Evaluating the Impact of Employment Protection on Firm-Provided Training in a RDD Framework

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Abstract

This paper exploits exceptions in the application of employment protection legislation (EPL) of small firms below a particular size threshold to test the hypothesis that EPL increases the incentives for firms to train their employees in a regression discontinuity setting. Using firm-level data from Finland and Italy, we do not find any empirical evidence for this hypothesis. Instead, the results point towards a potentially negative impact on the propensity of firms to train and a statistically insignificant effect on the amount of training hours per employee. However, we find some slight evidence that this negative effect on training propensity is driven by firms with a larger share of older workers, supporting the hypothesis that EPL causes a negative selection of workers, though this effect is statistically insignificant.

JEL: L5, K31, I21, J21

Keywords: Training, employment protection legislation, regression discontinuity design

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1. Introduction

A widespread belief among policy makers is that employment protection legislation (EPL)[2] decreases welfare by raising labour adjustment costs which weakens the ability of firms to adjust their cost structure in response to the increased integration of the world economy and rapid technological progress. In fact, nearly half of all OECD countries deregulated their employment protection regimes during the last decade (2000-2013) (see, e.g., Cazes et al., 2012 and Schömann, 2014)[3]. This belief of policy makers is not without a reason. The related theoretical and empirical considerations stem from one strand of the EPL literature (see e.g. Lazear, 1990) which argues that EPL leads to lower employment and higher unemployment levels over time. In contrast, the other strand of the literature states that by stabilising existing employment relations through higher adjustment costs EPL can have positive effects on employement and unemployment levels and thus welfare (e.g. Garibaldi and Violante, 2005). This way, EPL can serve as an insurance against the risk of dismissal, especially during economic downturns (Pissarides, 2010). By stabilising employment relations, EPL can also act as a mean to incentivise firms to invest in the human capital of their workforce in the form of training (Akerlof, 1984; Acemoglu and Pischke, 1998 and 1999; Fella, 2005; Wasmer, 2006; Belot et al. 2007, Balmaceda, 2009). However, while it is undoubted that EPL decreases the rate at which jobs are created and destructed, the overall effect of EPL on employment and unemployment remains theoretically and empirically unresolved[4].

The aim of this paper is to contribute to the latter strand of the literature by analysing the effect of EPL on the decision of firms to invest in the human capital of their workforce. Concretely, we want to test the hypothesis if stricter EPL increases the incidence and the amount of firm-provided training. However, also the effect of EPL on training is not free of ambiguity. Stricter EPL can also decrease the incentives for firms to provide training by increasing wages, or because they end up with a more heterogeneous workforce or make more intense use of temporary workers (Pierre and Scarpetta, 2004 or Brunello, 2006).

Despite this theoretical ambiguity, only a few studies have tested the effect of EPL on training provision empirically so far. Analysing cross-country data, Brunello et al. (2007) find a negative effect of EPL on training, while Almeida and Aterido (2011) and Pierre and Scarpetta (2004, 2013) find the opposite. Using firm-level data of Dutch firms, Piccio and van Ours (2011) also suggest that stricter EPL increases training. Finally, Messe and Rouland (2014) find that an increase in EPL in France increases training. In summary, the existing empirical evidence is rather scant and provides mixed evidence regarding a potential impact of EPL on training.

[2] EPL typically comprises measures such as notice periods; mandatory consultation with employee representatives; notification of dismissals to a public agency; a right of appeal against unfair dismissal; special protection for certain groups (e.g. older workers, the handicapped); and redundancy payments.

[3] According to the OECD Indicators of Employment Protection for individual and collective dismissals for workers with regular contracts, this corresponds to a drop by 0.14 index points to a value of 2.04 in 2013 for the OECD average (OECD 2015). For more details, see appendix A0.

[4] See e.g. Bertola (1990;1992), Bentolila and Bertola (1990) or Mortensen and Pissarides (1999) for the theoretical argumentation and Cazes et al., 2012 for an overview of the empirical literature.

This paper contributes to the existing literature in four ways. First, it provides evidence regarding the effect of EPL on training based on a regression discontinuity design that exploits the exceptions of small firms from EPL in Italy and Finland at the country-level. Thereby, it circumvents the use of indices quantifying EPL, whose quality could suffer from elements of subjectivity of those who construct them (Skedinger, 2010). In addition, by exploiting within-country variation, the identification strategy circumvents potential endogeneity problems due to general equilibrium effects at the cross-country level and correlations of EPL and country-specific labour market conditions that might contaminate cross-country comparisons (see, e.g., Noelke, 2011, or Hijzen et al. 2013).

The results provide little evidence that EPL increases training. In fact, the evidence points towards a negative effect of EPL on training propensity, though this effect is insignificant for Finland and depends on the model specification to some extent. Regarding the intensive margin measured by the hours of training per employee in training firms, the estimates are insignificantly negative in Finland. In Italy, the estimates are marginally positive at the optimal bandwidth. However, this result is relatively unstable for different bandwidth choices and model specifications. Hence, the results support rather a negative effect of EPL on training propensity, but provide little evidence that EPL increases training.

Secondly, the paper tests whether a negative effect of EPL on training might arise due to a negative selection of the workforce caused by EPL. Assuming that that an older workforce indicates a stronger negative selection due to EPL, we test whether the effect of EPL is stronger for firms with an older workforce. The results suggest that the negative effect of EPL is on training propensity is indeed driven by firms with a larger share of older workers. However, this difference is statistically insignificant.

Thirdly, unlike most of empirical papers mentioned above, we also account for the possible channel that EPL might increase the use of temporary workers, who are less likely to receive training than regular workers and that thereby EPL could have a negative effect on training (see, e.g., Pierre and Scarpetta, 2013). However, we do not find any statistically significant evidence for this effect.

And finally, we are the first to use within-country variation to analyse the effect of EPL on training for Italy and Finland. These countries are particularly interesting because the two countries differ substantially with respect to their economic development, political system and regulatory framework. Furthermore, both countries have stricter employment protection legislation than many other OECD countries (OECD, 2015). In addition, comparing the results of these countries allows to evaluate the external validity of our results for other countries.

The paper is organised as follows. The first section summarizes the existing theoretical and empirical literature to derive hypotheses. The second section describes the regulatory framework and the corresponding empirical methodology. Section three summarises the data. Section four analyses the validity of the RDD setting and section five presents the estimation results. Section six concludes.

2. Theory and Literature

EPL has a transfer and a tax component (Garibaldi and Violante, 2002). The transfer component comprises a severance payment the employee receives upon dismissal. Theoretically, this part of EPL should not affect the hiring decisions, and thus not the training decisions of firms, as it can be undone by a wage contract which lowers the initial wage by the amount of the severance payment (Lazear, 1990; Burda, 1992). On the contrary, the tax component of EPL involves red tape costs, which are vested upon dismissal. This component of EPL cannot be internalised in a wage contract and therefore affects the hiring (and therefore the training) decisions of firms. Therefore, in line with the existing literature, we focus on the tax component of EPL.

There are two channels through which EPL could increase the incentives of employers to train their workers. First, the positive effect of EPL on job duration gives employers an incentive to increase labour productivity by investing into the human capital of their workforce (Akerlof, 1984; Belot et al. 2007; Charlot and Malherbet, 2013).

Second, higher EPL causes labour market frictions and thereby compresses wages, i.e. creates a wedge between the productivity gains of workers and the actual wage they receive. If their productivity can be further raised through training, the wedge between the productivity gains and the wage could rise even further. Because wages are less responsive to an increase in productivity, the employer can reap a part of the increase in productivity, which could spur his incentives to train his workforce (Acemoglu and Pischke, 1998 and 1999).

However, there are also three theoretical arguments suggesting that higher EPL decreases training. First, higher EPL increases the bargaining power of workers who are on a regular contract due to the firing costs the firm would have to pay in case of a dismissal. This in turn raises their incentive to demand a higher wage once they are hired, labelled "insider wage". By forcing the employer to bear the sum of job creation and destruction costs, the increased wage reduces firm profits and thus the employers' willingness to invest in the human capital of their workers, which is the essence of a hold-up problem (see, e.g., Lindbeck and Snower, 1988; Mortensen and Pissarides, 1999).[5]

Second, under a stricter EPL regime firms cannot easily dismiss less able workers and thus end up with a more heterogeneous workforce in terms of ability. This reduces productivity and hence the incentives to train the workforce. Furthermore, reducing the average ability of the workforce decreases incentives to train due to the complementarity between training and ability. (Pierre and Scarpetta, 2004; Brunello, 2006).

Third, if temporary contracts are allowed alongside regular contracts and can serve as an alternative mode of employment, the way of how EPL affects employers' training decisions might change. The

[5]This first argument can be studied in a search equilibrium framework by comparing equilibrium conditions without a two-tier wage structure as compared to those with. Under a two-tier wage contract, the first tier wage is usually lower than the second tier. Once being "inside", the worker has an incentive to renegotiate the two-tier agreement and demand a higher wage, which creates a hold-up problem (Mortensen and Pissarides, 1999).

introduction of temporary contracts is likely to create a dual labour market, where one part of the working population is employed on regular contracts, while the others are employed on temporary contracts. The coexistence of relatively strictly regulated regular contracts and relatively less regulated temporary contracts provides a strong incentive for employers to substitute the former for the latter. Since temporary jobs are more likely to be destroyed and therefore less likely to be converted into permanent contracts, this reduces the incentives for employers to invest in the human capital of their employees, which would be lost in case of a dismissal (see e.g. Charlot and Malherbet, 2013; Pierre and Scarpetta, 2013) [6]. Consequently, a possibly positive effect of EPL on training provision for regular workers could be offset by an increase in the use of temporary work contracts. Hence, stricter EPL might decrease training provision on average.

All in all, the theoretical prediction of how EPL affects training remains ambiguous. Therefore, we propose two alternative hypotheses:

H1a: An increase in EPL increases training incidence and intensity

H1b: An increase in EPL decreases training incidence and intensity

Furthermore, we test two additional hypothesis' that allow us to analyse the second and third argument why EPL might have a negative effect on training. First, we argue that the negative selection of employees is more pronounced in firms with an older workforce. Therefore, we test whether

H2: The interaction of EPL and the share of workers above 55 years affects training provision negatively

Second, we examine whether an increase in the share temporary workers dampens the effect of EPL on training by testing whether

H3: The interaction of EPL and the use of temporary work contracts affects training provision negatively

There are only a few studies which have analysed the effect of EPL on training. Most of these have used cross-country data. Using a panel of 13 European countries and the OECD Index of Employment Protection for regular and temporary workers, Brunello et al. (2007) exploit within-country variation over time to estimate the effect of EPL on the incidence of workplace training. They find a significant negative effect of stricter EPL on training incidence for both types of workers. However, while the effect is highly significant and large in magnitude for regular workers, it is just slightly significant and low in magnitude for temporary workers. They account for the share of temporary workers receiving training. The effect is negative, but insignificant.

[6] According to Charlot and Malherbet (2013), in a dual labour market, higher firing costs always increase the use of temporary employment. Furthermore, a positive effect of EPL on training and job creation can only dominate in the absence of temporary jobs.

In a comparable study, Almeida and Aterido (2011) examine the effects of EPL on firm-provided training for a panel of developing countries. They use a difference-in-differences framework that combines variation in EPL and differences in de jure and de facto employment protection accounting for industry and country fixed effects. They find that firms that are subject to stricter labour regulations and enforcement are more likely to train. In addition, they find that stricter hiring regulations increase training, while stricter firing regulations decrease the provision of job training, but just for manufacturing firms.

Pierre and Scarpetta (2004) use a large dataset of developing and emerging economies exploring variation in firm managers' perception on how binding labour laws are to test if firms facing stricter employment protection invest more in training and/or make greater use of temporary employment. Employing a difference-in-differences approach, they find that firms use both strategies to counter high labour adjustment costs; especially when EPL for regular workers is stricter (training is preferred variant). While medium and larger firms are more likely to use both strategies, smaller firms tend to make more use of the temporary contracts. More innovative firms are more likely to use temporary contracts and, especially provide more training to upgrade the skills of their workforce than other firms. Lowering the regulation of temporary contracts, leaving that of regular contracts unchanged, does not significantly change the probability of training provision, while increasing that of the former and having lax regulations on the latter increases training (weak evidence). Facing stricter regulations of both variants, firms discourages firms to lower or keep employment stable. In a follow-up paper, using a comparable data set and method, Pierre and Scarpetta (2013) basically confirm their findings from the previous paper. In addition, they show that these effects are more prevalent in small firms and in sectors with high labour turnover. The drawback of both studies the use of data based on subjective managers' perceptions. Therefore, the findings can be questioned for being harder to interpret and subject to stronger endogeneity concerns.

The study of Messe and Rouland (2014) is, from an identification strategy point of view, very close to ours in the sense that it exploits a discontinuity in the applicability of EPL. Employing a difference-in-differences framework, it focusses on the effect of an increase in EPL due to an increase dismissal costs for older workers (>50 years) on the incentives for French firms to finance training. They show that the increase in EPL significantly raises the amount of training for workers aged 45-49, but not for those aged 50 and above.

Finally, though not directly analysing EPL, Picchio and van Ours (2011) analyse the impact of search frictions, which might result from EPL, on training. Exploiting within-firm variation of Dutch firms over time, they find that higher search frictions increases incentives for firms to invest in the training of their workers.

Most of the studies, except that of Brunello et al. (2007), find a positive effect of EPL on training, even if these results are not always very robust or small in magnitude. While some differentiate between EPL for regular and temporary workers, strictly speaking, only Pierre and Scarpetta (2013) account for the interdependence between training and the use of temporary contracts. A major drawback of these studies remains the use of cross-country data. Which, by potentially being affected by omitted variable and measurement problems, could bias the results.

3. Empirical Methodology

In this part of the paper, we first refer to our identification strategy which uses firm size exemptions to identify the effect of EPL on training. Then, we explain to which extent small firms are exempted from the employment regulations. And finally, we show the empirical specification used to identify the effect of EPL on training.

3.1 Identification Strategy

The literature analysing the effects of EPL on labour market outcomes at the country-level can be separated in two strands. The first strand exploits within-country variation across time and sectors. This approach utilizes the fact that, due to technological characteristics or incidence of aggregate shocks, industries differ with respect to the propensity to adjust their workforce. Hence, sectors differ in how strongly they are affected by EPL, allowing to analyse the effect of EPL allowing to employ a difference-in-difference approach (see, e.g., Rajan and Zingales, 1998; Haltiwanger et al., 2006; Bassanini and Garnero, 2013).

The second strand exploits exemptions in the applicability of EPL in terms of size (Hijzen et al., 2013), regions or type of workers (e.g. age in Messe and Rouland, 2014). Our main identification strategy belongs into this category. We employ a RDD that exploits the fact that firms beneath a certain firm-size threshold, measured in terms of the number of employees, are (partially) exempted from EPL in Italy and Finland. Assuming that firms just above the size threshold are good counterfactuals for firms just below the size threshold, we test the hypothesis that these firms, being subject to stricter EPL (treatment group), are more likely to train their employees than those below the threshold (control group).

