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Title: R&D subsidies and productivity in SMEs

Year: 2015

Version:

Please cite the original version:
Karhunen, H., & Huovari, J. (2015). R&D subsidies and productivity in SMEs. Small Business Economics, 45(4), 805-823. https://doi.org/10.1007/s11187-015-9658-9

CHAPTER 5
R&D SUBSIDIES AND PRODUCTIVITY IN SMES

Abstract*

This paper examines the effect of R&D subsidies on labour productivity. We use firm-level data on Finnish SMEs from 2000 to 2012 and apply a combined matching and difference-in-differences method to control for selection bias. We find no significant positive effect on labour productivity over the five-year period after a subsidy is granted. However, the results vary over time and indicate a 2–4 % negative effect on SMEs' annual productivity growth one to two years after the subsidy year. Nevertheless, subsidies generate a positive employment effect and enhance firm survival. Additional scrutiny reveals that subsidies positively affect the human capital level of low-skill firms.

JEL: D24, O25, O38, C21

Keywords: Productivity, subsidies, R&D, SMEs, industrial policy, conditional difference-in-differences.

* This paper is a joint paper with Janne Huovari and it has been accepted for publication in the *Small Business Economics*. We are grateful to Mika Haapanen, Mika Maliranta, Ari Hyytinen, Jaakko Pehkonen, Hannu Tervo, Petri Böckerman and Terhi Maczulskij for their helpful comments and suggestions. Karhunen gratefully acknowledges the financial support from the Alfred Kordelin Foundation, Yrjö Jahnsson Foundations (grant number 6029) and University of Jyväskylä. The usual disclaimer applies.

1 Introduction

Governments can subsidise private research and development (R&D) indirectly with tax incentives (e.g. Cappelen et al., 2012) and directly with subsidies. European policy makers are actively promoting innovation policies designed to enhance R&D in small and medium-sized enterprises (SMEs) (Ortega-Argilés et al., 2009). Granted subsidies are aimed at removing market imperfections and generating positive welfare effects (e.g. Hainz and Hakeness, 2012; Takalo et al., 2013). Nevertheless, the effectiveness of R&D subsidies is often questioned because it is not clear how they should be allocated to private firms (e.g. Cantner and Kösters, 2012; Koski and Pajarinen, 2014).

R&D investments and related technological improvements are a major source of productivity growth (e.g. Griliches, 1998). Returns on R&D have been studied extensively in earlier literature (Mairesse and Sassenou, 1991; Hall et al., 2010; Mohnen and Hall, 2013 for surveys). Firms' R&D activities strive to generate higher rates of innovation (product, process or other), which can enhance firms' economic performance, such as their productivity (e.g. Crépon et al., 1998; Hall, 2011).[1] Because of market imperfections, firms might invest less in R&D than would be optimal for the whole society (Arrow 1962). Thus, public R&D subsidies are needed to increase R&D investments.

Empirical studies have found mixed evidence for the effectiveness of R&D subsidies (e.g. David et al. 2000; Zúñiga-Vicente et al. 2014 for surveys). Their effectiveness is evaluated by studying input and output additionality effects. Subsidies have input additionality effects if they attract additional R&D investments from private sources.[2] Output additionality effects materialise in firms' operations, which enhances their market success (e.g., increased patent activity and sales).[3] A growing number of studies examine subsidies' effects on firm productivity, which is a key factor in firm success. The results of these studies are, however, inconclusive. The productivity effect of R&D subsidies is found to be insignificant in high-tech firms in the U.S. (Irwin and Klenow, 1996). Similarly, no evidence is found that regional subsidies improve firm productivity in Britain (Criscuolo et al., 2012) or in Italy (Bernini and Pellegrini, 2011; Cer-

1 Empirical literature indicates that returns on R&D differ by firm characteristics (e.g., Hall et al., 2008; Hall et al., 2009; Ortega-Argilés et al., 2010; Ortega-Argilés et al., 2011).

2 Many authors have reported that R&D subsidies stimulate private investments (e.g. Almus and Czarnitzki, 2003; Hyytinen and Toivanen, 2005; Czarnitzki, 2006; Görg and Strobl, 2007; Özçelik and Taymaz, 2008; Aerts and Schmidt, 2008; Hussinger, 2008; Meuleman and Maeseneire, 2012; Czarnitzki and Lopes-Bento, 2013), but studies have also found that these funds partly or fully crowd out some private investments (e.g. Wallsten, 2000; Lach, 2002; Busom, 2000; González and Pazó, 2008; Gelabert et al., 2009 Bronzini and Iachini, 2014).

3 Subsidies have been found to enhance employment growth (e.g. Girma et al., 2008; Koski and Pajarinen, 2013; Link and Scott, 2013; Moretti and Wilson, 2014), patent development/innovations (e.g. Czarnitzki et al., 2007; Berube and Mohnen, 2009) and sales/investments (e.g. Criscuolo et al., 2012; Einiö, 2014; Cerqua and Pellegrini, 2014).

qua and Pellegrini, 2014). In Finland, Einiö (2014) finds that R&D subsidies from the European Regional Development Fund (ERDF) have a positive effect on productivity three years after the subsidy is granted. Finally, Koski and Pajarinen (2013, 2014) evaluate all business subsidies in Finland, and the results indicate that different subsidies (including R&D subsidies) have a small negative or insignificant effect on productivity growth.

Prior evidence also shows that R&D subsidy effects vary according to firm characteristics, which is valuable information when designing innovation policies. Lach (2002) finds that subsidies stimulate private funding only in small firms. Similarly, González and Pazó (2008) report that public financing is more efficient in small firms that operate in the low-technology sector. Public funding is also found to be disproportionally more important for firms that rely on external sources of financing (Hyytinen and Toivanen, 2005). Surprisingly, the sources of the heterogeneity of R&D subsidy effects are rarely studied relative to employee education levels and skills. Recent evidence, however, shows that founders' (e.g. Honjo et al., 2014) and employees' (e.g. Andries and Czarnitzki, 2014) human capital enhances firms' innovation. Higher education provides a comparative advantage in utilising new technologies (e.g. Bartel and Lichtenberg, 1987), and knowledge accumulation and R&D enhance firms' absorptive capacities (e.g. Cohen and Levinthal, 1989).[4]

In this paper, we contribute to the existing literature on R&D subsidies by examining their effect on productivity. We exploit longitudinal data on Finnish private-sector SMEs to examine the effects over a five-year period after the subsidy is granted. We not only study overall productivity effects but also investigate how subsidies affect firms' employment, value added and employee education levels. At the start of an R&D project, SMEs might recruit new employees (or re-allocate old employees and other resources within the firm), and this activity could reduce productivity growth in the short term (e.g. Bernini and Pellegrini, 2011). Thus, this negative subsidy effect on productivity is understandable if employment growth is attributable to firms' actions to enhance innovation capacity (e.g., firms recruit new employees with more human capital).

Productivity—defined here as the labour productivity—is an important factor in national welfare. From the viewpoint of policy makers, a direct positive effect of R&D subsidies on firm productivity would be a sign, even if not conclusive, of successful innovation policy. We focus on private-sector SMEs that received an R&D subsidy from the Finnish Funding Agency for Technology and Innovation (Tekes). Tekes annually grants over 600 million euros in R&D subsidies to public and private entities, but prudent evaluations of subsidies and firm productivity are still rare. We address the subsidy selection process (i.e., subsidies are not granted randomly) by using matching and conditional difference-in-differences estimators. We utilise rich longitudinal data from different register-based data sources that include all Finnish firms from

4 Recent empirical literature indicates that absorptive capacity (or "learning capacity") at a regional level is essential for subsidy effectiveness (e.g. Griffith et al., 2003, 2004; Becker et al., 2013).

2000 to 2012. We conduct a number of robustness checks on our results and also study whether the subsidies have an effect on firm survival.

