in the other quartiles (see Online Appendix $C1$). However, the pattern is clear when we divide regions into quartiles based on the PISA maths test. As the average test score increases, so does the treated workers' probability, compared with the untreated ones, to have the same job after 30 months. Education inequalities deepen geographical divides impacting regional productivity and workers' careers. The geographical divide in education is what we want to measure to explain how knowledge spillovers create the conditions for a successful training contract. It cannot be due to other unmeasured geographical differences because there are no reasons for them to impact disproportionately those aged 29 rather than 30 before and after the reform.

Firms could be more productive because of agglomeration spillovers. A large number of papers show that firms are more productive in thick labour markets (Serafinelli 2019, Greenstone et al. 2010, Combes et al. 2012, Gathmann et al. 2020). As plants locate close to others, firms' productivity raises (Abowd and Kramarz 2003, Blatter et al. 2016, Helsley and Strange 1990).

Hence, the number of active firms in an area could matter. In thick labour markets, workers are more likely to move from unsuccessful to successful firms when their set of choices is larger. With better firms' production opportunities, the probability of offering an open-ended contract that entails some training rises. As the probability of finding a job that matches best with the worker's skills is higher, it is more likely that this job lasts. We submit these arguments to test, and Figure (4) shows what we find.

[Figure 4 about here]

In the top quartile, treated workers are one percentage point more likely than the untreated ones to be hired as apprentices (panel (b)). Their advantage in terms of the probability to be hired under an open-ended contract is slightly higher (panel (c)). Yet, the difference between the two effects is statistically equal to zero.[14] Instead, treated workers are likely to be hired under an open-ended or apprenticeship contract as high as untreated ones in the bottom quartile. We find in this quartile also workers in northern regions such as Trentino Alto Adige and Valle d'Aosta. Their size limits the number of firms that can be closely located. This limited capacity put a halt to the probability of moving from unsuccessful to successful firms. It capped the number of temporary jobs that could have been apprenticeships because of the reform. Yet, this limited capacity is not a barrier to a lasting job when most located firms are productive. Treated workers in the bottom quartile are eight percentage points more likely than untreated to have an open-ended job after 30 months. There is no difference between the top and the bottom quartiles. In Online Appendix $C1$, we report figures when we separate regions into quartiles based on the per capita number of active firms.[15] This indicator blends labour demand and supply factors and brings in the north-south divide. In the bottom quartile, treated workers are likely as high as untreated ones to be hired under an open-ended job. Yet, as treated workers are eight percentage points more likely than untreated ones to have the same open-ended job after 30 months in the top quartile, this advantage falls to four in the bottom. The same difference is estimated when we group regions into quartiles based on the PISA maths test. Our results have to be read as follow. Cahuc et al. (2016) show that firms with more long-term production opportunities use less fixed-term contracts. In our paper, we provide clear evidence of this argument. Productive firms are keen to offer training rather than temporary jobs if encouraged to do so as when the 2012 reform kicked in. Once started, these jobs are much more likely

[14] We measure this difference as the impact on the probability of starting a new job (panel (a)).

[15] In the same Online Appendix $C1$, it can be found the analysis when we group regions into quartiles based on firms' turnover rates, high-tech firms' share, employees' share in high-tech occupations.

to last. Firms can be more productive because of human capital externalities, agglomeration spillovers or both.

[Table 1 about here]

In Table (1) we revisit our analysis treating these two factors jointly and not in isolation. We divide regions into groups based on being in the top quartiles of labour demand and supply indicators. For instance, in the first rows of Table (1), the column named "high interaction" reads the results for workers in regions that are in the top quartile of the number of active firms and the share of students with the highest score in the PISA maths test. The column named "non-high interaction" groups all the other workers. Treated workers (compared with the untreated ones) in both top quartiles are twice as likely to start an open-ended job than treated workers (compared with the untreated ones) who are not in these top quartiles. In Online Appendix $A1$, we report our estimates after 30 months from the baseline.[16]

So far, we have grouped regions into quartiles for labour demand and supply factors. We have then assigned workers to quartiles according to their region of work. We now depart from this perspective to show that results do not depend on it.