In addition, we follow Hijzen et al. (2013) and combine the two literature strands by providing evidence based on a difference-in-difference approach that tests whether the effect of EPL on training below and above the size threshold is stronger for industries with high propensity to adjust their workforce.

3.2 Firm size exemptions from EPL

According to the OECD Indicators of Employment Protection[7], EPL was relatively high in Italy (index value of 2.76) in 2005, which is the reference year of the survey data used in the empirical part of the paper. In contrast, EPL in Finland was at the same level as the OECD average (index value of 2.17) in 2005 (OECD, 2015). Hence, EPL is relatively high in Italy. The following two paragraphs provide a detailed description of the discontinuity of EPL application in Finland and Italy (OECD, 2015).

[7] For individual and collective dismissals for workers with regular contracts.

The firm-size threshold in Finland applies for firms with less than 20 employees (<20). There are three major EPL measures from which firms below this threshold are exempted. All three involve red-tape costs. The first two concern notification procedures in the case of individual dismissal of a regular worker given a lack of work on the part of the firm. First, in companies with 20 or more employees, a notification must be given to the employment office and trade union representatives. In addition, consultation must be made on reasons and ways to avoid a lay-off. In firms with less than 20 employees, it is sufficient to notify the lay-off to the employment office (OECD 2015). Second, in firms with less than 20 employees no consultation has to take place, which reduces the time delay involved before notification can take place. And lastly, firms with less than 20 employees are exempted from the definition of collective dismissal (if >9 employees dismissed at a time), which would involve further red tape costs (ibid.). In addition, there is also an age-specific exemption from regular EPL for workers aged 68 or above. They can be dismissed at the end of each month without notice period (Venn, 2009).

Exemptions from EPL are much more encompassing in Italy than in Finland. Exempted are all firms with 15 or less employees (<16). They are not required to pay, back-pay or reinstate workers who are found to be unfairly dismissed (Venn, 2009). In detail, the exemptions concerns two EPL measures, both involving red-tape costs. In case of an unfair or unjustified dismissal (as decided by the labour court), firms with more than 15 employees have to give the employee severance pay, varying by age, tenure, number of employees and size of company. The severance pay can be higher in case of a lack of reasons in the written notice or violation of procedural aspects and highest in case of unfair or unlawful dismissal. In case of discriminatory dismissal or if the reason for dismissal is manifestly false or inapplicable, reinstatement will be ordered instead of monetary compensation. Firms with 15 employees or below have the choice between re-employment (different from reinstatement because it does not give rise to compensation for the period between the date of dismissal and the court decision) and financial compensation of the employee, varying by age, tenure and firm size. Second, firms with less than 15 employees are exempted from the definition of collective dismissal if they have been working over a period of 120 days, not in a single production unit, or several units within one province (OECD 2015).

3.3 Econometric Specification

Since the discontinuity stems from a law, we assume perfect compliance of the treated in this setup. Hence, we employ a sharp RD design to identify the local average treatment effect of EPL on training by fitting the following empirical specification:

$$Y_i = \alpha + \beta_1 D_i + \beta_2 f(F_i) + \varepsilon_i. \tag{1}$$

Y describes the training activities of firm i in terms of the propensity to train (extensive margin and the number of training hours per employee of training firms (intensive margin).D denotes a dummy variable that takes the value 1 for firms above the size threshold and 0 for firms beneath it. F is the size of firm i, measured as the number of employees. In our RDD, this is the assignment variable. The continuous function $f(\cdot)$ accounts for the different possible functional forms of the assignment variable; in our case, we allow up to third order polynomials of the assignment variable (including interactions). ε_i denotes the normally distributed error term with mean zero. We use logistic regression (Logit model) to estimate the training incidence (extensive margin) and OLS regression with robust standard errors for the intensity of training (intensive margin).

In a first step, we chose the optimal bandwidth of the assignment variable by employing the methodology of Imbens and Kalyanaraman (2012). Thereby, the optimal bandwidth is estimated non-parametrically. Our sample only contains firms with more than 10 employees, while the discontinuity starts at firm sizes of 16 and 20 in Italy and Finland, respectively. The results are reported in table A2.1 in the appendix.

In a second step, based on the chosen bandwidth, we test different functional forms on either side of the cut-off with up to third order polynomials and choose the best functional from according to the Akaike Information Criterion (AIC) as suggested by Lee and Lemieux (2010). These results appear in tables A2.2 and A2.3 in the appendix.

As mentioned in the beginning of this section, we follow Hijzen et al. (2013) by combining the firm-size difference from the RDD with cross-sector variation regarding employment volatility in a difference-in-differences (DiD) framework as a robustness check. This methodology allows us to eliminate the impact of confounding factors and doubts about a possible manipulation of the assignment variable. Furthermore, it helps to increase the precision of estimates if pre-treatment controls and post-treatment outcome variables are highly correlated (Hijzen et al., 2013).

Concretely, this approach exploits the fact that sectors differ in their need to adjust their workforce due to factors unrelated to EPL in reaction to changes in market conditions or technologies. Using cross-sectoral differences in employment volatility, we assume that sectors with a highly volatile output demand or a greater rate of use of new technologies, need to adjust their workforce more frequently. Consequently, these sectors are more affected by EPL than others where employment volatility is relatively low. Thus, we use the double difference: small versus large firms in high versus low volatility sectors for our difference-in-differences approach by estimating the following empirical specification:

$$Y_i = \alpha + \beta_1 D_i + \beta_2 f(F_i) + \beta_3 V_j + \beta_4 D_i{*}V_j + \varepsilon_i. \qquad (2)$$

V denotes the employment volatility of sector j to capture the relationship between employment volatility and training activities. D*V represents the interaction of EPL and employment volatility. Hence, we expect that β_1 and β_4 have the same sign.

4. Data and Descriptive Statistics

In the first part of this section we describe the data and variables used in the empirical analysis and then look at the descriptive statistics in the second part.

4.1 Data

This paper uses data from the third wave of the Continuing Vocational Training Survey (CVTS3), conducted by Eurostat among firms with more than 10 employees in 19 EU countries. The survey was carried out in 2006 for CVT activities which took place in the reference year 2005. Each sample is stratified by industry affiliation and firm size.

Training

The definition of training used in this paper refers to pre-planned formal (continuing vocational) training, which is clearly separated from the active work place, i.e. learning takes place off-site. The training must have a programme (e.g. curriculum) and objectives. It is provided by trainers, teachers or lecturers and can be organised by the enterprise or an external organisation. The definition does not comprise on-the-job training or other forms of informal training that are directly connected to the active workplace. It is financed at least partly by the enterprises for their employees, with working contract or unpaid family workers and casual workers. Persons with apprenticeship or training contract are not included.

We consider two outcome variables, corresponding to the extensive and intensive margin of training. Concretely, the extensive margin measures whether a firm provides training to at least one employee (*Train 0/1*). The intensive margin measures the average hours spent in training per employee of training firms, i.e. the amount of paid working hours spent in training activities of firms that train, divided by the number of its employees (*Train Hours*).[8]

Assignment variable

The assignment variable measures the number of all persons employed as in the end of 2005. This is a head-count measure, hence consists of integer values. The assignment-to-treatment-variable is a dummy which is one for firms just at or above the size cut-off (20 or 16 for Finland or Italy respectively). In addition, depending on the optimal functional form $f(F_i)$, we also include the "raw version" of the assignment variable or some higher order polynomials and their interactions (up to third order) of the assignment variable. Thereby, the assignment variable is centered at zero at the cut-off, which means that firms at the value zero correspond to those who receive treatment.

Observable firm characteristics

Though not directly included in the baseline regressions, the observed firm characteristics are important to examine the validity of the RDD in two ways. First, we examine whether the covariates are continuous at the threshold. Secondly, we report robustness checks showing that the inclusion of the covariates in the baseline regression doesn't affect the qualitative results.

[8] Using the number of trained employees to measure training intensity yields qualitatively the same results, which can be obtained from the authors upon request.

The observable firm characteristics comprise industry affiliation(1-digit NACE Rev 1.1), innovation propensity measured by the introduction of significantly new technological improved product, service or method (*Innovation*), average wages, calculated as labour costs divided by number of employees (*Average Wage*), the age distribution of employees, i.e. the share of workers in the age groups <25, 25-55, >55 years (*Share Young, Share Med Age, Share Old*), Furthermore, for training firms, we know whether a firm has any temporary workers (*Temp Emp*) and whether a firm has any part-time workers (*Part-Time Emp*).

Market volatility measure

The difference-differences identification strategy requires a sector-specific measure for intrinsic sector employment volatility. An adequate measure for employment volatility is the job reallocation rate, which is defined as the sum of the job creation and job destruction rate (Haltiwanger et al., 2006). This measure needs to be uncontaminated by the presence of EPL. To proxy for the intrinsic sector employment volatility, we use the sector-specific job reallocation rate for the USA provided by Haltiwanger et al. (2006). The USA is an ideal candidate for this measure, because it has the lowest EPL regulations among all OECD-countries (OECD, 2015). This "EPL-adjusted" intrinsic sector job reallocation volatility further has the advantage that it is exogenous to the political and regulatory framework in Finland and Italy. Thereby, we can ensure that it is also unaffected by other country-specific policies and regulations. In addition, the exogeneity of the measure for intrinsic sector job reallocation to idiosyncratic factors in Finland and Italy in 2005 is reinforced by the fact that we use data prior to the year the survey was conducted (2005), namely for the years 1990, 1991 and 1994-1996. Supposing that general equilibrium effects affecting the intrinsic sector employment volatility in the past are unrelated to that in the present the exogeneity argument regarding the employment volatility assumption holds.

There are three doubts questioning the validity of this approach. First, using the job flows of US-industries as a benchmark requires that these industries are representative for the same industries in other countries, which must not always be the case. Second, it has been questioned whether the measure represents long-term industry differences in job flows. If the measure also carries idiosyncratic shocks, the job flow measure could rather reflect short-term effects which are specific to the benchmark country and thus bias the estimates (Cingano et al. 2009).

Third, another doubt regarding the validity of the DiD approach arises due to the argument that EPL causes a negative selection of the workforce, thereby reducing training. This selection mechanism is most pronounced if employment volatility is low. Hence, assuming that this mechanism is important suggests that sectors with high employment volatility might actually be less affected by EPL than sectors with low employment volatility. Since this argument opposes the basic idea of the identification strategy, it remains unclear to what extent the identification strategy can be applied in this research setting.

4.2 Descriptive statistics

Tables 1 and 2 report country-specific descriptive statistics of dependent variables and observable covariates of the whole sample and for the firms below and above the threshold for Finland and Italy respectively. Though the complete dataset for Finland comprises 1240 firms, we finally use up to 406 observations for our RDD, which corresponds to roughly one third of the sample (Table1). For Italy we have much more data: 15470 firms in the overall sample and about 9728 in the sample we use for the RDD (about 63% of the sample). We analyse the RDD estimates also for bandwidths larger than the optimal bandwidth- that is up to a maximum of 15 employees on the right of the cut-off. Note that this suggests that the bandwidth is asymmetric since our data is truncated from below, i.e. because firms below ten employees are not included in the sample.

Tables 1 and 2 show the summary statistics of the variables used for Finland and Italy respectively. For Finland and Italy, the mean of the variable for the extensive margin of training is slightly higher for firms above the cut-off (firm sizes 20-34 and 16-30 respectively). In contrast, the mean of the variable for the intensive margin of training for firms above the cut-off in Finland is significantly higher (nearly twice as high) than for firms below the cut-off. This result is different for the intensive margin variable for Italy, where the mean for firms below the cut-off is higher than for those above.

Tables 1 and 2 further provide information regarding the comparability of firms below and above the threshold for Finland and Italy, thereby providing a first test for the validity of the RDD. Concretely, comparing the respective means of observable firm characteristics for both countries suggests that firms below and above the threshold are relatively similar with regard to industry affiliation, innovation propensity and employee age structure. However, there are some differences with regard to average wages which is lower for firms above the threshold and the use of part-time and temporary employment, which are both higher for firms above the threshold.

Since the RDD design identifies a local average treatment effect, the external validity of the results for larger firms is unclear. However, Tables 1 and 2 suggest that firms in the full sample and the employed sample in this study are similar in terms of averages wages, innovation propensity, employee age structure and part-time workers, providing some evidence that small firms are representative for the full population in these respects. However, the use of temporary workers is more prevalent in the full sample.

Table 1: Descriptive statistics Finland

	Full Sample			Firm Size				
				10-19		20-34		10-34
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Obs.**
Dependent variables								
Train 0/1	1240	0.70	0.46	0.60	0.49	0.70	0.46	406
Train Hours	896	10.6	11.9	8.7	8.7	14.0	14.3	216
Industry variables (NACE 19)								
Mining and quarrying (CA&CB)	1240	0.01	0.07	0.00	0.07	0.00	0.07	406
Manufacturing sector (DA-DN)								
Food products, beverages and tobacco	1240	0.02	0.15	0.02	0.14	0.02	0.15	406
Textiles & leather (products)	1240	0.01	0.11	0.01	0.08	0.01	0.12	406
Pulp, paper; publishing, printing and reproduction of recorded media	1240	0.03	0.17	0.03	0.16	0.02	0.15	406
Coke, refined petroleum products and nuclear fuel; chemicals and man-made fibres; rubber and plastic products & other non-metallic mineral products	1240	0.03	0.17	0.02	0.14	0.02	0.14	406
Basic metals and fabricated metal products	1240	0.06	0.23	0.06	0.24	0.05	0.22	406
Machinery and equipment n.e.c. & electrical and optical equipment	1240	0.06	0.24	0.06	0.23	0.06	0.24	406
Transport equipment	1240	0.01	0.10	0.00	0.05	0.01	0.12	406
Wood and wood products & manufacturing n.e.c.	1240	0.04	0.18	0.04	0.19	0.04	0.19	406
Electricity, gas and water supply (E)	1240	0.01	0.10	0.01	0.10	0.00	0.07	406
Construction (F)	1240	0.13	0.33	0.17	0.38	0.14	0.35	406
Service sector (G-O)								
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel	1240	0.03	0.17	0.04	0.19	0.04	0.19	406
Wholesale trade and commission trade	1240	0.08	0.28	0.10	0.30	0.06	0.24	406
Retail trade &repair of personal and household goods	1240	0.10	0.29	0.16	0.37	0.06	0.24	406
Hotels and restaurants	1240	0.04	0.20	0.06	0.24	0.03	0.18	406
Land transport; transport via pipelines; water and air transport; supporting and auxiliary transport activities; activities of travel agencies	1240	0.08	0.26	0.09	0.29	0.05	0.22	406
Post and telecommunications	1240	0.01	0.09	0.00	0.06	0.01	0.08	406
Financial intermediation, insurance and pension funding	1240	0.03	0.16	0.03	0.18	0.02	0.15	406
Real estate, renting and business activities; other community, social and personal service activities	1240	0.24	0.43	0.10	0.30	0.33	0.47	406
Average Wage	1205	34760.1	13490.4	36811.6	12696.2	32304.4	12586.8	406
Innovation	1117	0.28	0.45	0.25	0.43	0.24	0.43	365
Share Young	973	0.17	0.17	0.18	0.18	0.15	0.11	245
Share Med Age	1199	0.76	0.17	0.80	0.17	0.75	0.14	403
Share Old	1060	0.17	0.12	0.19	0.13	0.18	0.12	298
Part-Time Emp	812	0.50	0.50	0.36	0.48	0.51	0.50	186
Temp Emp	813	0.51	0.50	0.23	0.42	0.44	0.50	188
Sector volatility (USA)	1156	0.23	0.08	0.25	0.08	0.23	0.08	364

Note: Descriptive statistics are constructed by using sample weights.