The remainder of the paper is organised as follows. The next section presents the basic institutional features and introduces the data and the empirical method. Section 3 presents the results and the sensitivity analysis. Section 4 discusses the results, and the paper ends with concluding remarks in section 5.

2 Institutions, data and empirical methodology

2.1 R&D subsidies in Finland

Finland's R&D expenditures amounted to 3.78 % of GDP in 2011. Over 70 % of these R&D expenditures were funded by private business entrepreneurs, but the public sector offers R&D funding for firms to foster growth and innovation. Approximately 30 % of the public R&D funds are granted by Tekes, which is one of the agencies of the Ministry of Employment and the Economy. This amount is more than what universities or other research organisations receive directly from the state budget for R&D. In 2010, Tekes distributed 611 million euros to public and private parties. Tekes funds come mostly from the Finnish state budget, but some of the funds (less than 10 % of the total) come from the ERDF and are granted to public research projects. These public research projects include joint projects with several private parties.[5]

Tekes plays an important role in Finland because it facilitates the goals of innovation policy, which aims, amongst other things, to support firm renewal and productivity. The selection of firms for the Tekes subsidy programs is a rigorous and well-structured process. First, companies and research organisations that apply for funding must satisfy Tekes' national funding criteria. Companies that are based in Finland are eligible for funding if they meet these criteria according to Tekes experts. Second, all funding is competitive. Third, firms can apply for all funding directly during Tekes' applications rounds, in addition firms can also apply for ERDF funding in the application rounds in the provinces. Tekes funds part of each project with loans and direct subsidies or a combination of funding sources, but over 70 % of funding is in the form of direct subsidies. Grants for SMEs are usually 35 or 50 % of the total cost of the R&D project. [6]

2.2 Data

The data for this study come from a number of register databases. To combine the data sources, we use the firm-specific identifier codes provided by Statistics

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5 This information is based official statistics by Statistics Finland. E-publication (in English) is available at: http://tilastokeskus.fi/til/tkke/2011/tkke_2011_2012-10-31_tie_001_en.html.

6 More information on Tekes programs, see: http://www.tekes.fi/en.

Finland. We use firm-level data from the Business Register database (age, region, foreign trade, sector and industry code at the two-digit level), the Financial Statement database (number of full-time personnel, value added and turnover), the Patent database (patents applied for in Finland and in Europe and patents granted in the US), the Concern database (a firm belongs to larger group) and the Statistics on Business Subsidies database (all paid loans, paid subordinated loans and subsidies). These register-based databases are maintained by Statistics Finland. Firm-level data is combined with the Employee Characteristics database (firm-specific employee education characteristics) created using the Finnish Longitudinal Employer-Employee Data (FLEED) by Statistics Finland.

Our sample consists of private-sector firms that have 10 to 249 full-time employees and have an annual turnover not exceeding 50 million euros (or less than 43 million euros on the firm's balance sheet). Our sample thus includes firms defined as SMEs by the European Commission, except that we exclude firms with fewer than 10 employees. These firms are excluded from the sample because the FLEED database includes only those firms that have at least 10 full-time employees. Because it is crucial to control for previously paid subsidies (see, e.g. González and Pazó, 2008), our analysis uses two annual observations to control for these. Firms are followed for a five-year period after the subsidy was granted. After these restrictions, our final sample consists of 1,221 firms that were granted an R&D subsidy over the period from 2002 to 2007. The last observation year is 2012.

This study uses labour productivity to measure firm productivity. Labour productivity is the annual value added divided by the number of full-time employees (as defined by Statistics Finland).[7] Productivity is in logarithm form to level outliers and facilitate the interpretation of the results. Because productivity measures can take negative values, and are thus unspecified for logarithm, some firms were excluded from the sample (less than 5 % of all firm-level observations). As a robustness test, we examine subsidies' effects using absolute values rather than logarithms. The results remained intact (see the online appendix for non-logarithm results).[8] Although the granted R&D subsidy is normally between 35 and 50 % of the total cost of the R&D project, the absolute size of the project can vary by industry. In our analysis, we use a binary treatment variable to capture Tekes' decision to grant an R&D subsidy. The treatment variable takes a value of one if the firm was granted a subsidy (in the form of a loan, subordinated loan or subsidy) and zero otherwise.[9]

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7 Alternatively, productivity can be measured by calculating total factor productivity via a production function rather than calculating labour productivity from the raw data. We use labour productivity to avoid a priori assumptions, which are needed to estimate total factor productivity.

8 The causal interpretation of the results may also be sensitive to log-linearisation (see Fisher and Ciani, 2014).

9 In our sample, 899 firms received only a direct subsidy and 64 firms received only a loan-based subsidy (for more details on R&D subsidies, see Table W1 in the online appendix). The results remained qualitatively similar when we focused on firms that received only a direct subsidy (see online appendix Table W9).

The timing of the variables is important in matching models. There is a possibility that firms anticipate of receiving a subsidy, which could affect firm's behaviour. Therefore, the matching variables are measured one year before a subsidy is granted. Possible earlier subsidies are also measured two years before a subsidy is granted. Overall, when building the data set and key variables, we attempt to control for the possible decrease in firm productivity before the subsidy decision is made. If a firm hires people in anticipation of receiving a subsidy, then the so-called Ashenfelter's dip would distort the difference-in-differences (DID) results upwards.[10]

2.3 Econometric evaluation method

R&D subsidies are not randomly distributed (e.g. David et al., 2000; Klette et al., 2000; Meuleman and Maeseneire, 2012). Because we cannot directly compare group means, we need to find comparable subsidised and unsubsidised firms. We start by calculating a subsidy assignment probability-based probit model, which reduces the matching dimension to a single scalar called the propensity score $P(X)$ (Rosenbaum and Rubin, 1983). The estimated propensity is then used in the matching procedure to estimate the average treatment effect on the treated firm (ATT_{PS}). ATT_{PS} can be formulated as the difference in conditional outcomes between subsidised (Y^S) and unsubsidised firms (Y^C):

$$ATT_{PS} = \left(Y^S - Y^C \middle| P(X),\ T = 1\right) = \frac{1}{\mathrm{N_S}} \sum_{\mathrm{i}=1}^{N_S} \left(Y_i^S - \sum_{\mathrm{j}=1}^{N_C} \mathrm{W}(i,j)\, Y_j^C\right) \qquad (1)$$

where Y_i^S denotes the labour productivity for firm i, which receives a subsidy, and Y_j^C denotes the labour productivity for firm j, which does not. Term $\mathrm{W}(i,j)$ is a weight function that determines how an unsubsidised firm j is weighted relative to a subsidised firm i, and N_S and N_C indicate the number of observed firms in each group. A single treatment case (above) can be straightforwardly extended to multiple treatments to investigate if subsidy size affects our estimations (e.g. Imbens, 2000; Lechner, 2002; Görg and Strobl, 2007).