6.3 *Good* workers and labour demand and supply factors

Low productivity in Italy has long been a problem. Apprehended as the result of skills shortages, this is the issue that apprenticeships are supposed to solve. Yet, there are some problems to overcome. In this section, we support what we have shown so far. The worker's probability to be hired as an apprentice depends on local labour market factors.

We follow Serafinelli (2019) to define *good workers*. For Serafinelli (2019), good workers are those who come from good firms, and good firms are those that pay a relatively high wage premium. Here, *good workers* have a relatively high individual-specific probability to be hired as apprentices. These good workers can be recruited in highly or non-highly productive firms. Apprenticeships are an open-ended contract in Italy. Firms that offer more open-ended jobs are more productive (Cahuc et al. 2016). Firms with higher fixed effects might be more productive. Hence, firms with higher fixed effects might be more likely to recruit apprentices.

We use our data from January 2010 through December 2014 to run the following regression model to estimate fixed effects for workers and firms:

[16]Some placebo and robustness checks are available upon request from the author. These tests are the differences-in-difference-in-discontinuity version of those in Maida and Sonedda (Forthcoming), to which we direct for further details.

$$y_{ijt} = \theta_i + \psi_j + \phi_t + rw_{ijt} + r_i + s_{ijt} + b_1 X_{it} + u_{ijt} \quad (3)$$

The outcome is the worker's i probability to be recruited as an apprentice. This outcome is a function of fixed effects for workers and firms and other time-varying and time-invariant characteristics. This worker was born in region r, works in region rw and sector s for firm j at time t.[17]

[Figure 5 about here]

We define good workers as those in the top one-third of the estimated fixed effects for workers.[18] We divide these good workers into two groups based on the region where they work. The region is in the top quartile of the PISA maths test for workers in the first group (x-axis). Workers in all the other regions are in the second group (y-axis). Panel (a) of Figure 5 presents the quantile-quantile plot of the estimated fixed effects for these two groups in the subsample of good workers. Panel (b) reports the estimated fixed effects for firms in groups divided by being or not in the top quartile of the number of high tech firms. In the axes, we read the estimated fixed effects in units. As the quantile level is the same for each point of the 45 degree line in the quantile-quantile plot, the x values are higher than the y values if points are on the right-hand side of it. Hence, good workers are more likely to be in areas where the percentage of students with the highest score in the PISA maths test is higher. Good firms that recruit good workers are more likely to be in a place where the number of high-tech firms is large.

6.4 A tale of two local labour markets

When we divide regions into quartiles of the number of active firms, treated workers in the top quartile are one percentage point more likely than the untreated ones to be hired as apprentices. We now show that this is the result that the number of active firms is supposed to lead. We turn to the situation in one region, Piedmont, to prove that it does not come out from our grouping of regions. Piedmont is in the north-west of Italy with 4.5 million people (7.5% of the Italian

[17] We include month and year dummies to measure time fixed effects. We include as other covariates a job-specific (not an individual-specific) measure of the log of the hiring earnings and dummy variables measuring whether, in a given month and year, worker's education is in the bottom (top) quartile of the education distribution, conditional on age; whether the employee's experience is in the top quartile; whether the worker's number of jobs in a month was not in the bottom quartile; whether the job episode benefited from a labour cost reduction that is not in the bottom quartile of the distribution, conditional on age; and whether the job entailed social insurance benefits that are not in the bottom quartile of the distribution, conditional on age; whether the number of monthly job separations is not in the bottom quartile of the distribution, conditional on age and region of birth; whether the number of monthly net flows (hirings minus separations) is not in the bottom quartile.

[18] In Online Appendix $B1$, we display the distributions of these estimated fixed effects for workers and firms. We also report there the regional variations of these estimated fixed effects.

population). Manufacturing, financial services, commerce, publishing and tourism are the main sectors. Large firms in the automotive sector are located in Turin's district. Yet, smaller firms specialise in metal chemistry, food, garments, and textiles. The economy was hit by an economic crisis from 2010 to 2014, when the GDP drop was higher than the average in Italy, but the rise in the unemployment rate was slightly lower.