Table 2: Descriptive statistics Italy

	Full Sample			Firm Size				
				10-15		16-30		10-30
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Obs.**
Dependent variables								
Train 0/1	15470	0.27	0.44	0.19	0.40	0.26	0.44	9728
Train Hours	5985	11.2	19.5	12.2	23.0	10.4	18.3	2607
Industry variables								
Mining and quarrying (CA&CB)	15470	0.00	0.07	0.00	0.07	0.01	0.08	9728
Manufacturing sector (DA-DN)								
Food products, beverages and tobacco	15470	0.03	0.18	0.03	0.18	0.03	0.18	9728
Textiles & leather (products)	15470	0.07	0.26	0.06	0.24	0.08	0.28	9728
Pulp, paper; publishing, printing and reproduction of recorded media	15470	0.02	0.15	0.02	0.15	0.02	0.15	9728
Coke, refined petroleum products and nuclear fuel; chemicals, chemical products and man-made fibres ; rubber and plastic products & other non-metallic mineral products	15470	0.05	0.23	0.04	0.20	0.06	0.23	9728
Basic metals and fabricated metal products	15470	0.09	0.29	0.09	0.29	0.10	0.30	9728
Machinery and equipment n.e.c. & electrical and optical equipment	15470	0.08	0.27	0.06	0.23	0.09	0.29	9728
Transport equipment	15470	0.01	0.10	0.01	0.08	0.01	0.11	9728
Wood and wood products & manufacturing n.e.c.	15470	0.05	0.21	0.05	0.21	0.05	0.22	9728
Electricity, gas and water supply (E)	15470	0.00	0.05	0.00	0.04	0.00	0.05	9728
Construction (F)	15470	0.14	0.35	0.17	0.38	0.13	0.33	9728
Service sector (G-O)								
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel	15470	0.03	0.18	0.04	0.20	0.03	0.17	9728
Wholesale trade and commission trade	15470	0.07	0.26	0.08	0.27	0.07	0.25	9728
Retail trade &repair of personal and household goods	15470	0.06	0.24	0.08	0.27	0.06	0.24	9728
Hotels and restaurants	15470	0.07	0.25	0.09	0.28	0.05	0.23	9728
Land transport; transport via pipelines; water and air transport; supporting and auxiliary transport activities; activities of travel agencies	15470	0.06	0.23	0.05	0.21	0.06	0.23	9728
Post and telecommunications	15470	0.00	0.03	0.00	0.03	0.00	0.03	9728
Financial intermediation, insurance and pension funding	15470	0.01	0.11	0.01	0.09	0.01	0.09	9728
Real estate, renting and business activities; other community, social and personal service activities	15470	0.13	0.34	0.12	0.33	0.13	0.33	9728
Average Wage	15470	28319	12607.5	25809.7	11572.1	28785.9	11908.6	9728
Innovation	15470	0.24	0.43	0.21	0.41	0.24	0.43	9728
Share Young	8218	0.13	0.12	0.16	0.12	0.12	0.11	4576
Share Med Age	14493	0.86	0.13	0.86	0.13	0.86	0.12	9681
Share Old	9788	0.12	0.09	0.15	0.09	0.12	0.09	5648
Part-Time Emp	5986	0.62	0.48	0.51	0.50	0.58	0.49	2607
Temp Emp	5986	0.49	0.50	0.31	0.46	0.45	0.50	2607
Sector volatility (USA)	1156	0.23	0.08	0.25	0.08	0.23	0.08	364

Note: Descriptive statistics are constructed by using sample weights.

5. Validity of the RDD framework

The identification strategy of the RDD relies on the assumption that firms are “as good as” randomly assigned around the cut-off, i.e. that firms do not self-select into or out of treatment. This means that we want to isolate the different responses of firms with respect our outcome variable that are due to the differential role of EPL provisions applying to firms above and below the size threshold, and not those that are unrelated to EPL or the endogenous response of firms to EPL. Technically speaking, the identification assumption implies that the RDD is only valid if all other observable, but also unobservable factors influencing the assignment variable, in our case firm-size, are “continuously” related to it (random assignment assumption). The observable factors in our case are firm characteristics, whereas the unobservable factors could be other regulations applying at the same size threshold or non-quantifiable general equilibrium effects. While the validity of the identification assumption regarding the observable factors can be tested directly, this is not the case with respect to the unobservable factors, since we do not observe all factors that might affect the assignment variable. However, there are ways to test the random assignment assumption, also with respect to the unobservable factors. In this paper, we use two possible options to do so. The first test we use, the McCrary test (2008), accounts for both, the effects of observable and unobservable factors by looking at the distribution of the assignment variable The second test checks if the for the validity of the random assignment assumption by looking if the characteristics of firms just above and below the size threshold are “balanced” (do not differ substantially). Both are described in more detail now.

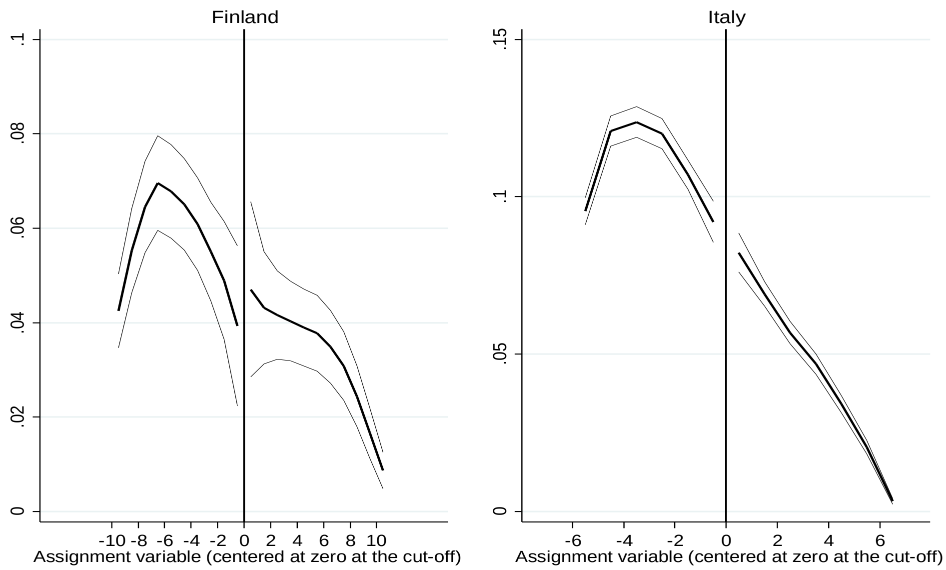
The McCrary test looks at the smoothness of the distribution of the assignment variable. It assesses whether the density function of the assignment variable firms-size has a jump at the threshold. In case of a significant discontinuity estimate for a given significance level, rejecting the null hypothesis of continuity of the density gives evidence for sorting around the threshold. If the estimate is negative, this a sign of selection under the threshold, which corresponds to manipulation of the assignment variable.

For the validity of the McCrary test, we have to assure that the possible self-selection occurs only in one direction, towards above or below the threshold. In the present case, we expect that, if at all, selection would take place below the threshold, i.e. that firms select to employ a lower number of employees in order to avoid being subject to EPL. The only possible reason for the rather unlikely case that firms select into being subject to EPL could be that firms use the selection into EPL as a device to signal commitment towards their employees (Schivardi and Torrini 2008). Though this would represent a causal effect of EPL on training, it might bias the estimation results due to unobserved heterogeneity between selecting and non-selecting firms.

The assumption of no manipulation of the assignment variable in our case requires that its distribution is continuous for each firm. However, because we only observe one observation per firm for one point in time, we cannot test this directly. We can just if this assumption holds on average, i.e. by testing if the continuity assumption holds for the aggregate distribution of the assignment variable. Figure displays the results of the McCrary test for Finland and Italy. In order to improve readability, the sample is restricted to the largest bandwidth allowing for a symmetric window across the threshold, i.e. for bandwidths of 10 and 6 for Finland and Italy respectively.

Visual inspection of the graphs suggest that the density of firms indicates no self-selection of firms under the threshold. This is supported by the corresponding insignificant discontinuity estimates reported in table A1.1 in the appendix. This is in line with Hijzen et al. (2013) who find no evidence of selection in a more comprehensive dataset for Italy.

Figure 1: McCrary Test for Finland and Italy



Secondly, we test the validity of the RDD design by examining whether observable firm characteristics, namely industry affiliation, innovation propensity (*Innovation*), Average Wages (*Average Wage*), employee age distribution (*Share Young, Share Med Age, Share Old*) and whether a firm has temporary workers (*Temp Emp*) or part-time workers (*Part-Time Emp*) are locally balanced on either side of the threshold, as suggested by Lee and Lemieux (2010). We test this by regressing the observable firm characteristics on the binary cut-off variable and a firm size polynomial of the first, second or third order using either OLS or Logit estimations, depending on the nature of the observable firm characteristic (continuous or binary). Since the sample consists of firms within the maximal bandwidth allowing for a balanced window around the cut-off, we cannot include other observable firm characteristic in the estimations, since we would run out of degrees of freedom otherwise.

The results of the discontinuity estimates are displayed in table A1.2 in the appendix. If there is no selection problem (i.e. continuity assumption holds), we expect that the discontinuity estimate to be insignificant, implying that the covariates are locally balanced on either side of the cut-off. For Finland, there are no significant discontinuity estimates. This is a little different for Italy, where significant discontinuity estimates can be found for four out of 19 industries, thereby exceeding the expected number of significant estimates slightly. However, this mainly occurs under inclusion of higher order polynomials of the assignment variable. We consider this not to be too much of a problem. Figures

A1.1a and A1.1b in the appendix allow graphical inspection of this relationship by plotting the covariates against the assignment variable, providing no indication of a jump of covariates at the threshold. Hence, similar to the McCrary test, we are confident that the RDD is valid for Finland and, with some very slight doubts, for Italy, too.

All in all, we conclude that both tests do not indicate a (serious) self-selection problem, neither for Finland, nor for Italy.

6. Results of the regression discontinuity design

This part of the paper contains our main conclusions. The results do not confirm our hypothesis that EPL increases the extensive and intensive margin of training. Instead, the results point towards a potentially negative impact. Analysing heterogeneous effects of EPL on training, we find some slight evidence that the negative effect on the extensive margin is driven by firms with a larger share of older workers, which supports the hypothesis that EPL causes a negative selection of workers. However, this effect is statistically insignificant.

In the first subsection, we analyse the relation between EPL and training graphically, then present our baseline results in the second subsection before we look at heterogeneous effects and robustness checks. Finally, we will look at the impact of EPL on training in sectors with high employment volatility compared to those with low employment volatility.

6.1 Graphical analysis of outcome and assignment variable

This section presents the results of the regression discontinuity design, starting with a visual analysis. Concretely, Figures 2a and 2b plot the average outcome variable of each firm against the assignment variable that takes the value zero at the threshold indicated by a vertical line. According to our hypothesis *H1a (EPL increases training)*, we would expect an upward jump in training at the threshold value of zero. However, the graphical results provide evidence rather in favour of hypothesis *H1b (EPL decreases training)*. For Finland, there is an increase in both training variables for firms just below the cut-off (firms with 20 employees and above), the one measuring the extensive and the intensive margin of training (figure 2a). This increase is more pronounced for the extensive margin. For Italy, there is only an increase in the training variable for the extensive margin for firms below the cut-off (figure 2b). In contrast, the intensity of training variable increases for firms just above the cut-off (firms with 16 employees and above).

Figure 2a: Outcome and assignment variables, Finland

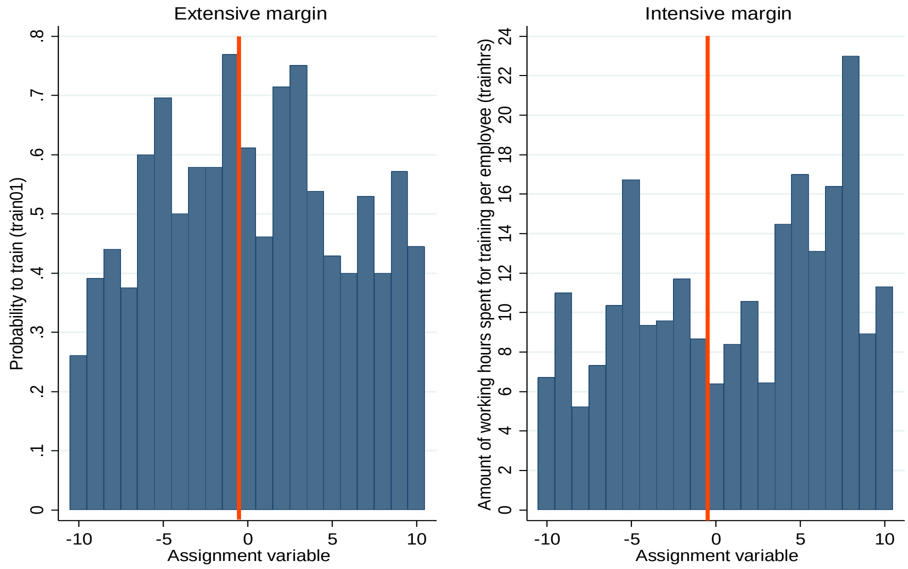
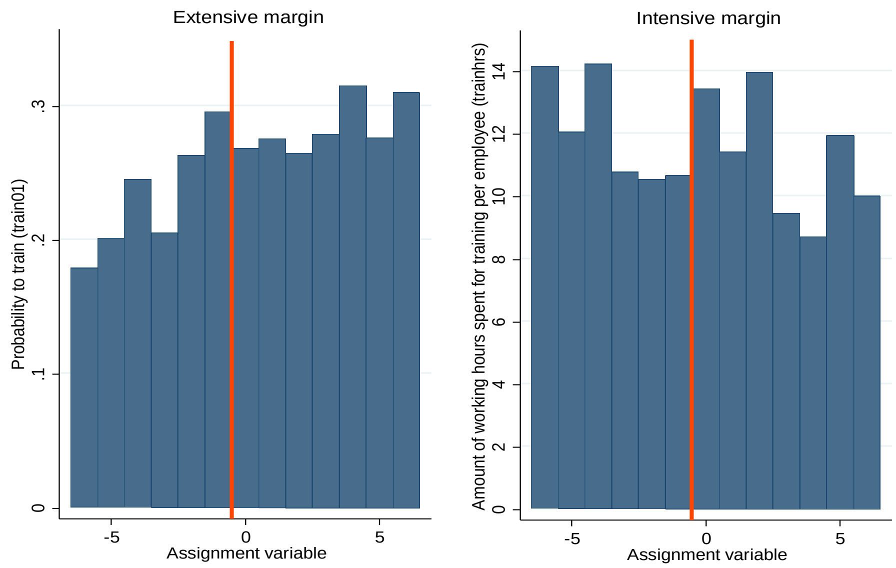