The matching approach has multiple advantages over traditional regressions (Imbens and Wooldridge, 2009). For example, we do not need to make any functional form or distributional assumptions, which would be the case if we estimated the standard Cobb-Douglas production function. Matching using propensity scores can reduce selection bias, but it is still based on observed covariates. We follow earlier literature and control for multiple background vari-

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10 The DID method is based on differencing outcomes before and after a treatment. Thus, if a firm can anticipate that it will receive a subsidy (and changes its behaviour, e.g., hires new employees), then DID estimates can be biased (for details, see Heckman and Smith, 1999). As robustness checks, we also repeated the estimations by matching firms three and four years before a subsidy was granted. Again, our results remained qualitatively unchanged.

ables that could affect both a firm's probability of receiving a subsidy and its productivity. Unfortunately, we do not have the exact numbers of R&D staff for each firm in our register-based data set (available innovation surveys do not include all small firms). To form proxy variables for firms' R&D staff, we use two firm-level measurements for employee education levels: i) the share of workers with higher-degree tertiary education (masters, licentiates and PhDs) in a technology or natural science field (R&D staff 1) and ii) the share of workers with higher-degree tertiary education in other fields (R&D staff 2). These variables (combined with other matching variables) are important for minimising the selection problem concerning firm-specific R&D variables (e.g. Hussinger, 2008). Our other control variables include firm age (age and age squared) and size (number of employees and turnover) because firm innovativeness is known to be related to these factors (e.g. Veugelers and Cassiman, 1999; Huergo and Jaumandreu, 2004).[11]

It also important to control for outcome variables before actual subsidy year (productivity and employment growth) so that compared subsidised and non-subsidised firms are in similar growth trajectories (e.g. Lechner and Wunsch, 2013). The probability of receiving a subsidy and firm-level outcomes are also related to subsidy history (e.g. González and Pazó, 2008). We use three different subsidy history variables: firm received funding from Tekes one year (prev. sub t-1) and two years (prev. sub t-2) earlier and firm received any other subsidies over a two-year period (other subsidies). We also use covariates that indicate if the firm belongs to a larger firm group (group), has foreign ownership (ownership), is involved in foreign trade (foreign trade), has applied for patents (patents) and is multi-establishment (one location). It is also plausible that there are regional and industry-specific differences between the probability of receiving an R&D subsidy and firm performance (e.g. Almus and Czarnitzki, 2003; Aerts and Schmidt, 2008; Hussinger, 2008). Thus, we include 18 regional dummies in our matching equation, and we also control for whether the firm is located in a regional centre municipality (centre). Different industries are taken into account with 14 dummy variables (see online appendix Figure W1 for industry distribution by treatment status). Finally, we also include subsidy year dummies to account for idiosyncratic time shocks during different subsidy years (see Appendix Table 6 for more details on the covariates used).

However, unobserved macroeconomic and firm-specific shocks might also affect firm productivity. Because we have longitudinal firm data, we can further reduce the possible biases by differencing our outcome variables before and after the treatment. In particular, the DID method removes the time-invariant productivity differences between firms. This is an robust evaluation approach, especially when it is prudently combined with a matching method (e.g., Blundell and Costa Dias, 2000; Imbens and Wooldridge, 2009). To further formulate the combined matching and difference-in-differences approach (CDID), we in-

11 Following Aerts and Schmidt (2008), employment and turnover are in logarithms to avoid potential biases caused by skewness of the data.

sert different time periods into Equation 1. Let t and t' indicate the time periods before and after the R&D subsidy is granted, and the CDID estimator is:

$$ATT_{CDID} = \frac{1}{N_S}\sum_{i=1}^{N_S}\left[Y_{it}^S - Y_{it'}^S - \sum_{J=1}^{N_C} W(i,j)\left(Y_{jt}^C - Y_{jt'}^C\right)\right], \tag{2}$$

where the average treatment effect on the treated (ATT_{CDID}) is examined in terms of differences rather than levels. As before, term $W(i,j)$ is the weighting function for constructing the comparison group from untreated firms j for each treated firm i. For causal interpretation, two basic identification assumptions are needed: the conditional independence assumption ($Y_i(S), Y_i(C) \perp T_i|P(X)$) and the common support assumption ($0 < Pr[S = 1|P(X)] < 1$). The conditional independence assumption (CIA) states that conditional treatment status (T_i) should be independent of potential outcomes $Y_i(S)$ and $Y_i(C)$. Note that this assumption is somewhat weaker when using the CDID estimator than when using the pure matching approach without differencing. If the conditional independence assumption does not hold, we can examine the average treatment effect for the treated firms as long as we can assume that the possible bias is constant (Heckman et al., 1997, 1998). In practise, this means that both the control group and the treatment group must have evolved (conditionally) in a similar manner had they not been treated. [12]

Finally, we need to choose how to compute the weights $W(i,j)$ for the propensity scores and estimators (Equations 1 and 2). Although there are many alternative matching methods for estimating the weights, we use the nearest neighbourhood method as a starting point. The two nearest firms in the control group (as measured by propensity scores) are used as comparisons for each subsidised firm. To examine the robustness of the main results, we also use a different number of neighbours in the matching process, trim the tails of the propensity score and use an alternative matching method.

3 Results

3.1 Firm selection and main results

Before focusing on the main results, it is informative to examine the selection into the treatment. Table 1 reports the results from the probit model, which estimates how different firm characteristics are related to the probability of receiving a subsidy. The results indicate that firm-specific education-level variables

12 We plot averages of our outcome variables over the three-year period before the subsidy year (and after) to show descriptively that the outcomes in the subsidised firm group developed in parallel to those in the unsubsidised firm group. Figures are available in the online appendix.

are important in the selection process. Firms that have a high share of workers with tertiary education have a higher likelihood of obtaining an R&D subsidy. Productivity growth before the subsidy year is also higher in subsidised firms than in unsubsidised firms.[13] Past R&D subsidies and other subsidies are also positively related to new R&D subsidies. These findings are consistent with Lerner (2002), who suggests that firms might learn from the application process over time. In addition, we observe that foreign trade is associated with a higher probability of receiving a subsidy, whereas foreign ownership decreases this probability. In the sample of SMEs, the average probability of obtaining a subsidy is 3.6%.

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13 This might indicate that funding authorities are attempting to follow the so-called "picking the winner" strategy (i.e., subsidies might be granted to relatively good firms rather than to marginal projects or firms that suffer market malfunctions, e.g. Cantner and Kösters, 2012).

TABLE 1 Selection to treatment (Probit model)

Dependent variable: Treatment	Coefficients (SE)		Marginal effects (SE)	
Age	-0.046	(0.030)	-0.002	(0.001)
Age^2	0.002	(0.002)	0.000	(0.000)
ln(turnover)	0.098**	(0.031)	0.003***	(0.001)
ln(employees)	0.077**	(0.038)	0.003**	(0.001)
Group	-0.060	(0.037)	-0.002	(0.001)
Ownership	-0.452***	(0.071)	-0.016***	(0.002)
Foreign trade	0.222***	(0.043)	0.008***	(0.002)
Patents	-0.003	(0.080)	0.001	(0.003)
R&D staff 1	1.613***	(0.162)	0.057***	(0.006)
R&D staff 2	0.683***	(0.203)	0.015***	(0.002)
Prev. sub t-1	0.534***	(0.046)	0.019***	(0.002)
Prev. sub t-2	0.416***	(0.047)	0.015***	(0.002)
Other subsidies	0.410***	(0.036)	0.014***	(0.001)
ln(prod. growth)	0.341***	(0.088)	0.012***	(0.003)
ln(emp. growth)	0.055	(0.048)	0.002	(0.002)
Centre region	0.028	(0.038)	0.001	(0.001)
One location	-0.034	(0.035)	-0.001	(0.001)
Food industry	0.573***	(0.105)	0.020***	(0.004)
Textile industry	0.550***	(0.124)	0.019***	(0.004)
Wood industry	0.421***	(0.112)	0.015***	(0.004)
Paper industry	0.378*	(0.203)	0.013*	(0.007)
Chemical industry	0.614***	(0.097)	0.022***	(0.003)
Metal industry	0.641***	(0.089)	0.023***	(0.003)
Machine industry	0.671***	(0.090)	0.024***	(0.003)
Electronic industry	0.749***	(0.099)	0.026***	(0.003)
Other industries	0.434***	(0.097)	0.015***	(0.003)
Utilities	0.405*	(0.214)	0.014*	(0.007)
Construction	0.182*	(0.096)	0.006*	(0.003)
Sales	-0.113	(0.095)	-0.004	(0.003)
Private services for business	0.639***	(0.087)	0.023***	(0.003)
Average propensity score	0.036			
Log-likelihood	- 3,909			
Number of observations	33,811			

Significance: 10 % level (*), 5 % level (**) and 1 % level (***). Standard errors are in parentheses. Note 1: Estimations also included dummies for NUTS3 regions (18) and subsidy year (6). Note 2: Marginal effects are evaluated at the means.