Our confidential data covers all job flows in Piedmont. Yet, we cannot construct the entire employment history of workers who migrate and change their domicile status. This problem is more severe for the estimation of the dynamic model where the effects depend on all past effects. Hence, we report estimates of Equation 1 for regional natives. We focus on local labour markets (LLMs) and collect data from Comuniverso.[19] They group municipalities within a certain distance of working-day commuting. Piedmont has 36 LLMs, to which we add four. They belong to a neighbouring region (Lombardia or Liguria) but include Piedmont municipalities. We divide these LLMs into quartiles of the number of active firms, and only the Turin district is in the top quartile.[20] Hence, we compare this district with all the other LLMs. The number of active firms in Turin's district is similar to the one in the top quartile using the national data. We expect to report estimates that are not far from those in Figure (4). Figure (6) proves this claim to be correct.

[Figure 6 about here]

We run our modified version of Equation 1[21], where we divide LLMs into two groups rather than quartiles from January 2010 to December 2014.[22] The outcomes in panels (a) and (b) are the hiring probability of apprentices and workers with an open-ended contract.[23] The probability of being hired as an apprentice of treated workers compared with the untreated ones in Turin's district is twice as high as those in the other LLMs. It is about one percentage point versus less than half a percentage point. With the increased apprenticeship probability, treated workers are more likely of being hired with an open-ended contract. In Turin's area, the primary driving force is the apprenticeship contract[24] which is a way to jobs that last longer. We cannot test this claim here, but we extrapolate it from what we previously found. This extrapolation is not too hazardous as long as we show that the apprenticeship's ability to lead to an open-ended job

[19] For more details, see http://www.comuniverso.it/index.cfm?Sistemi˙Locali˙del˙Lavoro menu=691.

[20] We do not have data on the PISA maths test score.

[21] We use the STATA command *areg* instead of *reg* to run our regressions to account for within-firm variation.

[22] In Online Appendix F1, we show estimates for the entire Piedmont region, where we do not break up LLMs into groups.

[23] In Online Appendix F1, we show results for the hiring probability.

[24] The effect on other LLMs is the sum of the small impact on apprenticeships and the impact on the hiring probability. The latter comes from a regional policy introduced in 2013 that encouraged firms to hire unemployed younger than 30 using an open-ended contract (see Online Appendix $F1$).

is the same in the Turin area and in the regions in the top quartile of the number of active firms distribution. These figures have in common not the geographic location, which they do not, but rather the presence of agglomeration spillovers.

7 Conclusions

Work has changed in the past decades. The flexible working trend has made hiring for open-ended positions an event that cannot be taken for granted. In this paper, we show the conditions that make a training contract secure a good job that lasts long. We break up regions into quartiles of the number of active firms and the PISA maths test score. Within each group of regions, we compare workers aged 29 and turning 30 to those aged 30 and turning 31 before and after the 2012 reform. This policy favoured apprenticeships as a way to open-ended positions. We show that the policy reached its goal, more in some groups of regions, less in others. We find that treated workers are a one percentage point more likely to be hired with an open-ended job compared with the untreated ones in regions in the top quartile of the number of active firms. Yet, treated workers in regions in the bottom quartile were as likely as untreated ones to start an open-ended job. These differences are not due to the geographical location of the regions in the top quartile. In this top quartile, we find regions in the north, centre, and south of Italy. We show the same result when we break up local labour markets in Piedmont in two groups, for being in the top quartile or not. It is the number of active firms that matters. There are two possible intertwined explanations for why it matters. When the labour market is thick, agglomeration spillovers may exist. Under such circumstances, firms are more productive, and more productive firms are keener to use more open-ended jobs, opening the position with training contracts. Second, with many firms in the same labour market, the workers' costs of moving from unsuccessful to successful firms are lower. Yet, the number of active firms does not appear to be a key determinant of a higher probability of having the same job after 30 months. Treated workers in the bottom quartile are about eight percentage points more likely than untreated ones to be in the same job after 30 months. This advantage is slightly lower for those in the top quartile. We need to factor in the PISA maths test score to show that treated workers in regions in the top quartile are twice more likely to have a higher probability of being in the same job after 30 months compared with the untreated ones than those in the bottom. The treatment effect is about four percentage points at the bottom and rises to eight percentage points at the top. Top and bottom quartiles appear to reflect the north-south divide. Yet, it is not this divide by itself that explains our results. We compare treated and untreated workers in the same labour market. Yet, a more productive economy increases the probability of an entry job as a trainee. Knowledge and skills developed at the high school help make this job successful. A possible interpretation is that they boost skills that will be learnt in the labour market. Better educated workers contribute to raising the labour market's human capital. With human capital externalities, firms' productivity rise creating a vicious or virtuous cycle that is difficult to break.