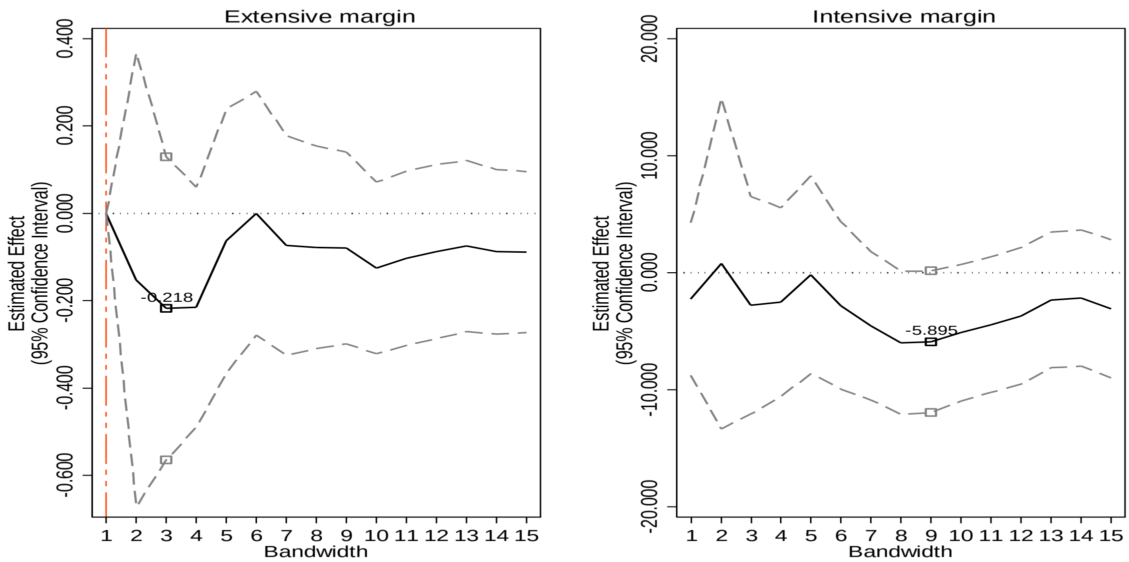
Figure 2b: Outcome and assignment variables, Italy



6.2 Baseline Results

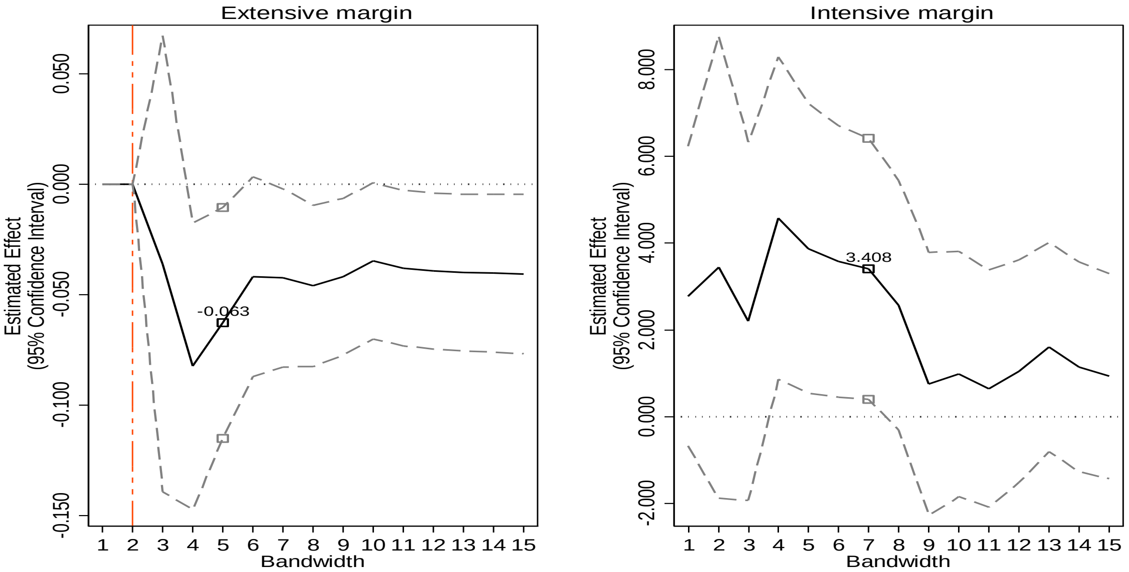
Figures 3a and 3b visualize the regression results reported in Tables A3.1a and A3.1b for Finland and Italy, respectively. They plot the estimated discontinuity coefficient (solid line) along with the upper and lower bound of the 95% confidence interval around this coefficient (dashed lines) over a specified bandwidth interval. A solid line above/below the zero line represents a positive/negative discontinuity estimate. This estimate is significant as long as *both* confidence bands are below the zero line when the coefficient is negative or above the zero line when it is positive. The number in the graph shows the discontinuity estimate at the optimal bandwidth. The vertical red and dashed line correspond to an estimate of zero of the discontinuity coefficient because of colinearity of the assignment-to-treatment variable with the versions of the assignment variable for the optimal functional form.

Figure 3a: RDD estimates Finland



Notes: The figure displays marginal effects and 95% confidence intervals of Logit estimates (Extensive margin) and OLS estimates with robust standard errors (Intensive margin) of the effect of EPL on training for different bandwidths around the threshold.

Figure 3b: RDD estimates Italy



Notes: The figure displays marginal effects and 95% confidence intervals of Logit estimates (Extensive margin) and OLS estimates with robust standard errors (Intensive margin) of the effect of EPL on training for different bandwidths around the threshold.

The discontinuity estimates of the extensive margin of training for Finland are negative and insignificant along the entire bandwidth interval including the optimal bandwidth (at bandwidth 3). The estimates for the intensive margin are mostly negative (except at bandwidth 2) but only statistically significant at the optimal bandwidth (bandwidth 9).

The effect of EPL on the extensive margin of training for Italy is negative and significant from bandwidth 4 onwards, including the optimal bandwidth 5, except at bandwidths 6 and 10. In contrast, the effect of EPL on the intensive margin of training is positive and insignificant at most bandwidths, except at bandwidths 4 to 7, whereby the latter is the optimal bandwidth.

To sum up, the RDD estimates confirm the results from the graphical analysis. We do not find statistically significant effect of EPL on the extensive margin of training for Finland, neither at the optimal, nor at any other bandwidth. For the intensive margin, we find a statistically significant negative effect only at the optimal bandwidth. This finding is not stable across different bandwidths. The signs of both margins suggest a negative effect of EPL on training. For Italy, we find a negative effect of EPL on the extensive and a positive effect on the intensive margin of training at the optimal bandwidth. Both effects are statistically significant. While the effect on the extensive margin is stable and statistically significant across different bandwidths, this is not the case for the intensive margin. Hence, the empirical results rather support H1b, i.e. that EPL decreases training but provide little evidence for H1a, i.e. that EPL increases training.

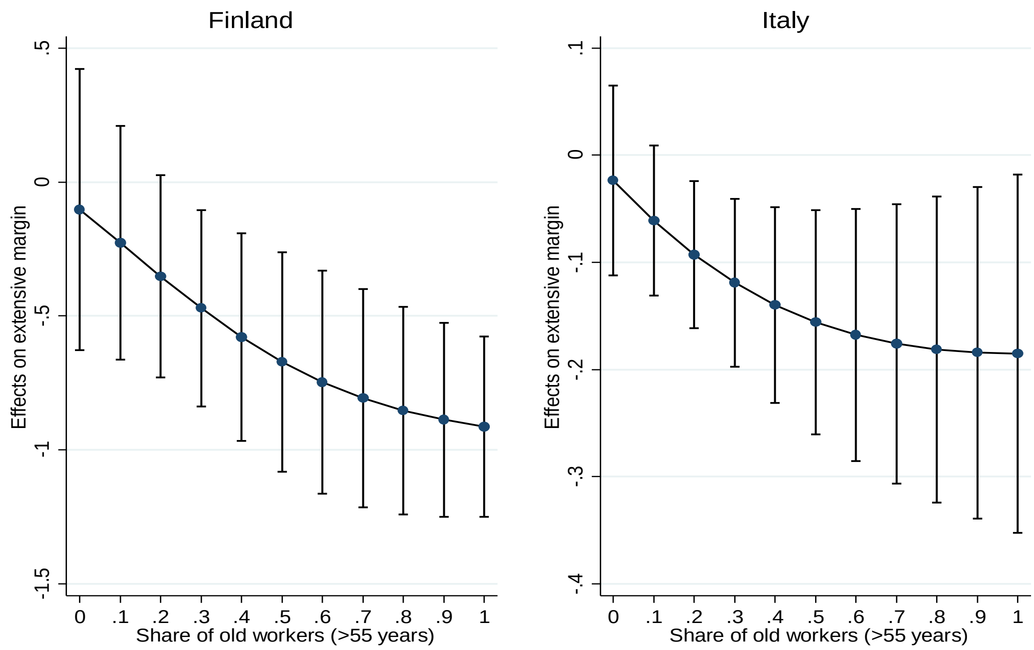
6.3 Heterogeneity

This section tests the two hypotheses H2 and H3, thereby evaluating two channels through which EPL might decrease training. Figures 4a, 4b and 5 display the results and Table A3.2 in the appendix reports the estimation results.

Hypothesis H2 tests whether firms with a more heterogeneous workforce are affected more negatively. We operationalise the idea by testing whether the interaction between EPL and the share of old workers (aged 55 and above) in a given firm is negative, i.e. assuming that this negative selection would increase in the share of old workers.

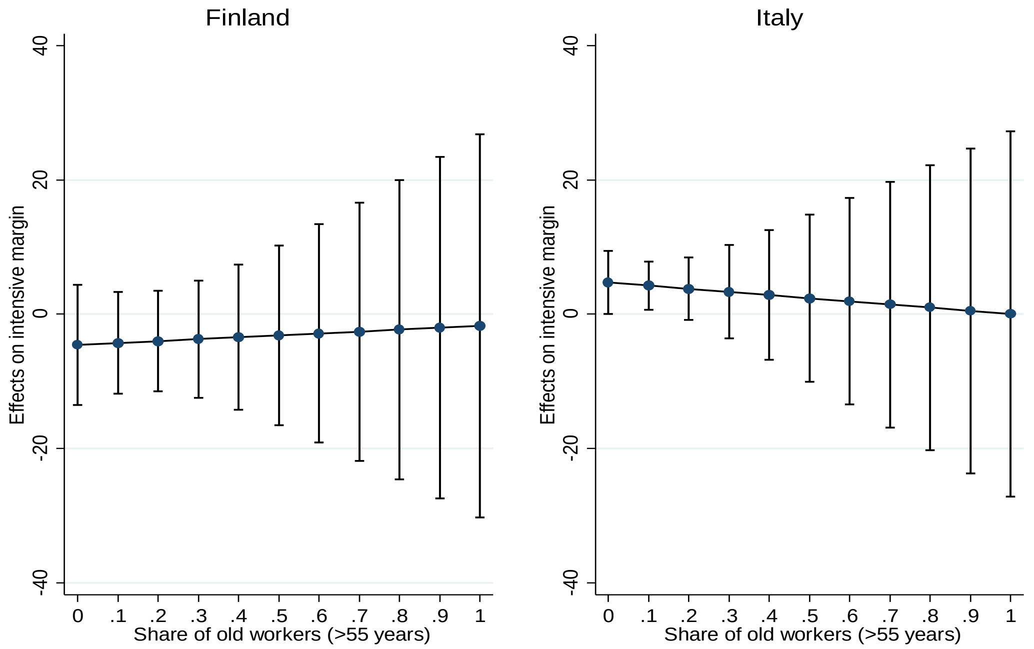
The results of the interaction between the assignment-to-treatment variable (EPL) and the share of old workers for the extensive margin and at the optimal bandwidth are displayed in Figure 4a for Finland and Italy respectively. The results for the extensive margin for both countries depict the same pattern: the higher the share of workers aged 55 and above, the more pronounced is the negative effect of EPL on training incidence. The average marginal effect is not statistically significant if the share of workers aged 55 and above is below 0.3 for Finland and below 0.2 for Italy. However, in neither country is the difference between the estimates significant as illustrated by the overlap of the confidence bands. Nevertheless, Figure 4a provides suggestive evidence for hypothesis H2 as the negative estimate appears to be primarily driven by firms with an older workforce. That is, the negative effect of strict EPL on training incidence is more pronounced in firms with more heterogeneous workforce, as measured by a higher share of older workers.

Figure 4a: Interaction of EPL and Share of Old Workers: Extensive Margin



Note: Applying the optimal bandwidth, the figure displays marginal effects and 95% confidence intervals of Logit estimates for the effect of EPL and its interaction with the share of workers above 55 years on the propensity to train.

Figure 4b: Interaction of EPL and Share of Old Workers: Intensive Margin



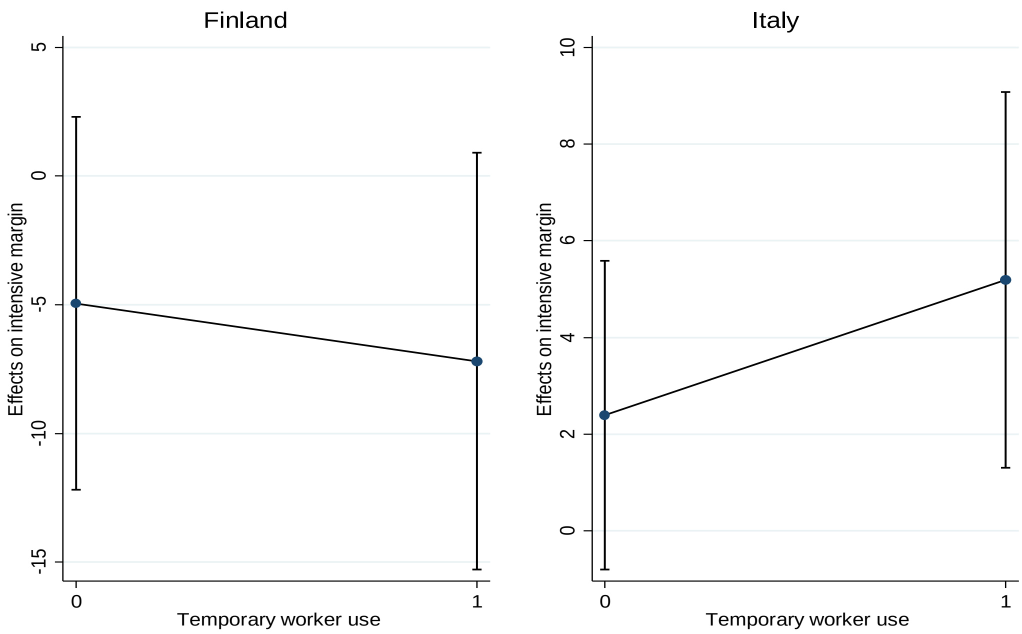
Note: Applying the optimal bandwidth, the figure displays marginal effects and 95% confidence intervals of OLS estimates with robust standard errors for the effect of EPL and its interaction with the share of workers above 55 years on the hours of training per employee in training firms.