TABLE 2 Descriptive statistics for the selected variables before and after matching

	Before matching				After matching			
	Mean				Mean			
Variable	Treat. group	Cont. group	B	p-value	Treat. group	Cont. group	B	p-value
*Pre-treatment outcome variables (levels) **								
Emp. (t-1)	50.12	33.98	43	0.000	50.16	50.73	-2	0.700
Emp. (t-2)	47.82	33.11	40	0.000	47.86	48.40	-2	0.750
Emp. (t-3)	45.77	32.31	37	0.000	45.82	46.34	-1	0.756
V.ad. (t-1)*	2.69	1.71	43	0.000	2.69	2.75	-2	0.335
V.ad. (t-2)	2.47	1.61	40	0.000	2.46	2.55	-3	0.394
V.ad. (t-3)	2.24	1.52	32	0.000	2.24	2.35	-5	0.335
Prod. (t-1)	53,660	50,238	13	0.000	53,665	54,131	-2	0.657
Prod. (t-2)	51,548	48,573	12	0.000	51,511	52,713	-5	0.265
Prod. (t-3)	48,916	47,010	8	0.014	48,949	50,721	-8	0.097
Pre-treatment outcome variables (growth rate)								
V.ad. (t-1)-(t-3)	0.45	0.19	27	0.000	0.6	0.40	7	0.110
Prod. (t-1)-(t-3)	4,744	3,228	10	0.000	4,716	3,421	7	0.114
Matching variables								
Age	16.15	17.86	14	0.000	16.16	16.36	1	0.674
ln(turnover)	1.56	1.22	35	0.000	1.56	1.60	-4	0.326
ln(employees)	3.63	3.27	51	0.000	3.63	3.64	-1	0.759
Group	0.64	0.74	20	0.000	0.64	0.63	3	0.436
Ownership	0.04	0.08	16	0.000	0.04	0.04	0	0.921
ln(prod.growth)	0.06	0.03	15	0.000	0.06	0.05	4	0.432
ln(emp.growth)	10.75	10.70	12	0.000	10.75	10.76	-3	0.523
Foreign trade	0.70	0.44	55	0.000	0.69	0.70	-2	0.629
Patents	0.06	0.01	28	0.000	0.07	0.07	3	0.685
R&D staff 1	0.08	0.02	57	0.000	0.08	0.07	5	0.382
R&D staff 2	0.03	0.02	13	0.000	0.03	0.03	1	0.905
Prev. sub t-1	0.40	0.05	95	0.000	0.40	0.38	6	0.253
Prev. sub t-2	0.39	0.05	86	0.000	0.38	0.36	5	0.304
Other subs.	0.61	0.21	89	0.000	0.61	0.63	-4	0.381
Centre region	0.51	0.54	-7	0.018	0.51	0.50	2	0.557
One location	0.66	0.70	-8	0.003	0.66	0.67	-2	0.637
Observations	1,221	32,590			1,221	1,874		

* Value added is in millions of euros. Note 1: Period (t) indicates subsidy (treatment) year. Note 2: p-values indicate two-sided t-tests for mean equality. Note 3: Other matching variables include age squared and dummies for NUTS3 regions (18), industry (14) and subsidy years (6). Note 4: See Table 6 in the Appendix for definitions of variables. Table W2 in the online appendix shows that matching successfully balanced all covariates used in the analysis. Note 5: Letter B indicates % of bias before and after matching.

Table 2 reports the descriptive statistics of the key variables before and after the matching procedure, which balances the differences between the treated and untreated groups. Before matching, a comparison of the mean values between the subsidised firms and the unweighted control group indicated significant differences between all variables (see the t-test results). Differences are notable in the outcome variables from the pre-treatment period. Subsidised firms are, on average, larger and more productive than unsubsidised firms. This underlines the fact that we cannot compare subsidised and unsubsidised firms directly and that it is necessary to select control firms with similar characteristics for each subsidised firm. The matching procedure introduced earlier strives to balance the differences between the treated and untreated firms so that firms are similar in observed covariates except for subsidy decision. The results in Table 2 indicate that after matching, the bias between the groups is successfully minimised: the p-values indicate that the means of the two groups' variables are nearly identical.[14]

Table 3 presents the results from both the matching and the conditional difference-in-differences approaches (CDID). Panel A reports the results regarding firm productivity, and Panels B and C show the results regarding employment and value added, respectively. The sample size of firms that received a subsidy (treated) and firms that were used to construct the comparison group (all) and actual control group are reported at the bottom of the table. Estimations are performed with a common support restriction, which excludes treated firms with propensity scores that are too high compared with the highest value in the control group (only a small number of the treated firms are off support). Accordingly, the matching year shows the treatment effect before the actual treatment, which should be statistically insignificant in structure. The treatment year equals the year when a subsidy is granted, and the sequential numbers indicate the years afterward. It should be stressed that each coefficient is estimated separately using the estimation procedure outlined in the previous section.

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14 Table W2 in the online appendix further shows how the matching method succeeds in removing significant differences for all used covariates between subsidised and unsubsidised firms.

TABLE 3 Impact of R&D subsidies on labor productivity, employment and value added

	Matching		CDID	
	ATT	(s.e.)	ATT	(s.e.)
Panel A - Dependent variable: log (productivity)				
Matching year	- 0.003	(0.014)	.	.
Treatment year	- 0.022	(0.014)	- 0.018	(0.011)
T + 1	- 0.039	(0.015)***	- 0.036	(0.013)***
T + 2	- 0.027	(0.015)*	- 0.024	(0.015)
T + 3	- 0.014	(0.014)	- 0.011	(0.014)
T + 4	- 0.022	(0.015)	- 0.019	(0.015)
T + 5	0.002	(0.016)	0.006	(0.016)
Panel B - Dependent variable: log (employment)				
Matching year	0.005	(0.017)	.	.
Treatment year	0.023	(0.017)	0.019	(0.005)***
T + 1	0.030	(0.018)*	0.025	(0.009)***
T + 2	0.033	(0.018)*	0.028	(0.011)**
T + 3	0.031	(0.019)*	0.027	(0.013)**
T + 4	0.030	(0.020)	0.025	(0.014)*
T + 5	0.036	(0.021)*	0.031	(0.016)**
Panel C - Dependent variable: log (value added)				
Matching year	0.002	(0.021)	.	.
Treatment year	0.002	(0.022)	0.001	(0.012)
T + 1	- 0.010	(0.023)	- 0.011	(0.015)
T + 2	0.006	(0.024)	0.005	(0.018)
T + 3	0.017	(0.022)	0.015	(0.019)
T + 4	0.008	(0.024)	0.006	(0.021)
T + 5	0.038	(0.026)	0.036	(0.022)
Treated (off support): 1,215 (6)			Control (all): 1,874 (32,590)	

Significance: 10 % level (*), 5 % level (**) and 1 % level (***). Robust standard errors are in parentheses (Abadie and Imbens 2009). *Note:* The matching year refers to the year before the subsidy decision when the matching is performed, the treatment year is when a subsidy is granted, and the sequential numbers indicate the years after a subsidy is granted.

The results in Panel A of Table 3 suggest that R&D subsidies have a negative effect on productivity after the subsidy is granted. When potential time-invariant effects are controlled for in the CDID estimations, subsidies decrease average labour productivity by 3.6 % one year after the treatment year. Two years after the subsidy year, the negative effect on labour productivity is 2.4 % (significant at the 12 % level). The results indicate that the productivity of treated firms catches up with that of unsubsidised firms five years after a subsidy is granted (the difference is statistically insignificant).[15] It is important to note that even though we do not find any significant positive effects on productivity, the point estimates show clear differences over time.