Low educated workers are more likely to face job insecurity. Understood as due to the lack of adequate skills, this is the problem that apprenticeships are supposed to solve. In such a case, on-the-job training compensate for low education. In this paper, we show that a successful training contract isn't for everyone. Some conditions on both the demand and the supply side of the market are required to make it succeed. Future research might address why these training contracts are not more widespread in contexts where these conditions are met. The answer could relate to the firms' unwillingness to offer them to anyone to avoid paying high screening costs. It could also be possible that not all workers would accept this job if offered because a training contract is costly, not least in terms of a lower hiring wage. Some might find it favourable and trade off these costs for a secure job; others might not.

References

Abowd, J. and Kramarz, F. (2003). The costs of hiring and separations, *Labour Economics* **10**(5): 499–530.

Autor, D. (2001). Why do temporary help firms provide free general skills training?, *The Quarterly Journal of Economics* **116**(4): 1409–1448.

Berton, F. and Garibaldi, P. (2012). Workers and firms sorting into temporary jobs, *Economic Journal* **122**(562): F125–F154.

Blanchard, O. and Landier, A. (2002). The perverse effects of partial labour market reform: fixed-term contracts in france, *Economic Journal* **112**(480): F214–F244.

Blatter, M., Muehlemann, S., Schenker, S. and Wolter, S. (2016). Hiring costs for skilled workers and the supply of firm-provided training, *Oxford Economic Papers* **68**(1): 238–257.

Cabrales, A., Dolado, J. and Mora Villarrubia, R. (2017). Dual employment protection and (lack of) on-the-job training: Piaac evidence for Spain and other European countries, *SERIEs: Journal of the Spanish Economic Association* **8**(4): 345–371.

Caggese, A. and Cuñat, V. (2008). Financing constraints and fixed-term employment contracts, *Economic Journal* **118**(533): 2013–2046.

Cahuc, P., Charlot, O. and Malherbet, F. (2016). Explaining the spread of temporary jobs and its impcat on labour turnover, *International Economic Review* **57**: 533–572.

Cappellari, L., Dell'Aringa, C. and Leonardi, M. (2012). Temporary employment, job flows and productivity: A tale of two reforms, *Economic Journal* **122**(562): F188–F215.

Citino, L. and Fenizia, A. (2022). Are subsidies to apprenticeships a bad deal? evidence from a recent italian reform, *mimeo*.

Combes, P.-P., Duranton, G., Gobillon, L., Puga, D. and Roux, S. (2012). The productivity advantages of large cities: Distinguishing agglomeration from firm selection, *Econometrica* **80**(6): 2543–2594.

Dolado, J. (2017). *EU Dual Labour Markets: Consequences and Potential Reforms*, Cambridge University Press, chapter 2, pp. 6–44.

Dustmann, C. and Schönberg, U. (2009). Training and union wages, *The Review of Economics and Statistics* **91**(2): 363–376.

Dustmann, C. and Schönberg, U. (2012). What makes firm-based vocational training schemes successful? the role of commitment, *American Economic Journal: Applied Economics* **4**(2): 36–61.

Fialho, P. (2017). Who gains from labour market flexibility at the margin?, *mimeo*.

García-Pérez, J. I., Marinescu, I. and Vall Castello, J. (2019). Can fixed-term contracts put low skilled youth on a better career path? Evidence from Spain, *The Economic Journal* **129**(620): 1693–1730.

Gathmann, C., Helm, I. and Schönberg, U. (2020). Spillover effects of mass layoffs, *Journal of the European Economic Association* **18**(1): 427–468.

Glaeser, E. (1999). Learning in cities, *Journal of Urban Economics* **46**(2): 254–277.

Greenstone, M., Hornbeck, R. and Moretti, E. (2010). Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings, *Journal of Political Economy* **118**(3): 536–598.

Guglielminetti, E. and Nur, J. (2017). Dual labour markets and (lack of) on-the-job training: Piaac evidence from spain and other eu countries, *mimeo*.