Figure 4b displays the results for the intensive margins in Finland and Italy. For Finland, the effect of EPL is actually increasing, refuting hypothesis H2. In the case of Italy, the effect of EPL is decreasing, supporting hypothesis H2. However, in neither country is the difference even close to being statistically significant.

Second, we want to test hypothesis H3 suggesting that EPL decreases average training by increasing the use of temporary work contracts. Assuming that temporary workers are less likely to receive training, a higher use of temporary contracts would imply less training overall (see, e.g. Pierre and Scarpetta, 2013). Concretely, we want to test whether the interaction between EPL and the use of temporary work contracts is negative. Unfortunately, this test is only possible for the intensive margin of training because the information concerning temporary work contracts is not available for firms that do not train.

The results for the intensive margin at the optimal bandwidth can be found in Figure 5. The results show that the interaction of EPL and the indicator variable for the use of temporary workers is negative in Finland but positive in Italy. However, in both countries, the estimates are insignificant independently of whether temporary workers are employed or not. Furthermore, the difference is highly insignificant. Hence, the results do not support Hypothesis H3.

Figure 5: Interaction of EPL and Temporary Worker Use: Intensive Margin



Note: Applying the optimal bandwidth, the figure displays marginal effects and 95% confidence intervals of OLS estimates with robust standard errors for the effect of EPL and its interaction with a dummy whether a firm has temporary workers on the hours of training per employee in training firms.

6.4 Robustness checks

Table 3 displays a number of robustness checks for our main estimation strategy based on the optimal bandwidth. Figures A3.1 to A3.4 in the appendix display the corresponding regression results for different bandwidth choices.

The first robustness check is commonly labelled a “donut regression” (see, e.g., Barreca et al., 2011). In this robustness check, observations of the assignment variable just below and above the cut-off are excluded from the RDD regression, since these are most susceptible to manipulation and thus selection of firms above or below the threshold. Second, we test whether the inclusion of observable firm characteristics in the estimation affects our results. Third, we report estimation results by using sample weights and by regressing the treatment variable on the dependent variable without including the assignment variable, i.e. comparing the mean of the dependent variable below and above the threshold.

Table 2: RDD results

Country	**Finland**		**Italy**	
Margins	**Extensive**	**Intensive**	**Extensive**	**Intensive**
Functional form	Linear	Linear interaction	Quadratic	Linear
Baseline model				
Treatment	-0.218	-5.895	-0.063*	3.408*
	[0.177]	[3.063]	[0.03]	[1.534]
Extensive margin: Pseudo R-squared Intensive margin: R-squared	0.010	0.055	0.004	0.004
N	96	173	6314	1858
Donut regression (Leaving out 1 observation of the assignment variable on each side of the cut-off)				
Treatment	-0.394***	-5.037	-0.028	2.200
	[0.118]	[3.841]	[0.03]	[1.784]
Extensive margin: Pseudo R-squared Intensive margin: R-squared	0.039	0.033	0.003	0.002
N	75	157	5005	1799
Covariates				
Treatment	-0.288	-5.182	-0.060*	2.994*
	[0.183]	[2.997]	[0.03]	[1.498]
Extensive margin: Pseudo R-squared Intensive margin: R-squared	0.208	0.260	0.0557	0.07
N	86	173	6314	1858
With weights				
Treatment	-0.273	-3.585	-0.037	0.658
	[0.18]	[3.229]	[0.04]	[1.969]
Extensive margin: Pseudo R-squared Intensive margin: R-squared	0.021	0.136	0.004	0.004
N	96	173	6314	1858
Excluding assignment variable polynomial				
Treatment	-0.027	1.300	0.038**	-0.415
	[0.1]	[1.847]	[0.01]	[0.898]
Extensive margin: Pseudo R-squared Intensive margin: R-squared	0.001	0.003	0.002	0.000
N	96	173	6314	1858

Notes: The table shows marginal effects of Logit estimates for the extensive margin and OLS coefficients for the intensive margin. Standard errors in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. Robust standard errors were used for the OLS estimates

Table 3 displays the results of the donut RDD regressions, leaving out one observation to the right and left of the cut-off. Dropping one observation of the assignment variable on each side of the cut-off affects the magnitude of all RDD estimates. In addition, the extensive margin estimate for Finland turns statistically significant, while those of the extensive and intensive margin for Italy turn insignificant. This finding hints at a potential self-selection problem around the cut-off for Italy and in part for Finland, despite the fact that our diagnostic checks did not indicate a selection problem.

Next, we include some of the observable firm covariates in the regressions of EPL on training, namely average wages and industry dummies. Including covariates in the estimation affects the standard errors but not coefficient estimates in a valid RDD setting (Lee and Lemieux, 2010). Indeed, the coefficient estimates of the extensive margin remain relatively stable, in terms of significance, sign and magnitude, thereby supporting the validity of the RDD.

When we run the RDD regressions by using sample weights, the discontinuity estimates maintain the sign of the baseline model, but change in magnitude and loose significance in the case of Italy. Similar to the robustness check including covariates, these estimates can be seen as a specification test that casts some doubt on the significance of the negative results, but provides no evidence that EPL increases training.

Overall, these robustness checks indicate that the negative effects reported in the baseline results for Finland and the mixed effects for the extensive and intensive margin for Italy are qualitatively robust but that the significance of the estimates depends on the estimation model to some extent.

6.5 Accounting for sector-specific employment volatility

Rajan and Zingales (1998) argue that the impact of EPL on training should be larger in high volatility than in low volatility sectors. Hence, using a difference- in-differences (DiD) approach we test whether the interaction of the threshold (treatment) variable with the employment volatility variable (intrinsic sector job reallocation rates) has the same sign as the treatment indicator itself.

The key assumption for this strategy is that the variation in the impact of EPL across sectors, thus intrinsic sector volatility, is independent of the variation due to self-selection into size groups across sectors (Hijzen et al., 2013). To test the validity of this assumption, we conduct the McCrary test for the assignment variable by industry (at the 1-digit level of the NACE). While each selection test is insignificant for almost all industries, relating sector volatility and McCrary test coefficients suggests a negative albeit small correlation. This suggests that high volatility sectors are more likely to select below the threshold than firms in low volatility sector, thereby casting some doubt whether complementing the RDD with the DiD approach may be appropriate in the present context. This empirical question is in addition to the discussed problems of this identification strategy, namely to what extent sector volatility in the US represents sector volatility in Italy and Spain, whether sector volatility reflects long-term industry differences in job flows (Cingano et al. 2009) and finally whether the identification strategy works if EPL affects training through the selection channel.

Since this DiD identification strategy remains questionable in the present context despite the application of this DiD identification strategy in the literature (see, e.g., Hijzen et al. 2013), the detailed results are reported in Tables A3.3a and A3.3b in the appendix.[9] The results for Finland suggest that there is no statistical evidence for an impact of EPL on training - neither in high volatility nor in low

[9] Conducting the robustness checks presented for the RDD setting yield qualitatively the same results, which can be obtained from the authors upon request.

volatility sectors at the optimal bandwidth. The discontinuity estimate as well as the interaction term between the threshold dummy and the volatility variable are both insignificant for both extensive and intensive margin. For Italy, the results indicate that EPL decreases the incidence of training in low volatility and increases training intensity in high volatility sectors. Only the discontinuity estimate of the extensive and interaction term of intensive margin variable are statistically significant.

Hence, the DiD results differ between Finland and Italy. Furthermore, the results do not support the hypothesis that high volatility magnifies the effect of EPL, but rather dampens it. Hence, we conclude that the DiD estimates also provide no evidence that EPL increases training.

7. Conclusion

Neither visual inspection of the relation between assignment and outcome variables nor a series of RDD and DiD estimates provide any support for the hypothesis that EPL increases training for Finland. Instead, the results rather suggest the opposite causality direction- that EPL decreases training propensity. For Italy, there is some mild evidence of a negative effect of EPL on the extensive and a positive effect on the intensive margin. However, both results are not very robust. Hence, the presented evidence rather points towards a negative effect of EPL on training propensity. Hypothesizing that this might be due to a negative selection of the workforce, we find some indication that the negative effect on the extensive margin is driven by firms with a larger share of old workers. The hypothesis that EPL might decrease training by increasing the share of temporary workers in a firm is not supported by our results.

Hence, contrary to the scant existing empirical evidence (Almeido and Aterido, 2011, Pierre and Scarpetta, 2011, 2013, Piccio and van Ours, 2011, Messe and Rouland, 2014), we conclude that exploiting within-country variation that arises because Finland and Italy exempt small firms from EPL to some extent, yields no evidence that EPL increases training.

However, this study suffers from a number of drawbacks that should be addressed in future research. First, we only know whether firms have temporary workers or not. We cannot account for different effects of EPL on training at varying shares of temporary workers. Furthermore, we only have this information for firms who train their employees. Hence, we cannot test whether our extensive margin estimations are biased by a shift in temporary worker share due to EPL. Second, our measure of negative selection is very crude. It remains to future studies to examine whether a more refined measure of worker selection provides more convincing results in this regard. Third, relying on within-country variation improves internal validity of our results, but also jeopardizes external validity. This is particularly true for the present analysis that focuses on small firms. Hence, our results might not be applicable for medium-sized and large firms as well as in other countries.

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Appendix

Appendix A.0: Introduction

Table A0.1: Changes in EPL in the OECD countries, 2000-2013

Measure	Decreased	Unchanged	Increased	Insufficient data of the EPL index
Number of OECD countries in the respective group	16	6	6	6
Country names	Austria, Czech Republic, Finland, Greece, Hungary, Ireland, Italy, Japan, Mexico, Netherlands, Portugal, Slovak Republic, Spain, Sweden, Turkey, United Kingdom	Canada, Korea, Norway, Poland, Switzerland, USA	Australia, Belgium, Denmark, France, Germany, New Zealand	Chile, Estonia, Iceland, Israel, Luxembourg, Slovenia

Source: based on OECD Employment protection legislation (EPL) database (2015), individual and collective dismissals (regular contracts).

Appendix A1: Validity of RDD Design

Table A1.1: McCrary test results

Finland	Bandwidth	**15**	**30**
	Discontinuity estimate	0.298	0.121
		[0.352]	[0.261]
Italy	Bandwidth	**15**	**30**
	Discontinuity estimate	0.047	0.029
		[0.078]	[0.062]

Notes: The table shows coefficients and standard errors of a estimation evaluating via local linear regression whether a jump in the density of firms at the threshold occurs. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table A1.2a: Industry-specific McCrary test results: Finland

	Bandwidth 15			Bandwidth 30		
Industry variables (NACE 19)	Theta	SE	T-test	Theta	SE	T-test
Mining and quarrying (CA&CB)	-	-	-	-	-	-
Manufacturing sector (DA-DN)						
Food products, beverages and tobacco (DA)	-	-	-	-2.27	2.73	-0.83
Textiles and textile products (DB) & leather and leather products (DC)	1.83	2.79	0.65	1.63	2.78	0.59
Pulp, paper, paper products; publishing, printing and reproduction of recorded media (DE)	-0.63	1.44	-0.44	0.44	1.09	0.4
Coke, refined petroleum products and nuclear fuel (DF); chemicals, chemical products and man-made fibres (DG); rubber and plastic products (DH) & other non-metallic mineral products (DI)	-	-	-	2.28	1.96	1.16
Basic metals and fabricated metal products (DJ)	0.22	1.21	0.18	-0.03	0.91	-0.03
Machinery and equipment n.e.c. (DK) & electrical and optical equipment (DL)	0.32	1.32	0.24	0.31	0.91	0.34
Transport equipment (DM)	-0.85	1.92	-0.44	0.19	1.35	0.14
Wood and wood products (DD) & manufacturing n.e.c. (DN)	-0.89	1.04	-0.86	-0.96	0.94	-1.03
Electricity, gas and water supply (E)	-	-	-	-	-	-
Construction (F)	-1.4	2.23	-0.63	-1.1	1.38	-0.8
Service sector (G-O)						
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel (G)	4.26	5.96	0.71	4.16	5.7	0.73
Wholesale trade and commission trade, except of motor vehicles and motorcycles (G)	-2.19	2.89	-0.76	-0.95	1.64	-0.58
Retail trade, except of motor vehicles and motorcycles &repair of personal and household goods (G)	0	1.63	-	0	1.63	-
Hotels and restaurants (H)	1.12	1.42	0.79	1.5	1.53	0.98
Land transport; transport via pipelines; water and air transport; supporting and auxiliary transport activities; activities of travel agencies (I)	0.72	1.72	0.42	-0.05	1.24	-0.04
Post and telecommunications (I)	-	-	-	-	-	-
Financial intermediation, except insurance and pension funding; insurance and pension funding, except compulsory social security (J)	0.91	1	0.91	0.91	1	0.91
Real estate, renting and business activities (K); other community, social and personal service activities (O)	-	-	-	-	-	-

Notes: The table shows coefficients and standard errors of a estimation evaluating via local linear regression whether a jump in the density of firms at the threshold occurs. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table A1.2b: Industry-specific McCrary test results: Italy

	Bandwidth 15			Bandwidth 30		
Industry variables (NACE 19)	Theta	SE	T-test	Theta	SE	T-test
Mining and quarrying (CA&CB)	0.46	0.47	0.97	0.09	0.37	0.26
Manufacturing sector						
Food products, beverages and tobacco (DA)	-0.37	0.36	-1.05	-0.39	0.31	-1.27
Textiles and textile products (DB) & leather and leather products (DC)	1.4	0.52	2.67	0.54	0.31	1.74
Pulp, paper, paper products; publishing, printing and reproduction of recorded media (DE)	-0.76	0.36	-2.11	-0.59	0.21	-2.84
Coke, refined petroleum products and nuclear fuel (DF); chemicals, chemical products and man-made fibres (DG); rubber and plastic products (DH) & other non-metallic mineral products (DI)	0.1	0.3	0.33	0.21	0.25	0.83
Basic metals and fabricated metal products (DJ)	0.4	0.3	1.34	0.13	0.24	0.53
Machinery and equipment n.e.c. (DK) & electrical and optical equipment (DL)	0.63	0.28	2.23	0.42	0.24	1.77
Transport equipment (DM)	-0.63	0.59	-1.06	-0.38	0.48	-0.79
Wood and wood products (DD) & manufacturing n.e.c. (DN)	-0.27	0.26	-1.05	-0.52	0.21	-2.5
Electricity, gas and water supply (E)	-1.1	0.81	-1.35	-0.65	0.34	-1.93
Construction (F)	0.03	0.13	0.2	0.02	0.11	0.14
Service sector (G-O)						
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel (G)	-0.71	0.34	-2.13	-0.55	0.28	-1.94
Wholesale trade and commission trade, except of motor vehicles and motorcycles (G)	-0.17	0.26	-0.64	-0.22	0.22	-1.03
Retail trade, except of motor vehicles and motorcycles &repair of personal and household goods (G)	-0.08	0.32	-0.24	-0.06	0.3	-0.2
Hotels and restaurants (H)	0.62	0.49	1.26	0.15	0.32	0.45
Land transport; transport via pipelines; water and air transport; supporting and auxiliary transport activities; activities of travel agencies (I)	-0.11	0.38	-0.28	-0.25	0.27	-0.93
Post and telecommunications (I)	-0.38	0.83	-0.46	-0.63	0.73	-0.86
Financial intermediation, except insurance and pension funding; insurance and pension funding, except compulsory social security (J)	0.35	0.36	0.97	0.37	0.32	1.18
Real estate, renting and business activities (K); other community, social and personal service activities (O)	0.13	0.19	0.66	0.15	0.16	0.97