The decline in productivity after a subsidy decision is reasonable because new R&D projects might begin by recruiting new employees or re-allocating old employees (and other resources) from the daily business to the R&D project. The increase in the number of staff negatively affects productivity growth if there is no sufficient increase in value added at the same time. This finding is in line with earlier studies by Bernini and Pellegrini (2011) and Koski and Pajarinen (2014). In Panels B and C of Table 3, we study in greater detail why no positive productivity effect is observed over the five-year period after a subsidy is granted. We recalculate the matching and CDID models using a logarithm of full-time employees and value added as dependent variables. The results indicate that an R&D subsidy has a significant positive effect on employment of approximately 2–3 %. Alternately, R&D subsidies contribute mainly positively on value added, but the estimates are statistically insignificant (throughout the period). The results thus indicate that R&D subsidies have a relatively steady, positive effect on employment growth but that the effect on value added is essentially zero; however, this effect might be realised with a significant lag.

3.2 Low- and high-skill firms

The R&D subsidy effect could be heterogeneous because firms have different abilities to carry out R&D projects that can further affect productivity and future R&D efforts (e.g. Cohen and Levinthal, 1989). We would expect that subsidies have a more significant positive effect on productivity in firms with employees who have higher levels of human capital. We divide the total sample into low- and high-skill firms by using the median share of employees with higher tertiary education.[16] Thus, in our subsamples, we compare subsidised low- and high-skill firms more prudently with similar unsubsidised firms. The subsidy effect might also depend on the size of the subsidy (e.g. Görg and Strobl, 2007). In Table 4, we redefine three separate treatment groups: all subsidies (as in our previous estimations), small subsidies (subsidies per employee under the median) and large subsidies (subsidies per employee at the median

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15 We also re-run our estimations by excluding the covariates that measure employees' education and earlier subsidies from the matching model. In this case, productivity growth was more rapid, and the effect was significant and positive five years after the treatment. This indicates that without controlling for firm-specific education variables and covariates regarding earlier subsidies in the estimations, the estimation results would be biased upwards (as noted earlier by Gonzalez and Pazo 2008). This finding highlights the need to consider the selection problem in different evaluations of subsidies.

16 By higher tertiary education, we mean employees who have master's, licentiate or PhD degrees. The median share of employees with higher tertiary education (in our sample of subsidised firms) is 4.6 %. The correlation between firm size and the share of higher tertiary education is relatively small (-0.12); see online appendix Figure W2 for illustration. As a robustness test, we also study the subsidy effect on productivity by firm size, but the results are mainly insignificant (online appendix Table W5).

or above). In Panel A of Table 4, we repeat the estimations for all firms, and in Panels B and C, we study the effects separately for low-skill and high-skill firms.

The results indicate that firms that receive large subsidies experience (on average) greater productivity decline after the treatment year than firms that receive small subsidies. When we divide the firm sample into skill groups, subsidised low-skill firms (Panel B) experience 3 % productivity decline one to four years after the treatment year (the effect is also relatively long-term for the larger subsidies). The initial productivity decline is greater in subsidised high-skill firms (but the effect is statistically insignificant when we divide subsidies by size). Separate analyses of value added and employment reveal that the subsidy effect is more significant and larger among high-skill firms (Appendix Table 7). Thus, although we see no positive effect on productivity in either group, subsidies have significant positive effects on employment and value added among high-skill firms in particular.

What could explain the differences over time between subsidised low- and high-skill firms? A recent study by Wanzenböck et al. (2013) indicates that R&D-intensive firms are less likely to change their innovation behaviour because of subsidies. Earlier literature reports that R&D subsidies might increase R&D intensity more significantly among firms that were not R&D-intensive before public funding (e.g. Özçelik and Taymaz 2008) and that employees' skills are vital for firms' innovation activities (e.g. Leiponen 2005; Mohnen and Röller 2005). We therefore examine whether firms' innovation capacity changes after subsidies are granted by studying firms' employee education levels. We have already observed that subsidies have a positive effect on employment but not on productivity. Still, if employment growth (caused by the subsidies) enhances firms' innovation capacity, the insignificant effect on firm productivity would be understandable.[17]

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[17] It should be stressed that the goal of the R&D subsidies is also to enhance firms' innovation capacity, the benefits of which (such as enhanced productivity) are observed in the long term.

TABLE 4 R&D subsidy effect (ATT) on labour productivity by share of employees with higher tertiary education (CDID)

Dependent variable: log (productivity)			
	Relative size of the subsidy		
	All subsidies	Small subsidies	Large subsidies
Panel A: All firms			
Treatment year	- 0.018 (0.011)	- 0.008 (0.012)	- 0.037 (0.021)*
T + 1	-0.036 0.013)***	- 0.011 (0.014)	-0.057 (0.026)**
T + 2	- 0.024 (0.015)	- 0.031 (0.018)*	- 0.041 (0.025)
T + 3	- 0.011 (0.014)	- 0.020 (0.017)	- 0.041 (0.025)*
T + 4	- 0.019 (0.015)	- 0.011 (0.019)	- 0.020 (0.027)
T + 5	0.006 (0.016)	- 0.004 (0.019)	- 0.011 (0.027)
Treated (off):	1,215 (6)	624	596 (1)
Control (all):	1,874 (32,590)	1,124 (32,590)	982 (32,590)
Panel B: Low-skill firms (share of workers with higher tertiary education under the median)			
Treatment year	- 0.022 (0.012)*	- 0.008 (0.013)	- 0.036 (0.022)*
T + 1	- 0.028 (0.015)*	- 0.006 (0.015)	-0.065 0.024)***
T + 2	- 0.027 (0.016)*	- 0.004 (0.018)	- 0.041 (0.025)*
T + 3	- 0.023 (0.017)	- 0.005 (0.019)	- 0.023 (0.025)
T + 4	- 0.025 (0.018)	0.031 (0.022)	- 0.054 (0.029)*
T + 5	0.001 (0.021)	0.031 (0.023)	- 0.043 (0.028)
Treated (off):	632 (1)	388	260
Control (all):	1,049 (24,881)	691 (24,881)	428 (24,881)
Panel C: High-skill firms (share of workers with higher tertiary education above the median)			
Treatment year	- 0.028 (0.020)	0.001 (0.029)	- 0.025 (0.037)
T + 1	-0.059 (0.023)**	- 0.016 (0.032)	- 0.076 (0.041)
T + 2	- 0.046 (0.026)*	- 0.039 (0.036)	- 0.037 (0.043)
T + 3	- 0.017 (0.025)	- 0.021 (0.037)	- 0.021 (0.039)
T + 4	- 0.013 (0.026)	- 0.017 (0.035)	- 0.002 (0.042)
T + 5	- 0.005 (0.025)	0.025 (0.037)	0.014 (0.044)
Treated (off):	580 (8)	234 (2)	333 (4)
Control (all):	785 (7,709)	397 (7,709)	478 (7,709)

Significance: 10 % level (*), 5 % level (**) and 1 % level (***). Robust standard errors are in parentheses (Abadie and Imbens 2009). Small subsidies: Granted R&D subsidy per employee is under 1,650 euros (50 percentile). Large subsidies: Granted R&D subsidy per employee is over 1,649 euros.

We repeat our CDID estimations using three different firm-level measurements for employees' education, which are utilised to measure the firms' human capital intensity.[18] The estimations in the first column of Table 5 utilise the percentage of employees with higher tertiary education in natural science and technology as a dependent variable. The second column examines the subsidy effect on the share of employees with higher tertiary education in other fields. The dependent variable in the third column is the percentage of employees with less than higher tertiary education. Because the different measurements for education are percentages (which sum up to one), significant positive effects in the first two columns would indicate that firms became more human capital intensive.