Helsley, R. and Strange, W. (1990). Matching and agglomeration economies in a system of cities, *Regional Science and Urban Economics* **20**(2): 189–212.

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

Lee, D. S. and Lemieux, T. (2010). Regression discontinuity designs in economics, *Journal of Economic Literature* **48**(2): 281–355.

Maida, A. and Sonedda, D. (Forthcoming). Breaking from the starting gate on the right foot: Employment effects of an investment in human capital, *Journal of Human Resources* .

Marshall, A. (1890). *The Principles of Economics*, McMaster University Archive for the History of Economic Thought.

Moretti, E. (2004). Workers' education, spillovers, and productivity: Evidence from plant-level production functions, *American Economic Review* **94**(3): 656–690.

Moretti, E. (2011). Local labor markets, 1 edn, Vol. 4B, Elsevier, chapter 14, pp. 1237–1313.

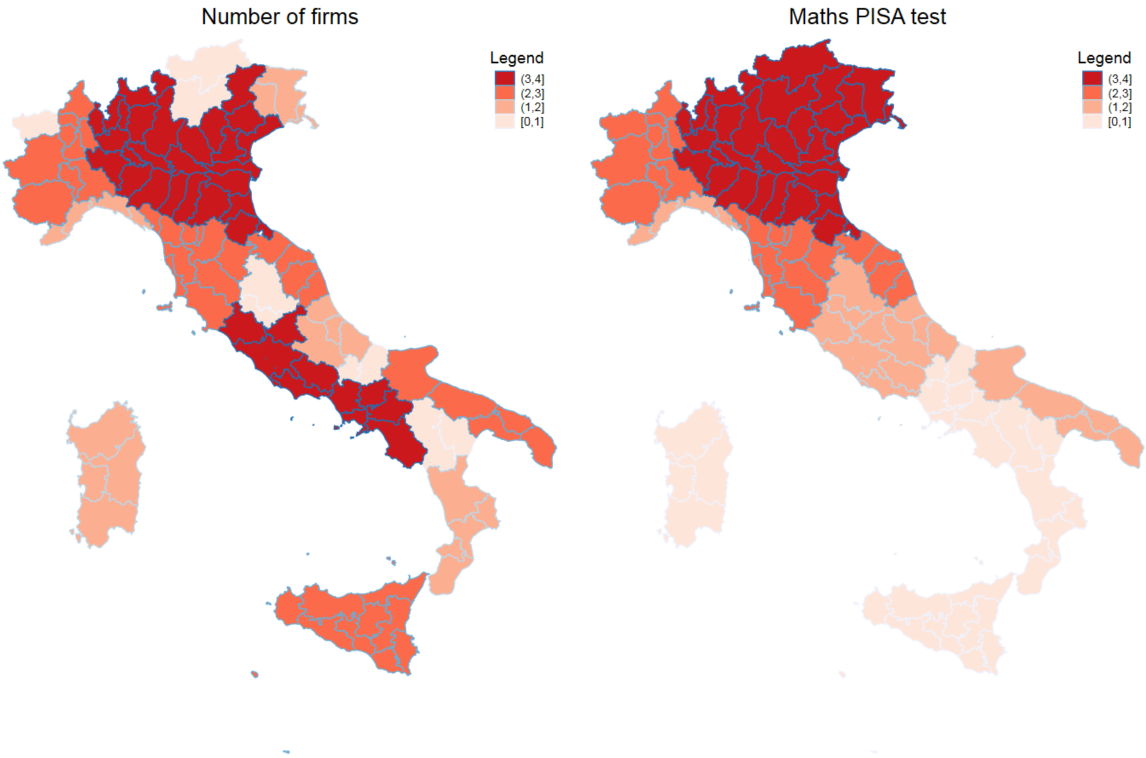
Picchio, M. and Filomena, M. (Forthcoming). Are temporary jobs stepping stones or dead end? a meta-analytical review of the literature, *International Journal of Manpower* .

Serafinelli, M. (2019). *Good* firms, worker flows and local productivity, *Journal of Labor Economics* **37**(3): 747 – 792.

Tealdi, C. (2019). The adverse effects of short-term contracts on young workers: Evidence from Italy, *Manchester School* **87**(6): 751–793.