Notes: The table shows coefficients and standard errors of a estimation evaluating via local linear regression whether a jump in the density of firms at the threshold occurs. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Figure A1.1a: Observable firm characteristics around the threshold: Finland

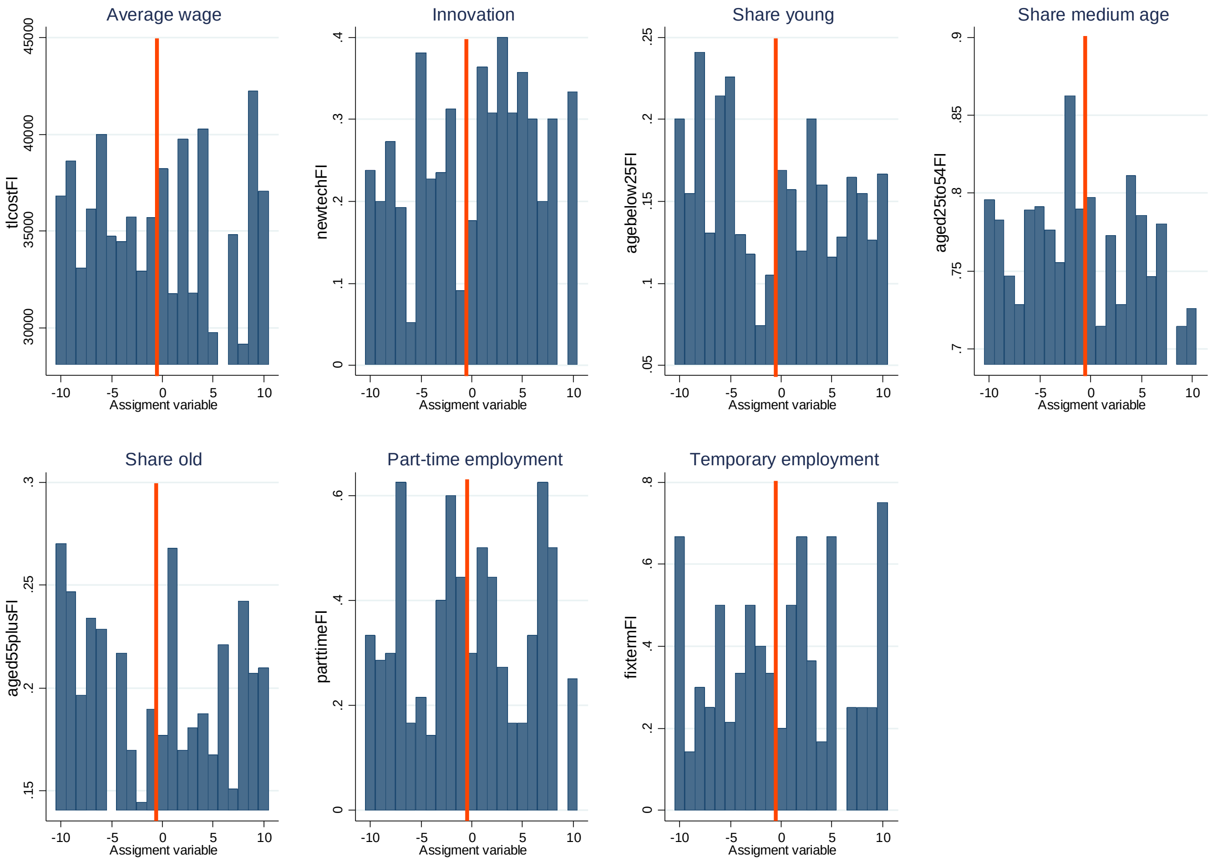


Figure A1.1b: Observable firm characteristics around the threshold: Italy

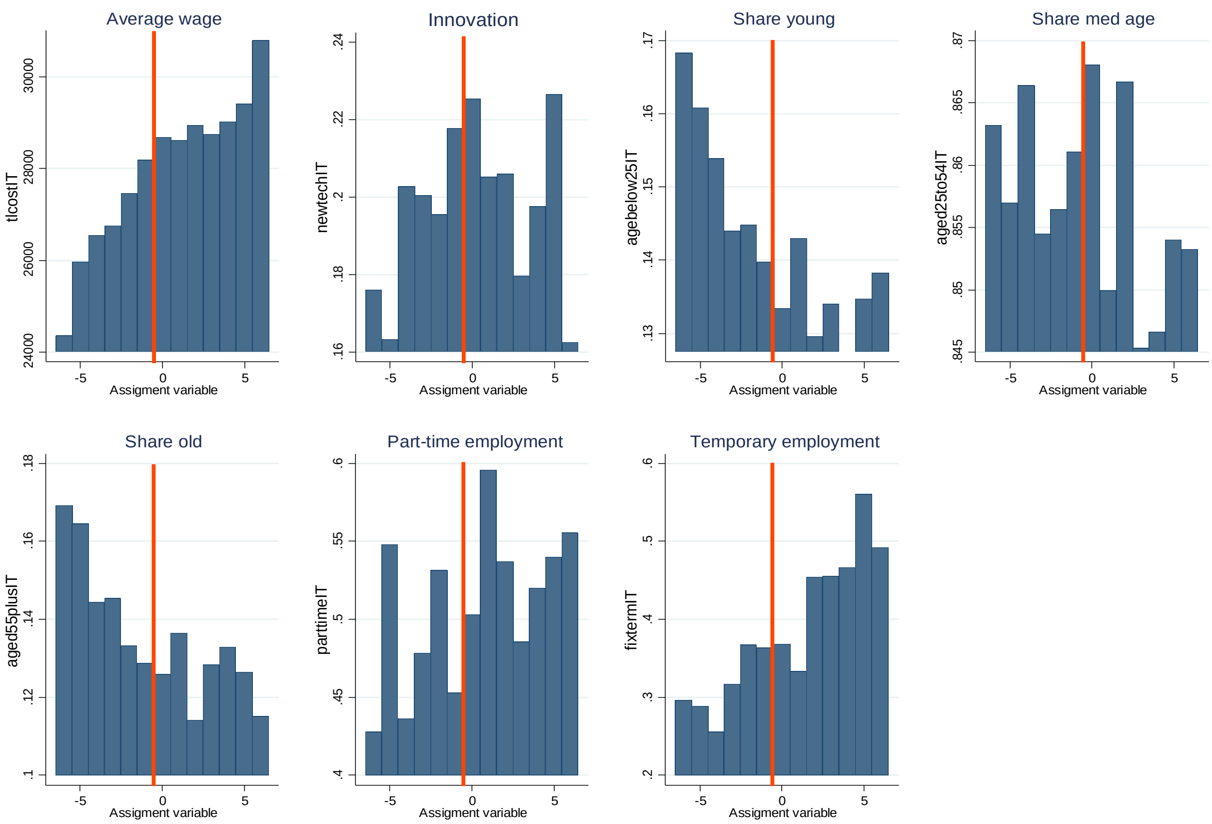


Table A1.2: Observable firm characteristics around the threshold: regression

	Finland				Italy			
Assignment Variable Polynomial	**1st order**	**2nd order**	**3rd order**	**N**	**1st order**	**2nd order**	**3rd order**	**N**
Industry variables (NACE 19)								
Mining and quarrying (CA&CB)	0.000817	-0.0117	0.0663		-0.00517	0.00468	0.00801	
	[0.0540]	[0.0577]	[0.124]		[0.00553]	[0.00726]	[0.00979]	
Manufacturing sector (DA-DN)								
Food products, beverages and tobacco	-0.069	-0.0468	-0.0626		-0.0065	0.00275	-0.0113	
	[0.0587]	[0.0531]	[0.0714]		[0.00657]	[0.00833]	[0.00759]	
Textiles & leather and leather (products)	0.0198	0.0237	0.0537		0.0104	0.00882	0.0175	
	[0.0507]	[0.0538]	[0.0859]		[0.00977]	[0.00991]	[0.0146]	
Pulp, paper,; publishing, printing and reproduction of recorded media	0.102	0.101	-0.0219		-0.0107	-0.0113	-0.0123	
	[0.0941]	[0.0945]	[0.0692]		[0.00815]	[0.00847]	[0.0111]	
Coke, refined petroleum products and nuclear fuel; chemicals, chemical products and man-made fibres; rubber and plastic products & other non-metallic mineral products	0.0347	0.0382	0.136		0.0131	0.0272*	0.0102	
	[0.0540]	[0.0577]	[0.124]		[0.00553]	[0.00726]	[0.00979]	
Basic metals and fabricated metal products	0.0045	0.0117	-0.0366		0.00213	0.00234	0.00938	
	[0.0569]	[0.0569]	[0.0680]		[0.00989]	[0.0102]	[0.0143]	
Machinery and equipment n.e.c. & electrical and optical equipment	0.0772	0.09	-0.016		0.0131	0.0131	0.017	
	[0.0845]	[0.0874]	[0.0688]		[0.0104]	[0.0105]	[0.0146]	
Transport equipment	0.00657	0.0234	0.0469		-0.00156	0.00125	-0.00443	
	[0.0399]	[0.0496]	[0.0851]		[0.00433]	[0.00521]	[0.00497]	
Wood (products) & manufacturing n.e.c.	-0.0618	-0.0622	-0.0993		-0.0187*	-0.0196*	-0.0095	
	[0.0606]	[0.0627]	[0.0887]		[0.00874]	[0.00921]	[0.0125]	
Electricity, gas and water supply (E)	-0.0739	-0.0789	-0.0834		-0.000976	-0.00141	-0.00866	
	[0.0538]	[0.0677]	[0.0868]		[0.00395]	[0.00408]	[0.00669]	
Construction (F)	-0.0113	-0.027	-0.0745	353	-0.0219	-0.0555*	-0.0241	7387
	[0.0491]	[0.0539]	[0.0858]		[0.0218]	[0.0223]	[0.0301]	
Service sector (G-O)								
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel	0.0528	0.166	0.173		-0.0106	-0.000319	-0.0169*	
	[0.0861]	[0.187]	[0.217]		[0.00722]	[0.00877]	[0.00856]	
Wholesale trade and commission trade	-0.0162	-0.0163	-0.0381		-0.0135	-0.0145	-0.00333	
	[0.0381]	[0.0395]	[0.0619]		[0.00939]	[0.00969]	[0.0134]	
Retail trade &repair of personal and household goods	-0.0164	-0.0155	0.0833		0.0108	0.0197	-0.0042	
	[0.0433]	[0.0469]	[0.146]		[0.0101]	[0.0121]	[0.0103]	
Hotels and restaurants	0.0581	0.0697	0.0976		0.00599	-0.00433	0.0067	
	[0.0864]	[0.0977]	[0.156]		[0.00995]	[0.0101]	[0.0150]	
Land transport; transport via pipelines; water and air transport; supporting and auxiliary transport activities; activities of travel agencies	-0.0556	-0.0344	-0.0182		-0.00139	-0.000521	-0.00221	
	[0.0506]	[0.0393]	[0.0447]		[0.00698]	[0.00714]	[0.00926]	
Post and telecommunications	-0.0132	-0.0122	0.0149		-0.00304	-0.00226	-0.00139	
	[0.0379]	[0.0417]	[0.0558]		[0.00220]	[0.00223]	[0.00272]	
Financial intermediation, insurance and pension funding	0.00423	0.0154	0.121		0.0174	0.0163	0.0108	
	[0.0612]	[0.0589]	[0.118]		[0.0107]	[0.0109]	[0.0134]	
Real estate, renting and business activities ; other community, social and personal service activities	0.0368	0.237	-0.158		0.0254	0.0667***	0.0301	
	[0.0570]	[0.228]	[0.320]		[0.0165]	[0.0197]	[0.0214]	
Innovation	0.0861	0.0934	-0.0203	319	-0.0105	-0.00146	0.0112	
	[0.105]	[0.104]	[0.131]		[0.0180]	[0.0188]	[0.0251]	
Part-Time Emp	-0.0966	-0.091	-0.208	158	0.047	0.0535	0.074	1795
	[0.140]	[0.141]	[0.157]		[0.0452]	[0.0463]	[0.0601]	
Temp Emp	0.045	0.0562	-0.108	160	-0.0347	-0.0443	-0.0686	
	[0.149]	[0.149]	[0.181]		[0.0411]	[0.0415]	[0.0528]	
Average Wage(1)	2058.1	2043.4	4494.5	353	-478.3	29.64	478.7	7387
	[2823.3]	[2867.3]	[3837.0]		[544.0]	[565.9]	[741.9]	
Share Young (1)	0.0625	0.0587	0.092	204	0.00562	0.00217	-0.000801	3278
	[0.0409]	[0.0410]	[0.0565]		[0.00788]	[0.00809]	[0.0108]	
Share Med Age (1)	-0.0302	-0.0237	-0.084	351	0.0059	0.00771	0.00823	7378
	[0.0350]	[0.0355]	[0.0473]		[0.00613]	[0.00638]	[0.00836]	
Share Old(1)	0.0491	0.0406	0.043	254	0.0107	0.0043	0.0044	4078
	[0.0342]	[0.0342]	[0.0461]		[0.00573]	[0.00589]	[0.00775]	

Notes: *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. The table displays marginal effects of a Logit model or, those marked with a (1), with OLS (robust standard errors used for OLS estimation). Each entry corresponds to a regression of the observable firm characteristics on the threshold, controlling for a first order (1st order), second order (2nd order)or third order (3rd order) polynomial of the assignment variable, respectively.

Appendix A2: Optimal Bandwidth and Functional Form

The first step in choosing the bandwidth and functional form is to estimate optimal bandwidths based on the Imbens/Kalyanaraman (2012) methodology using the Stata-package provided by Imbens[10]. The resulting bandwidth choice is shown in Table A2.1 together with the maximum bandwidth that allows to estimate the RDD with a symmetric window.