The reported results in Panel A of Table 5 show that subsidised firms become more human capital intensive because of the subsidies. The percentage of employees with higher tertiary education (in natural science and technology) increases annually 0.3–0.4 %-points after the subsidies. The results in column 3 also indicate that the share of employees without a higher tertiary degree decreases after the subsidy year. There are clear differences between subsidised low- and high-skill firm groups. In low-skill firms (Panel B), subsidies increase the share of employees with a degree in natural science and technology in the subsidy year (0.2 %- points) and the subsequent two-year period. Contrary to the results for all firms (Panel A), the positive effect on the share of employees from other fields is also significant. As the average share of higher tertiary education is only 0.45–0.55 % in subsidised low-skill firms in the year before the subsidy year, the average share of higher tertiary education more than doubles over the four-year period (relative to the base year). The results in Table 5 also indicate that high-skill firms become more human capital intensive, although the effect is smaller and more short-term. In subsidised high-skill firms, the average share of tertiary education is 7–16 %, which underlines how small the point estimates are.[19]

The finding that R&D subsidies affect human capital levels in low-skill firms in particular is consistent with the earlier literature on R&D subsidies. It is understandable that firms that begin R&D work because of the subsidies (i.e. "switch" R&D development on) increase their R&D efforts relatively more than firms that are already R&D intensive (e.g. Almus and Czarnitzki, 2003; Czarnitzki, 2006; Özçelik and Taymaz, 2008). High-skill firms already have relatively high human capital levels, and subsidies enhance growth in employment and value added (as shown in Appendix Table 7), but these firms do not necessarily become more human capital intensive.

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18 We focus on the three-year period after the treatment year because employee education data were not available for later years.

19 In online appendix Table W6, we show that our results by firm skill groups are robust even if we use different cut-off points for low-and high-skill firms.

TABLE 5 R&D subsidy effect (ATT) on employee education levels (CDID)

Dependent variable: The percentage share of workers at different levels/fields of education			
	Higher tertiary education		Less than higher tertiary education
	Natural science and technology	Other fields	
Panel A: All firms			
Treatment year	0.269 (0.118)**	0.025 (0.081)	- 0.041 (0.139)
T + 1	0.389 (0.153)**	0.139 (0.103)	- 0.298 (0.184)
T + 2	0.384 (0.170)**	0.080 (0.120)	- 0.481(0.209)**
T + 3	0.309 (0.191)	- 0.515 (0.130)	- 0.514 (0.231)**
Average share (%)	8.03	3.49	88.48
Treated (off support):	1,216 (5)	Control (all): 1,872 (32,590)	
Panel B: Low-skill firms (share of workers with higher tertiary education under the median)			
Treatment year	0.180 (0.053)***	0.030 (0.037)	0.099 (0.062)
T + 1	0.150 (0.070)**	0.201(0.060)***	- 0.143 (0.086)**
T + 2	0.187 (0.074)**	0.260 (0.074)***	- 0.287 (0.110)***
T + 3	0.138 (0.089)	0.219 (0.079)***	- 0.376 (0.121)***
Average share (%)	0.55	0.45	99.00
Treated (off support):	632 (1)	Control (all): 1,049 (24,881)	
Panel C: High-skill firms (share of workers with higher tertiary education above the median)			
Treatment year	0.564 (0.227)**	- 0.004 (0.126)	- 0.191 (0.300)
T + 1	0.432 (0.295)	0.085 (0.214)	- 0.663 (0.364)*
T + 2	0.471 (0.336)	- 0.246 (0.248)	- 0.691 (0.415)*
T + 3	0.407 (0.381)	- 0.300 (0.259)	- 0.425 (0.464)
Average share (%)	15.94	6.78	77.28
Treated (off support):	580 (8)	Control (all): 785 (7,709)	

Significance: 10 % level (*), 5 % level (**) and 1 % level (***). Robust standard errors are in parentheses (Abadie and Imbens 2009). Note 1: Higher tertiary education comprises employees with master's, licentiate or PhD degrees. Note 2: Average share (%) indicates the percentage of workers with specific education in the subsidised firm group before the subsidy year.

3.3 Sensitivity analysis

Our identification strategy is based on the assumption that a large number of firm background variables can minimise the selection bias problem (Assumption 1, unconfoundedness). Moreover, the CDID approach removes unobserved time-invariant effects and is a more robust approach to addressing the selection problem (e.g. Imbens and Wooldridge, 2009). Unconfoundedness cannot be tested directly, but the sensitivity of results can be reviewed indirectly by estimating "placebo effects" before the actual treatment. Negative subsidy effect on firm productivity before the subsidy is granted would indicate that our results are driven by some factor other than the R&D subsidy. The CDID results in Table 8 of the Appendix show that this is not the case.[20] Although we find that there is a positive effect on productivity two years before the subsidy year, no effect is found three or four years before (or one year before). Positive effects two years before might indicate that subsidised firms have higher prior productivity growth than otherwise similar control firms (indicating the so-called "picking the winner" strategy). Because the results in Table 9 are estimated using a different study period (subsidy years 2004 to 2007) than that used for our main results, the estimations also show that the results are not sensitive to the chosen time period. We also estimate placebo effects for our education variables used in Table 5. We find no significant placebo effects in the two years before the subsidy year (online appendix Table W7).

The assumption regarding common support (Assumption 2) is easier to assess and evaluate because the density distribution of the propensity score in both the treated and the untreated groups is available. In our estimations, we impose a common support by dropping the treatment observations with propensity scores higher than the maximum or lower than the minimum for the control firms. This restriction eliminates only a small number of firms from our sample (indicated as "off support" in the tables). We additionally trim our sample estimations at the 2 % and 5 % levels, but the results remain qualitatively the same. The results are also robust when we use different matching methods and when we divide the total sample into separate firm groups by sector. In online appendix (Panel D of Table W3) we match firms exactly by sector, because propensity score matching might compare firms from different sectors. Results show that this has no impact on our results. Table W10 of online appendix shows that initial decline in productivity is, on average, more significant in industrial sector than in service sector. We also repeat the main estimations using different definitions for the treatment variable (only direct subsidies), but this does not affect our conclusions (these results are also available in the online appendix).

This study uses a balanced panel over the study period. Productivity is important for firm survival, but we exclude by structure those firms that did

[20] We focus on subsidy years 2004–2007 to study possible placebo effects due to data constraints. Placebo effect is calculated by moving one year "window" (a difference between reference year and comparison year) to pre-treatment period.

not survive the entire period. Next, we attempt to evaluate if this might affect our results. First, we repeat our estimations using shorter panels over one year and three years after the subsidy year. The obtained productivity results are similar to those from our earlier estimations using a five-year panel (online appendix Table W8).[21] Second, we also study if the R&D subsidies affect firm survival propensity over the five-year period after the subsidy is granted. Earlier literature suggested that public subsidies affect firm survival (e.g. Ebersberger, 2011). Our dependent variable takes the value of one if the firm remains in the market and zero otherwise.[22] We repeat the survival estimations (using the same control covariates as before). Interestingly, the results in Appendix Table 9 show that R&D subsidies have a significant positive effect on firm survival. Although no effect is found one year after the subsidy year, the subsidy effect on survival rates is positive (2–4%) and significant three to five years later (the effect is notably similar for firm groups).

A positive subsidy effect on firm survival might indicate two things. First, if subsidies are allocated to relatively inefficient firms, they might enhance the firms' probability of surviving in the marketplace without positively affecting firm productivity. This could distort the market mechanism (i.e., natural firm exits) in that the survival of inefficient firms might also affect unsubsidised firms (e.g. Santarelli and Vivarelli 2002; Koski and Pajarinen 2014).[23] Second, if subsidies successfully correct market inefficiencies, and thus lead to improvements in firms' innovation activities, then the positive effect on firm survival might indicate that subsidies could have an effect on firms' long-term productivity. Unfortunately, this study is unable to investigate the long-term effects of R&D subsidies.