Figures and Tables

1 Figures

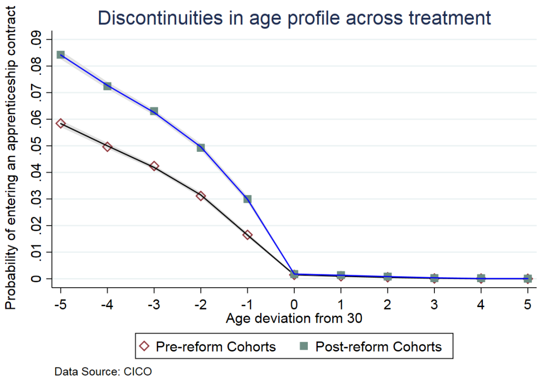


(a) Number of active firms in a region (b) Percentage with high scores on maths PISA test

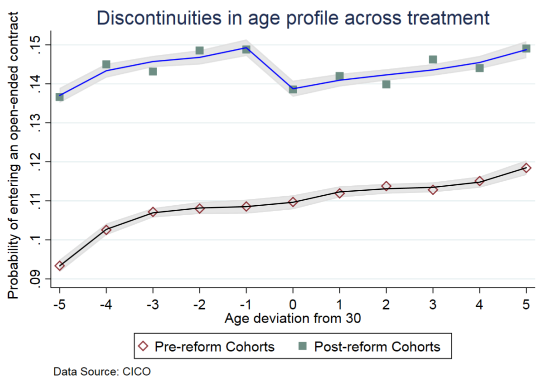
Notes: Data source: Italian Office for National Statistics.

Figure 1: Number of active firms and share of those with high PISA test scores in maths broken down by quartiles

Figure 2: Difference-in-discontinuity across consecutive cohorts generated by Law No. 92/2012 at the age cutoff for regions grouped by the top quartile of the PISA maths test score distribution

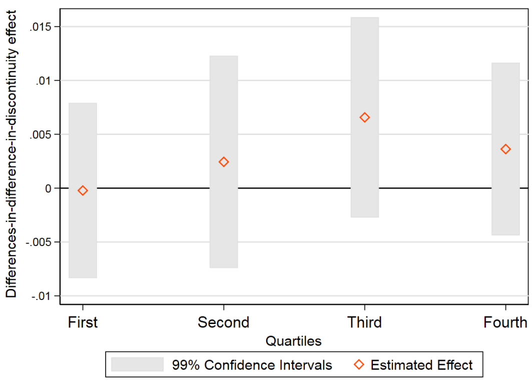


(a) Apprenticeship Probability

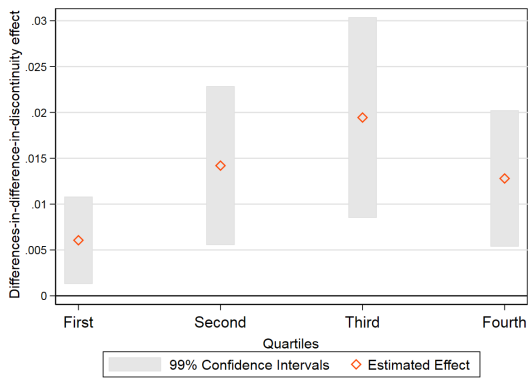


(b) Open-ended job Probability

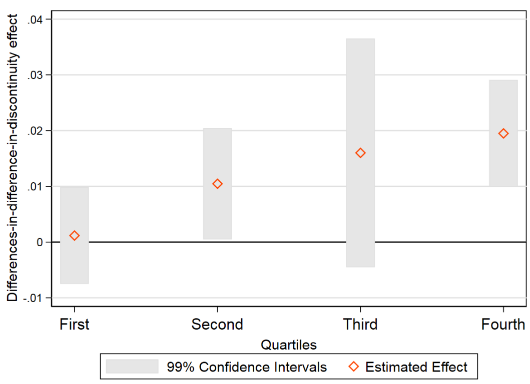
Notes: The dots are averaged raw data points; the line and the grey area refer to the parametric fit (third-order polynomial in age) and its 99% confidence intervals. Standard errors are robust to heteroskedasticity.