Table A2.1 Optimal bandwidth

Variable	Optimal bandwidth
Finland	
Train 0/1	3
Train Hours	9
Italy	
Train 0/1	5
Train Hours	7

Based on the optimal bandwidth, we run the RDD for six possible ways to model the functional form of the assignment variable. The corresponding regression results are shown in Tables A2.2 for Finland and Tables A2.3 for Italy, respectively. The Akaike Information Criterion (AIC) serves to select the best-fitting model. In the case of the extensive margin estimates for Finland and Italy, the AIC suggests to use linear and quadratic interactions of the assignment variable in the estimation respectively. For the intensive margin, the AIC suggests the linear interaction and quadratic form of the assignment variable for Finland and Italy respectively.

[10]The package can be downloaded from: http://faculty-gsb.stanford.edu/imbens/RegressionDiscontinuity.html.

Table A2.2 Functional form: Finland

	Train 0/1						Train Hours					
	Linear	Linear interaction	Quadratic	Quadratic interaction	Cubic	Cubic interaction	Linear	Linear interaction	Quadratic	Quadratic interaction	Cubic	Cubic interaction
Treatment	0.283	0.386	2.963	2.214	-2.412	-2.412	0.852**	0.27	-0.461	-1.827	-4.491	-6.749
	[0.257]	[0.371]	[1.955]	[2.592]	[2.291]	[2.291]	[0.314]	[0.408]	[1.537]	[2.118]	[4.391]	[5.196]
Assignment variable	-0.973	-1.112	-3.253	-2.523	0	0	-5.891	-5.895	-5.11	-0.921	2.356	4.126
	[0.882]	[0.963]	[1.938]	[2.522]	[.]	[.]	[3.148]	[3.063]	[3.486]	[4.536]	[5.816]	[6.278]
Assignment variable*D		-0.201	-3.991	-3.658	0.126	0.126		1.419*	2.708	2.549	3.933	7.938
		[0.515]	[2.856]	[2.931]	[2.296]	[2.296]		[0.606]	[2.657]	[2.618]	[3.354]	[6.188]
Assignment variable^2			0.623	0.443	-2.08	-2.08			-0.0736	-0.211	-0.842	-1.377
			[0.458]	[0.618]	[1.975]	[1.975]			[0.153]	[0.215]	[0.971]	[1.187]
Assignment variable^2*D				0.396	4.18	4.18				0.339	1.443	1.332
				[0.918]	[3.246]	[3.246]				[0.297]	[1.693]	[1.710]
Assignment variable^3					-0.421	-0.421					-0.0422	-0.0779
					[0.420]	[0.420]					[0.0652]	[0.0804]
Assignment variable^3*D						0						0.0933
						[.]						[0.136]
Constant	1.126	1.351	3.65	2.975	0.452	0.452	14.52***	11.62***	10.24**	7.672	4.851	2.46
	[0.620]	[0.854]	[1.987]	[2.474]	[0.486]	[0.486]	[2.060]	[2.461]	[3.398]	[4.167]	[5.497]	[6.056]
N	96	96	96	96	96	96	173	173	173	173	173	173
AIC	132.8	134.6	134.7	136.5	136.5	136.5	1347.4	1345.6	1347.4	1348.2	1349.9	1351.5

Notes: The table shows Logit estimates for the extensive margin and OLS estimates for the intensive margin at the optimal bandwidths. Standard errors in parentheses (robust standard errors used for OLS estimation). *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. Grey estimates indicate the choice of the functional form based on the Akaike Information Criterion (AIC).

Table A2.3 Functional form: Italy

	Train 0/1						Train Hours					
	Linear	Linear interaction	Quadratic	Quadratic interaction	Cubic	Cubic interaction	Linear	Linear interaction	Quadratic	Quadratic interaction	Cubic	Cubic interaction
Treatment	0.0846***	0.110***	0.265*	0.268*	0.853*	0.952	-0.676**	-0.734*	-0.292	-0.734	1.319	2.005
	[0.0214]	[0.0267]	[0.109]	[0.133]	[0.434]	[0.534]	[0.245]	[0.353]	[1.007]	[1.657]	[3.238]	[5.313]
Assignment variable	-0.199	-0.201	-0.346*	-0.351	-0.791*	-0.856*	3.408*	3.443*	3.095*	3.877	1.981	1.492
	[0.118]	[0.116]	[0.153]	[0.198]	[0.367]	[0.418]	[1.534]	[1.538]	[1.566]	[2.552]	[3.544]	[4.508]
Assignment variable*D		-0.0715	-0.322	-0.321	-0.713*	-0.872		0.128	-0.667	-0.527	-1.438	-2.358
		[0.0448]	[0.176]	[0.176]	[0.328]	[0.592]		[0.484]	[1.856]	[1.964]	[2.060]	[5.909]
Assignment variable^2			0.0258	0.0263	0.249	0.286			0.0642	-9.2E-05	0.682	0.91
			[0.0175]	[0.0216]	[0.159]	[0.198]			[0.146]	[0.247]	[1.047]	[1.830]
Assignment variable^2*D				-0.00148	-0.366	-0.36				0.119	-1.124	-1.236
				[0.0371]	[0.261]	[0.261]				[0.300]	[1.967]	[2.148]
Assignment variable^3					0.0246	0.0288					0.0652	0.087
					[0.0174]	[0.0218]					[0.103]	[0.182]
Assignment variable^3*D						-0.0118						-0.0352
						[0.0363]						[0.220]
Constant	-0.900***	-0.823***	-0.639***	-0.636***	-0.217	-0.146	9.754***	9.559***	10.14***	9.558***	11.19***	11.73
	[0.0750]	[0.0884]	[0.153]	[0.178]	[0.343]	[0.408]	[0.852]	[1.096]	[1.516]	[2.186]	[2.947]	[4.275]
N	6314	6314	6314	6314	6314	6314	1858	1858	1858	1858	1858	1858
AIC	7097	7096.5	7096.3	7098.3	7098.3	7100.2	16305.8	16307.8	16309.6	16311.5	16313.1	16315.1

Notes: The table shows Logit estimates for the extensive margin and OLS estimates for the intensive margin at the optimal bandwidths. Standard errors in parentheses (robust standard errors used for OLS estimation). *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. Grey estimates indicate the choice of the functional form based on the Akaike Information Criterion (AIC).

Appendix A3: Estimation Results of RDD Estimates

Table A3.1a: RDD Results for Finland

Extensive margin (Train 0/1)															
Bandwidth	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Treatment	0	-0.152	-0.218	-0.215	-0.063	0.000	-0.074	-0.078	-0.079	-0.125	-0.103	-0.088	-0.075	-0.088	-0.089
	[.]	[0.273]	[0.181]	[0.141]	[0.155]	[0.143]	[0.13]	[0.12]	[0.113]	[0.101]	[0.102]	[0.102]	[0.1]	[0.097]	[0.095]
Pseudo R^2	0.0227	0.0094	0.0097	0.0211	0.0013	0.0004	0.0017	0.0026	0.003	0.0097	0.0069	0.0056	0.005	0.0073	0.0081
N	31	63	96	136	172	206	248	290	323	353	362	370	381	389	395
Intensive margin (Train Hours)															
Bandwidth	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Treatment	-2.266	0.788	-2.795	-2.505	-0.183	-2.809	-4.534	-6.000*	-5.895*	-5.129*	-4.448	-3.699	-2.322	-2.177	-3.095
	[3.112]	[6.954]	[4.642]	[4.05]	[4.256]	[3.608]	[3.211]	[3.102]	[3.063]	[2.961]	[2.932]	[2.956]	[2.942]	[2.953]	[2.991]
R^2	0.028	0.049	0.02	0.011	0.038	0.032	0.023	0.038	0.055	0.04	0.033	0.023	0.007	0.007	0.02
N	21	38	59	83	106	124	140	160	173	183	187	191	197	203	207

Table A3.1b: RDD Results for Italy

Extensive margin (Train 0/1)															
Bandwidth	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Treatment	0	0	-0.036	-0.082**	-0.063**	-0.042*	-0.042**	-0.046**	-0.042**	-0.035*	-0.038**	-0.039**	-0.040**	-0.040**	-0.041**
	[.]	[.]	[0.053]	[0.033]	[0.027]	[0.023]	[0.021]	[0.019]	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]
Pseudo R^2	0.0008	0.0007	0.0045	0.0027	0.0044	0.0066	0.0069	0.0081	0.0086	0.0079	0.0088	0.0099	0.0115	0.0125	0.013
N	1288	2588	3904	5194	6314	7387	7590	7895	8199	8479	8738	8954	9183	9396	9571
Intensive margin (Train Hours)															
Bandwidth	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Treatment	2.777	3.450	2.203	4.575**	3.877**	3.578**	3.408**	2.569*	0.751	0.982	0.642	1.048	1.604	1.143	0.930
	[1.758]	[2.719]	[2.108]	[1.896]	[1.701]	[1.596]	[1.534]	[1.468]	[1.547]	[1.444]	[1.395]	[1.309]	[1.231]	[1.233]	1.206
R^2	0.007	0.004	0.004	0.004	0.004	0.004	0.004	0.002	0	0	0	0	0.001	0	0
N	364	712	1006	1334	1586	1795	1858	1962	2060	2135	2227	2308	2399	2480	2545

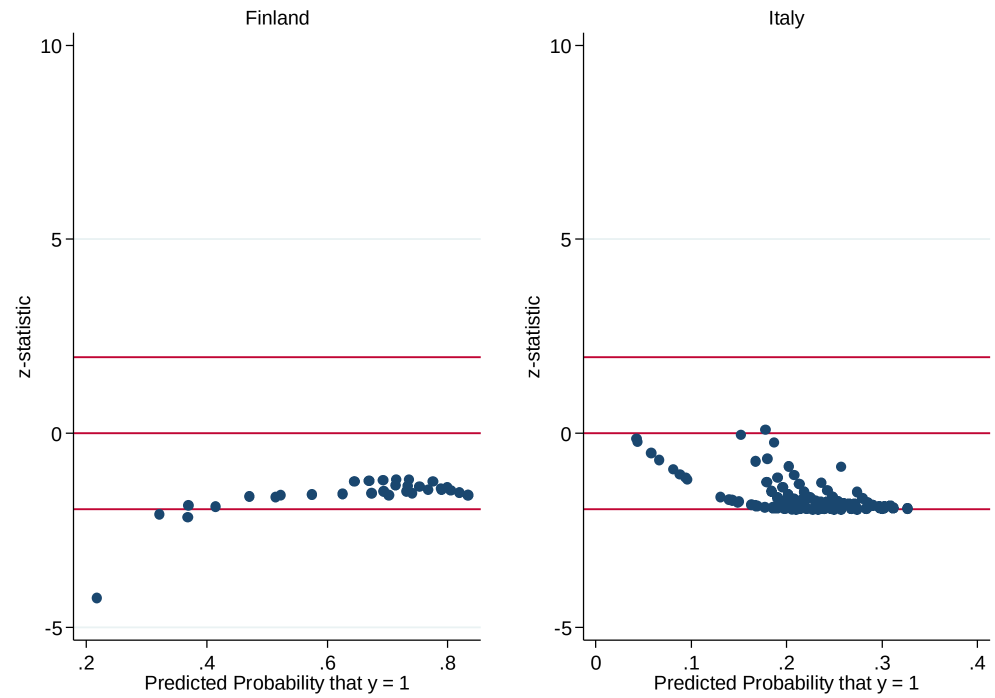
Notes for tables A31a& A31b: The tables show Logit estimates for the extensive margin and OLS estimates for the intensive margin over different bandwidths. Standard errors in parentheses (robust standard errors used for OLS estimation). *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. (1) indicates insufficient degrees of freedom. Extensive margin estimates for Finland are based on a linear specification of the assignment variable and for Italy on a quadratic interactions of the assignment variable. Intensive margin estimates for Finland include a linear interaction and those for Italy a linear specification of the assignment variable in the estimation. Grey estimates indicate the optimal bandwidth.

Table A3.3: RDD results, heterogeneous groups

Country	Finland		Italy	
Margin	**Extensive margin**	**Intensive margin**	**Extensive margin**	**Intensive margin**
Interaction of Treatment and Share of old workers (>55years)				
Functional form	Linear	Linear interaction	Quadratic	Linear
Treatment[1]	-0.32[1]	-4.586	-0.07[1]	4.729*
	[0.19]	[4.536]	[0.03]	[2.397]
Share Old	1.82	-14.68	-0.42	-8.06
	[3.70]	[10.63]	[0.56]	[9.452]
Treatment*Share Old[2]	-6.01[2]	2.851	-2.10[2]	-4.711
	[4.56]	[16.55]	[1.00]	[15.27]
(Pseudo) R-squared	0.06	0.065	0.0078	0.007
N	74	130	3555	1039
Average marginal effect for the interaction term using Stat *inteff* command (Norton et al., 2004)				
Interaction: Treatment*Share Old	-1.20987		-0.32564	
Std. error	0.838289		0.176543	
Z-Statistic	-1.50744		-1.82456	
Interaction of Treatment and Temporary Worker Use				
Treatment		-4.943		2.396
		[3.663]		[1.627]
Temporary Employment		-2.245		2.793
		[4.004]		[1.801]
Treatment*Temporary Employment		0.897		-1.569
		[2.915]		[1.180]
R-squared		0.066		0.005
N		150		1858

Notes: The table shows the Logit coefficients for the extensive margin and the OLS coefficients for the intensive margin, both at the optimal bandwidths. Standard errors in parentheses (robust standard errors used for OLS estimation). *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. [1]Marginal effects for the treatment variable, [2]no marginal effects (normal regression output after Logit) for the interaction term.

Figure A3.1: Z-statistics of the interaction effects after Logit (Norton et al., 2004) for the extensive margin for Finland and Italy



Note: Only z-values for the predicted probabilities outside the upper and lower (red) lines indicate statistically significant interaction effects.