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21 In our study period, 32 % of subsidised firms exited our sample during the five-year period.

22 From our data, we cannot distinguish between mergers, acquisitions and firms that went out of business. Still, most business exits indicate that the business was unsuccessful (Coad 2013). Firm survival is studied similarly in earlier literature (e.g. Hyytinen et al. 2014).

23 We studied descriptively how starting/initial (year) productivity is related to firm survival. Simple cross tabulations show that subsidized firms whose initial productivity are below median productivity are more likely to survive than subsidized firms whose initial productivity is above the median (see online appendix Table W11). This might indicate that subsidies are more important for low productivity firms. But it should be stressed that we cannot observe whether R&D subsidies also affect unsubsidised firms. Our empirical approach does not allow spillovers (the so-called stable unit treatment value assumption; see Imbens and Wooldridge 2009). If subsidies also affect unsubsidised firms, then the subsidy effect on productivity might be under- or overestimated. When more accurate databases become available for research, it would be interesting to evaluate if different research results that focus on subsidy effects are affected by this possibility.

4 Discussion

4.1 Summary of the results

This study has examined whether the public R&D subsidies granted by Tekes enhance productivity in private-sector SMEs. Annual Tekes funding for private firms is approximately 600 million euros, making Tekes one of the most significant public source of R&D funding in Finland. The results indicate that one to two years after a subsidy is granted, firm productivity declines by 2–4% compared to similar unsubsidised firms. We find that R&D subsidies positively affect firm employment growth. When we study the education levels of firm employees, we find that low-skill firms in particular become more human capital intensive because of the subsidies. The results also suggest that R&D subsidies have a positive effect on firm survival.

4.2 Limitations of the study

There are at least three important limitations to consider. First, the results indicate that firms do not receive subsidies randomly. Our approach (combined matching and difference-in-differences method) might not be able to remove all of the bias resulting from positive or negative selection. Still, our results are robust to many specifications used in the analyses. Second, we focus on the five-year period after the subsidy is granted. However, benefits from R&D projects could materialise after considerable time lags. For example, if subsidies enhance firms' overall innovative capabilities, the positive subsidy effect on productivity might be observed in the longer term. Third, R&D subsidies might have spillover effects (short- and long-term), which would violate the assumptions of our econometric approach. Spillovers could also be part of the assessment of social benefits gained from R&D subsidies. Unfortunately, evaluating spillover effects is out of reach of this study.

4.3 Policy and research implications

Our findings indicate that on average, public R&D subsidies have negative or insignificant short-term effect on firm productivity and that subsidies enhance firm survival. Positively, we find that subsidies foster employment growth and firms become more human capital intensive as the result of subsidies. These are also the goals of Finnish innovation policy. Nevertheless, further empirical scrutiny is needed for the efficient use of scare public resources. If subsidies do not positively affect firm productivity growth in the longer term, subsidies might artificially help inefficient firms to stay in the market and thus hinder aggregate productivity growth. For more prudent evaluations, government agencies should be more transparent regarding their subsidy decision-making processes. It would be beneficial to have more detailed information on the applications of both subsidised firms and firms that apply for but do not receive subsidies.

In future research, it would be valuable to identify in more detail the different channels through which R&D subsidies affect firm productivity. Although earlier research has shown the relationship between R&D and productivity, evidence of the effects of R&D subsidies on productivity is still inconclusive. Empirical research at the firm level also needs to recognise that subsidies can affect unsubsidised firms. For example, this study reports (as have a number of other earlier studies) that R&D subsidies have a significant positive employment effect. It would be instructive to examine the sources of the observed increases in employment. Such an analysis might bring new information not only on the factors that determine subsidies' effects on firm productivity but also on whether public subsidies affect unsubsidised firms.

5 Concluding remarks

We find no evidence of an economically significant positive effect of R&D subsidies on firm productivity over the five-year period after a subsidy is granted, which should arise in the case of grave capital market imperfections. Over the five-year period after a subsidy is granted, public funding contributes significantly to firm growth in terms of number of employees and human capital intensity but does not result in productivity growth.

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Appendix (Tables 6–9)

TABLE 6 Variable definitions

Variables	Definition
Dependent variable	
Productivity	ln(value added / number of full-time employees)
Treatment variable	
R&D subsidy	If the firm was awarded an R&D subsidy = 1, otherwise = 0
Firm-specific variables	
Age	Age/10 of the firm in years
Age^2	(Age/10) squared
ln(turnover)	ln(Turnover, million euros)
ln(employees)	ln(Number of employees)
ln(prod. growth)	ln(productivity (t-1) /productivity (t-2))
ln(emp. growth)	ln(employment (t-1) /employment(t-2))
Foreign trade	If the firm exports or imports or both = 1, otherwise = 0.
Group	If the firm is part of a larger group = 1, otherwise = 0
Ownership	If the firm has foreign ownership (majority) = 1, otherwise = 0
R&D development	
Patents	If the firm has applied for a patent = 1, otherwise = 0.
R&D staff 1	The share of workers with tertiary education (master's, licentiate or doctoral degree) in technology or natural science.
R&D staff 2	The share of workers with tertiary education (master's, licentiate or doctoral degree) in other than technology or natural science.
Prev. sub. t-1	Received R&D subsidy payments one year before the treatment
Prev. sub. t-2	Received R&D subsidy payments two years before the treatment
Other subsidies	Received a subsidy before (in a two-year period) from another source (e.g., Finnvera) = 1, otherwise = 0
Industry classification	
Food industry	Food and drink industry (15–16)
Textile industry	Textile industry (17–19)
Wood industry	Wood industry (20)
Paper industry	Pulp and paper industry (21)
Chemical industry	Pharmaceutical and chemical industry (23–26)
Metal industry	Metal industry (27–28)
Machine industry	Machine industry (29, 34, 35)
Electronic industry	Electronics industry (30,31,32,33)
Other industries	Other industry (22, 36)
Utilities	Utilities (37, 40, 41, 90)
Construction	Construction (45)
Sales	Sales (50,51,52)
Private services for business	Business services (67,72, 73, 74)
Other private services	Other services (55, 60, 61, 62, 63, 64, 65, 66, 70, 71)
Regional variables	
Region	A dummy for each NUTS 3 region (18 regions)
One location	Located only in one region = 1, otherwise = 0.
Centre region	Regional (NUTS 3) centre municipality = 1, otherwise = 0

Note: Estimations also include year dummies for the treatment years (2002–2007).

TABLE 7 R&D subsidy effect (ATT) on employment and value added by employee skill level (CDID)

Dependent variable:	log (employment)	log (value added)
Panel A: Low-skill firms (share of workers with higher tertiary education under the median)		
Treatment year	0.017 (0.007)**	- 0.005 (0.014)
T + 1	0.027 (0.011)**	- 0.001 (0.018)
T + 2	0.035 (0.013)***	0.008 (0.021)
T + 3	0.047 (0.015)***	0.024 (0.022)
T + 4	0.050 (0.017)***	0.025 (0.024)
T + 5	0.047 (0.020)**	0.049 (0.028)
Treated (off support): 632 (1) Control (all): 1,049 (24,881)		
Panel B: High-skill firms (share of workers with higher tertiary education above the median)		
Treatment year	0.029 (0.009)***	0.001 (0.022)
T + 1	0.045 (0.014)***	- 0.014 (0.027)
T + 2	0.046 (0.017)**	0.001 (0.032)
T + 3	0.061 (0.021)***	0.044 (0.033)
T + 4	0.065 (0.023)***	0.053 (0.035)
T + 5	0.080 (0.025)***	0.075 (0.036)**
Treated (off support): 580 (8) Control (all): 785 (7,709)		

Significance: 10 % level (*), 5 % level (**) and 1 % level (***). Robust standard errors are in parentheses (Abadie and Imbens 2009).