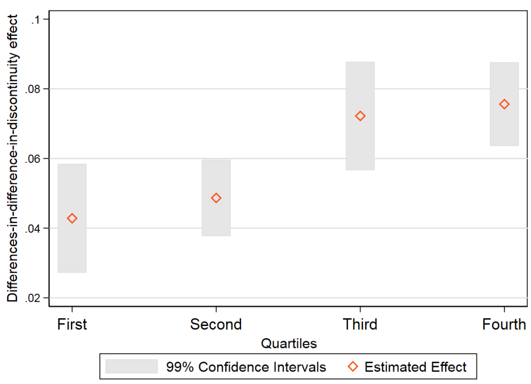
(a) Employment Prob.



(b) Apprenticeship Prob.

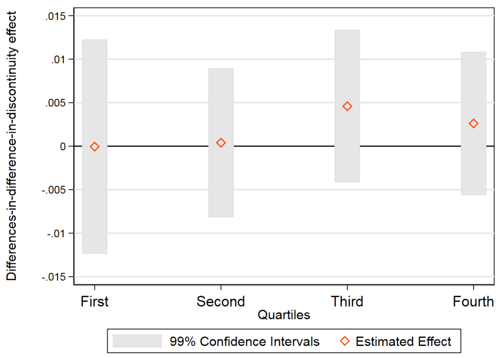


(c) Permanent Employment Prob.

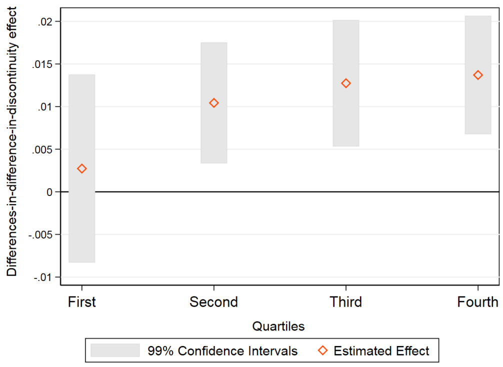


(d) Permanent Employment Prob: after 30 months

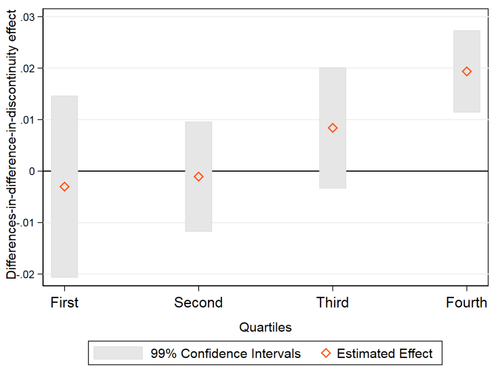
Figure 3: Differences-in-difference-in-discontinuity across quartiles of the distribution of the regional percentage of the highest maths PISA test scores



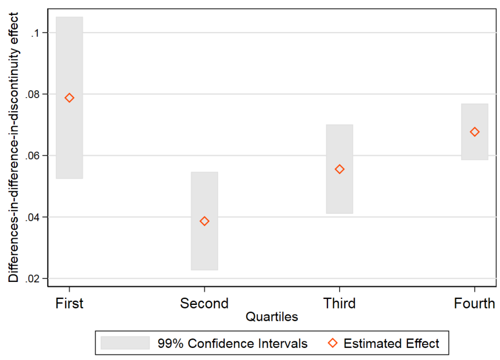
(a) Employment Prob.



(b) Apprenticeship Prob.

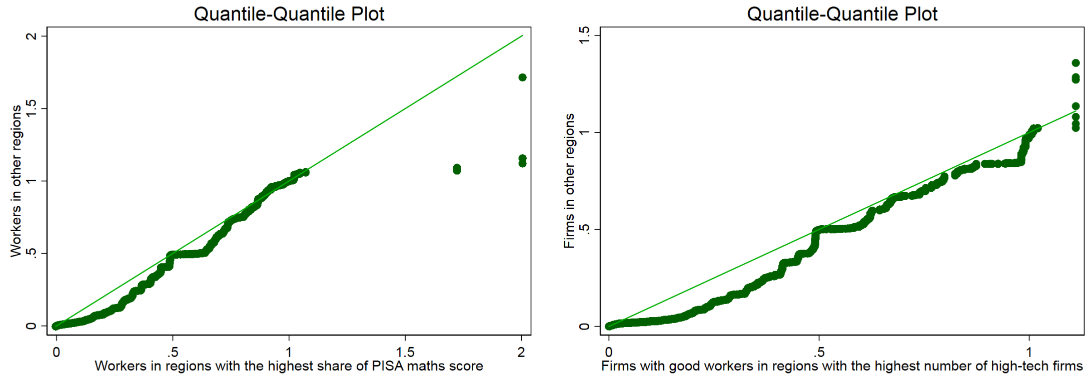


(c) Permanent Employment Prob.