Table A3.3a: DiD Results for Finland

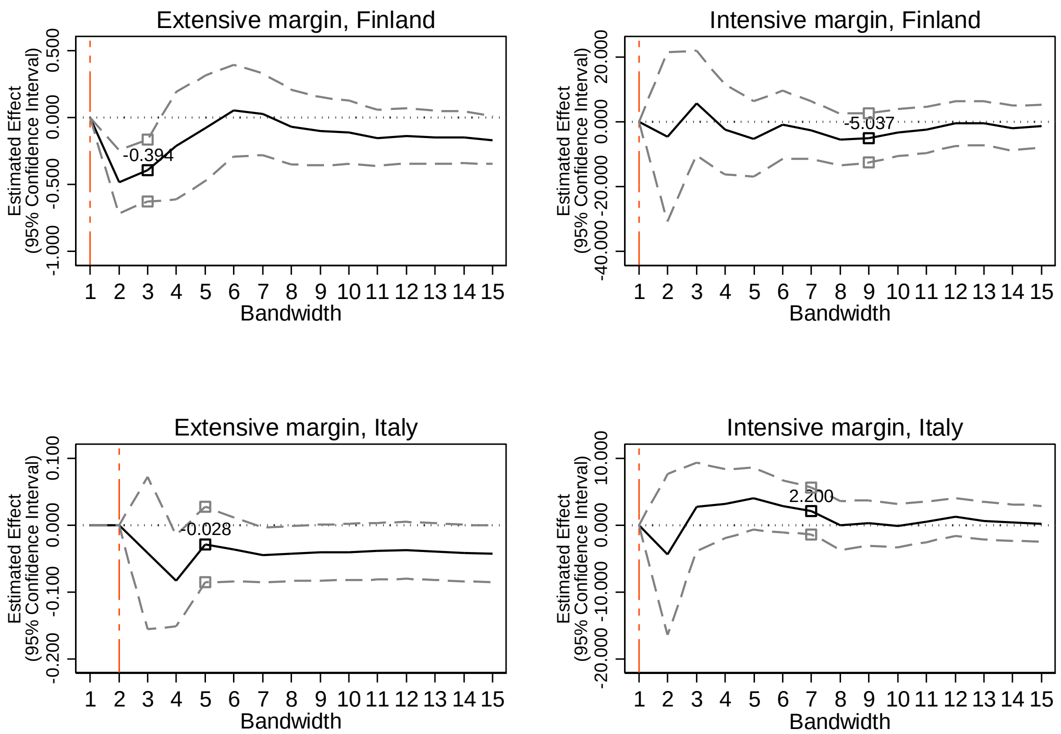
Extensive margin (Train 0/1)															
Bandwidth	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Treatment		0.424***	0.257	-0.04	0.277	0.261	0.152	0.118	-0.05	-0.106	-0.055	-0.052	-0.018	-0.03	-0.054
		[0.108]	[0.334]	[0.36]	[0.224]	[0.203]	[0.245]	[0.234]	[0.231]	[0.207]	[0.215]	[0.214]	[0.214]	[0.209]	[0.198]
Treatment*Volatility		-3.387*	-1.942	-0.645	-1.628	-1.224	-0.971	-0.75	-0.088	-0.096	-0.245	-0.164	-0.254	-0.242	-0.158
		[1.861]	[1.645]	[1.396]	[1.259]	[1.152]	[1.091]	[0.998]	[0.951]	[0.888]	[0.871]	[0.858]	[0.842]	[0.834]	[0.815]
Pseudo R^2		0.0741	0.047	0.0279	0.0213	0.02	0.02	0.0199	0.0183	0.0196	0.0159	0.0139	0.0123	0.0149	0.0177
N		59	92	126	156	186	222	260	289	316	324	332	341	349	354
Intensive margin (Train Hours)															
Bandwidth	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Treatment	1.413	6.187	4.533	0.593	-7.866	-2.123	-5.329	-3.703	-4.71	-4.255	-4.057	-5.39	-3.902	-3.9	-3.621
	[6.461]	[12.615]	[9.346]	[7.87]	[9.472]	[8.545]	[7.951]	[7.067]	[6.649]	[6.377]	[6.322]	[6.344]	[6.217]	[6.153]	[5.876]
Treatment*Volatility	-6.795	-12.727	-25.045	-12.892	25.513	-2.527	7.503	-3.705	-0.163	3.327	5.278	14.526	13.662	14.556	9.382
	[32.217]	[44.252]	[39.763]	[30.732]	[37.452]	[34.281]	[32.481]	[28.762]	[27.705]	[26.242]	[25.851]	[26.133]	[25.461]	[25.111]	[23.847]
R^2	0.48	0.121	0.034	0.022	0.032	0.036	0.035	0.056	0.087	0.066	0.058	0.05	0.026	0.026	0.042
N	19	36	57	78	97	114	130	149	160	169	173	177	182	188	192

Table A3.3b: DiD Results for Italy

Extensive margin (Train 0/1)															
Bandwidth	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Treatment	0	0	-0.092	-0.113**	-0.084**	-0.069**	-0.070**	-0.082***	-0.073**	-0.065**	-0.072**	-0.076**	-0.083***	-0.086***	-0.083***
	[.]	[.]	[0.063]	[0.044]	[0.038]	[0.035]	[0.033]	[0.031]	[0.031]	[0.031]	[0.031]	[0.031]	[0.03]	[0.03]	[0.03]
Treatment*Volatility	0.19	0.119	0.217	0.131	0.111	0.141	0.122	0.124	0.1	0.097	0.117	0.125	0.148	0.158*	0.146
	[0.254]	[0.18]	[0.144]	[0.128]	[0.116]	[0.107]	[0.105]	[0.101]	[0.099]	[0.097]	[0.095]	[0.094]	[0.093]	[0.093]	[0.092]
Pseudo R^2	0.0061	0.0061	0.0093	0.0067	0.0086	0.012	0.0122	0.0138	0.0142	0.0134	0.0146	0.0159	0.0181	0.0193	0.0196
N	1251	2517	3797	5044	6142	7198	7399	7687	7979	8249	8502	8712	8931	9132	9302
Intensive margin (Train Hours)															
Bandwidth	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Treatment	7.481	6.248	2.425	2.222	-0.682	-1.481	-2.201	-3.14	-4.47	-4.282	-4.235	-3.9	-3.479	-3.564	-3.843
	[5.949]	[5.32]	[4.347]	[3.694]	[3.432]	[3.382]	[3.253]	[3.143]	[3.382]	[3.272]	[3.16]	[3.076]	[2.955]	[2.937]	[2.886]
Treatment*Volatility	-15.809	-8.43	-0.076	9.57	17.104*	19.511**	21.360**	21.921**	20.263**	20.153**	18.668**	18.867**	19.168**	17.927**	17.941**
	[16.916][	[13.79]	[11.441]	[10.339]	[9.934]	[9.777]	[9.353]	[8.892]	[9.437]	[9.201]	[9.1]	[8.84]	[8.513]	[8.42]	[8.3]
R^2	0.025	0.023	0.019	0.022	0.023	0.021	0.021	0.019	0.014	0.014	0.013	0.013	0.014	0.013	0.013
N	350	687	974	1294	1542	1748	1811	1912	2008	2079	2168	2247	2335	2412	2475

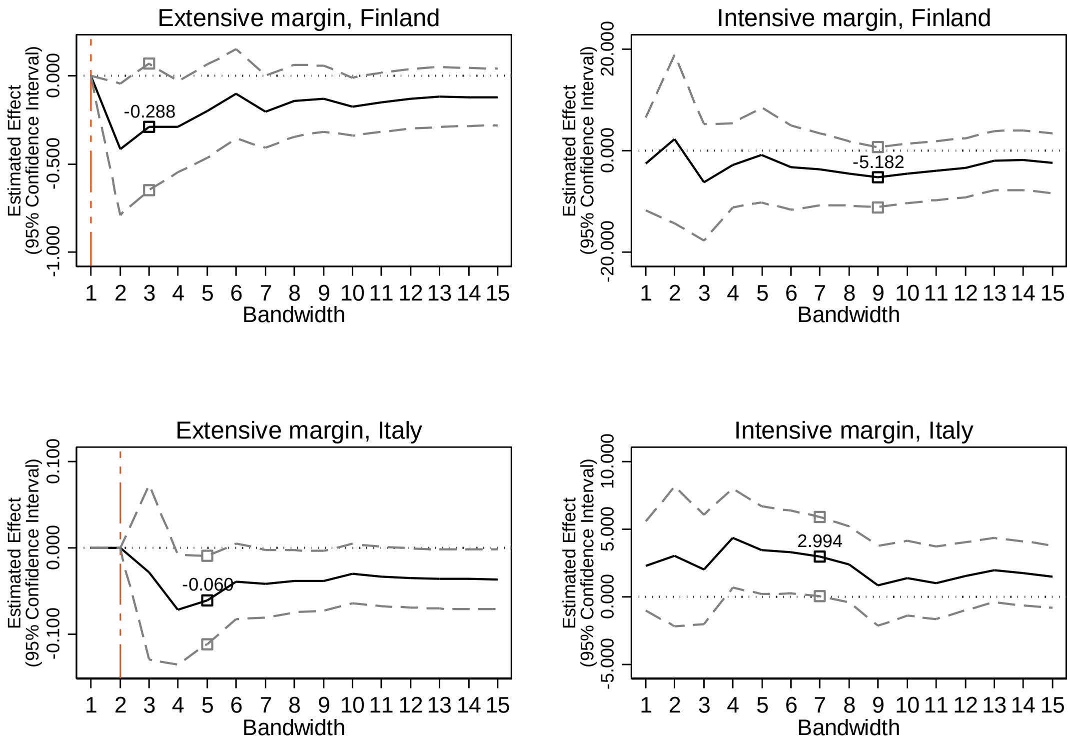
Notes for table A3.3a and A3.3b: The tables show Logit estimates for the extensive margin and OLS coefficients for the intensive margin over different bandwidths. Standard errors in parentheses (robust standard errors used for OLS estimation). *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. (1) indicates insufficient degrees of freedom. . Extensive margin estimates for Finland are based on a linear specification of the assignment variable and for Italy on a quadratic interactions of the assignment variable. Intensive margin estimates for Finland include a linear interaction and those for Italy a linear specification of the assignment variable in the estimation. Grey estimates indicate the optimal bandwidth.

Figure A3.1: RDD-donut regressions



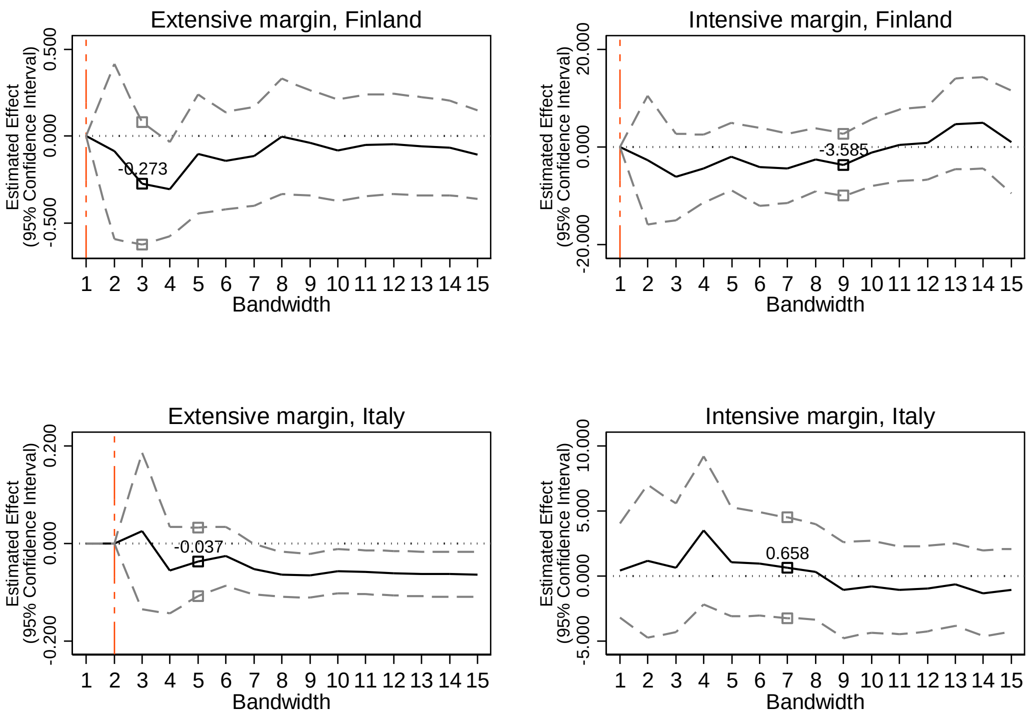
Notes: The figure displays marginal effects and 95% confidence intervals of Logit estimates (Extensive margin) and OLS estimates with robust standard errors (Intensive margin) of the effect of EPL on training for different bandwidths around the threshold. The respective numbers denote the estimate at the optimal bandwidth.

Figure A3.2: RDD regressions with firm characteristics



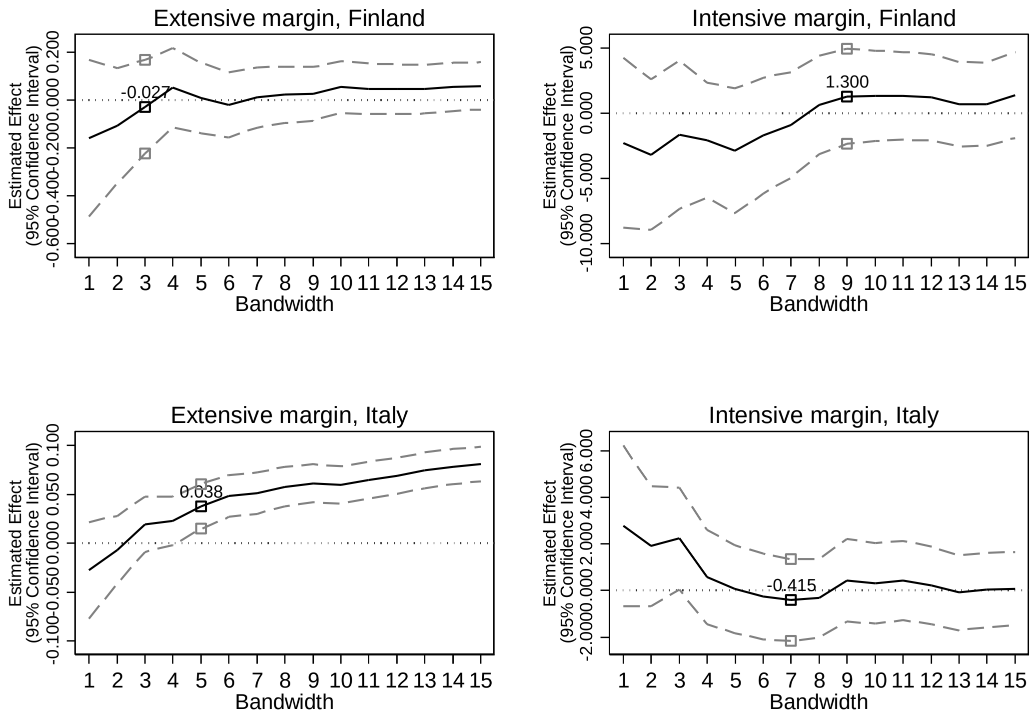
Notes: The figure displays marginal effects and 95% confidence intervals of Logit estimates (Extensive margin) and OLS estimates with robust standard errors (Intensive margin) of the effect of EPL on training for different bandwidths around the threshold. The respective numbers denote the estimate at the optimal bandwidth.

Figure A3.3: RDD regressions with sample weights



Notes: The figure displays marginal effects and 95% confidence intervals of Logit estimates (Extensive margin) and OLS estimates with robust standard errors (Intensive margin) of the effect of EPL on training for different bandwidths around the threshold. The respective numbers denote the estimate at the optimal bandwidth.

Figure A3.4: RDD regressions excluding assignment variable polynomial



Notes: The figure displays marginal effects and 95% confidence intervals of Logit estimates (Extensive margin) and OLS estimates with robust standard errors (Intensive margin) of the effect of EPL on training for different bandwidths around the threshold. The respective numbers denote the estimate at the optimal bandwidth.