(d) Permanent Employment Prob: after 30 months

Figure 4: Differences-in-difference-in-discontinuity across the thickness of the labour market

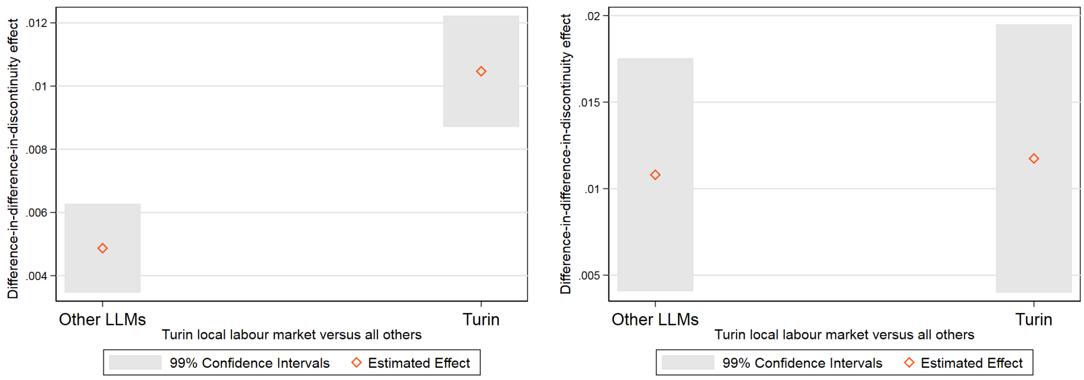


(a) Fixed effects for workers

(b) Fixed effects for firms

Notes: Panel (a) shows fixed effects for workers comparing workers in areas grouped by scores in maths PISA test. Panel (b) displays fixed effects for firms comparing firms in areas grouped by the number of high-tech firms.

Figure 5: Quantile-quantile plot: worker and firm fixed effects



(a) Apprenticeship Prob.

(b) Permanent Employment Prob.

Figure 6: Differences-in-difference-in-discontinuity across the thickness of the labour market in Piedmont

2 Tables

	Probability of entering an open-ended contract	
	Non-high interaction	High interaction
High number of firms and high maths score	0.009***	0.019***
	0.003	0.005
	[0.001-0.017]	[0.007-0.030]
High firm turnover rate and high maths score	0.011***	0.016***
	0.003	0.005
	[0.003-0.019]	[0.003-0.028]
High employment rate in high-tech firms and high maths score	0.009***	0.021***
	0.003	0.006
	[0.001-0.017]	[0.007-0.035]
High number of high-tech firms and high maths score	0.011***	0.019***
	0.003	0.007
	[0.003-0.018]	[0.001-0.037]
High number of high-tech firms and low repeating schooling year rate	0.012***	0.012
	0.003	0.017
	[0.005-0.019]	[−0.031-0.055]
High number of high-tech firms and low ratio of n. students per class	0.012******	0.002
	0.003	0.012
	[0.005-0.019]	[−0.028-0.033]
High number of high-tech firms and low drop-out rate in upper secondary schools	0.012***	0.007
	0.003	0.013
	[0.005-0.019]	[−0.027-0.041]
High number of high-tech firms and low ratio of n. students per school	0.010***	0.017***
	0.003	0.005
	[0.002-0.019]	[0.004-0.031]

Notes: (Non)-High interaction is a dummy variable that takes the value of 1 (0) if the region sits both in the top quartile of the quality indicator of the upper secondary school system (i.e., in the bottom quartile when higher quality is associated with a lower value of the indicator, such in the case of the drop-out rate) and in the top quartile of the distribution of characteristics of the production system (such as the number of active firms).

Table 1: Differences-in-difference-in-discontinuity impact on the probability of having an open-ended contract: interaction between education quality and the thickness of the labour market.