TABLE 8 R&D subsidy effect on labour productivity before and after the subsidy (CDID). Constrained sample includes only subsidised firms in the period 2004–2007.

Dependent variable:	Productivity		log (Productivity)	
	ATT	(s.e.)	ATT	(s.e.)
T-4	298	(727)	0.022	(0.021)
T-3	745	(783)	0.004	(0.015)
T-2	1,755	(815)**	0.029	(0.017)*
T-1	515	(595)	- 0.007	(0.008)
Treatment year	- 1,206	(725)*	- 0.017	(0.012)
T + 1	- 2,979	(854)***	- 0.033	(0.015)**
T + 2	- 2,032	(1,003)**	- 0.015	(0.019)
T + 3	- 1,092	(1,023)	0.005	(0.017)
T + 4	469	(1,099)	0.020	(0.020)
T + 5	438	(1,181)	0.008	(0.019)
Treated (off support):	643 (3)		628 (2)	
Control (all):	1,018 (16,751)		1,008 (16,699)	

Significance: 10 % level (*), 5 % level (**) and 1 % level (***). Robust standard errors are in parentheses (Abadie and Imbens 2009).

TABLE 9 R&D subsidy and survival propensity over the five-year period after the subsidy year

Dependent variable: 1 = Firm survives until year T + x, 0 = otherwise.			
	All firms	Low-skill firms	High-skill firms
T + 1	0.004	0.003	0.001
	(0.003)	(0.003)	(0.003)
T + 2	0.026***	0.028***	0.022***
	(0.005)	(0.006)	(0.008)
T + 3	0.033***	0.035***	0.038***
	(0.007)	(0.009)	(0.012)
T + 4	0.042***	0.042***	0.049***
	(0.009)	(0.011)	(0.014)
T + 5	0.042***	0.054***	0.046***
	(0.011)	(0.013)	(0.016)
Treated (off support):	1,800 (8)	878	927(2)
Control (all):	2,896 (52,492)	1,543 (39,561)	1,339 (12,931)

Significance: 10 % level (*), 5 % level (**) and 1 % level (***). Robust standard errors are in parentheses (Abadie and Imbens 2009).

Supplementary Online Appendix

TABLE W1 R&D subsidies and subsidised firms in the used sample

Year	Subsidised firms	Only direct subsidies	Only loans	Only subordinated loans	Average subsidy per employee, €
2002	166	101	14	2	4,385
2003	221	158	9	1	3,826
2004	213	161	10	3	4,009
2005	201	143	6	0	4,911
2006	213	172	5	0	4,505
2007	207	164	14	0	5,671
Total	1221	899	58	6	4,551

TABLE W2 Balancing condition before and after the matching

	Unmatched		NN (2)	
Panel A: All firms				
	t-test	Bias>10	t-test	Bias>10
Number of imbalanced covariates	36	28	0	0
Percent of imbalanced covariates	66 %	52 %	0 %	0 %
Mean bias	10.8		2.2	
Panel B: Low-skill firms				
	Unmatched		NN (2)	
	t-test	Bias>10	t-test	Bias>10
Number of imbalanced covariates	37	28	0	0
Percent of imbalanced covariates	67 %	52 %	0 %	0 %
Medium bias	13.2		2.6	
Panel C: High-skill firms				
	Unmatched		NN (2)	
	t-test	Bias>10	t-test	Bias>10
Number of imbalanced covariates	32	28	1	1
Percent of imbalanced covariates	59 %	52 %	2 %	2 %
Medium bias	11.0		3.1	

Bias>10: Rosenbaum & Rubin (1985) standardised bias criteria indicating covariates with standardised bias over 10. NN (2): Nearest neighbourhood matching using two nearest neighbours by propensity score. Note 1: two-tailed t-test indicates the covariate mean differences at the 5 per cent level. Note 2: the one covariate that is not balanced in the high-skill firm group is a dummy variable for the machine industry. Excluding this one group has no impact on the main results.

TABLE W3 R&D subsidy effect on firm productivity – Trimming the propensity score (2 % and 5 %) and experiments with alternative matching strategies

Dependent variable:	Productivity		Log(Productivity)	
	ATT	s.e	ATT	s.e
Panel A: Nearest neighbour (2), trimmed 2 %				
Treatment year	- 1,057	(707)	- 0.008	(0.012)
T + 1	- 1,903	(895)**	- 0.029	(0.014)**
T + 2	- 1,004	(1,038)	- 0.010	(0.017)
T + 3	- 888	(1,047)	- 0.004	(0.016)
T + 4	265	(1,161)	0.007	(0.017)
T + 5	410	(1,183)	0.031	(0.018)*
Treated (off support):	1,250 (26)		1,197 (24)	
Control (all):	33,077		32,590	
Panel B: Nearest neighbour (2), trimmed 5 %				
Treatment year	- 1,515	(730)**	- 0.012	(0.012)
T + 1	- 2,755	(822)***	- 0.024	(0.013)*
T + 2	- 1,740	(906)*	- 0.016	(0.016)
T + 3	- 1,431	(949)	- 0.002	(0.015)
T + 4	- 182	(1,004)	0.003	(0.016)
T + 5	108	(1,091)	0.018	(0.018)
Treated (off support):	1215 (63)		1,160 (61)	
Control (all):	1,910 (33,077)		1,863 (32,590)	
Panel C: Nearest neighbour (4)				
Treatment year	- 1,441	(640)**	- 0.010	(0.010)
T + 1	- 2,326	(725)***	- 0.026	(0.012)**
T + 2	- 1,347	(817)*	- 0.019	(0.014)
T + 3	- 836	(846)	- 0.002	(0.013)
T + 4	143	(874)	0.007	(0.014)
T + 5	- 7	(948)	0.027	(0.015)
Treated (off support):	1,273 (3)		1,216 (5)	
Control (all):	3,417 (33,077)		3,312 (32,590)	
Panel D: Mahalanobis one-to-one nearest neighbourhood matching (exact industry)				
Treatment year	- 958	(703)	- 0.019	(0.013)
T + 1	- 2,306	(840)***	- 0.029	(0.014)**
T + 2	- 1,743	(939)*	- 0.017	(0.016)
T + 3	- 1,556	(949)	- 0.006	(0.016)
T + 4	- 352	(1,013)	0.001	(0.016)
T + 5	- 1,055	(1,066)	0.007	(0.019)
Treated (off support):	1,273 (3)		1,221	
Control (all):	1,023 (33,077)		1,023 (32,590)	

Significance: 10 per cent level (*), 5 per cent level (**) and 1 per cent level (***). Robust standard errors are in parentheses; see Abadie and Imbens (2009). Note: The treatment year is the year when a subsidy is granted, and the sequential numbers indicate the years after the subsidy is granted.

TABLE W4 R&D subsidy effect (CDID) on firm productivity, employment, and value added without log transformation.

	ATT	s.e
Dependent variable: Productivity		
Treatment year	- 1,282	(624) **
T + 1	- 2,017	(677)** *
T + 2	- 1,560	(781) **
T + 3	- 1,332	(830)
T + 4	- 1,583	(890) *
T + 5	- 657	(917)
Dependent variable: Employment		
Treatment year	0.949	(0.322)** *
T + 1	1.095	(0.556)**
T + 2	1.204	(0.694)*
T + 3	1.191	(0.806)
T + 4	1.252	(0.917)
T + 5	1.444	(1.010)
Dependent variable: Value added		
Treatment year	- 21,127	(29,867)
T + 1	- 33,721	(29,867)
T + 2	- 14,325	(52,485)
T + 3	- 7,963	(60,621)
T + 4	- 65	(69,063)
T + 5	17,550	(75,595)
Treated (off): 1,273 (2)	Control (all): 1,912 (33,077)	

TABLE W5 R&D subsidy effect on labour productivity by firm size (CDID)

Dependent variable: log (productivity)			
	Relative size of the subsidy		
	All subsidies	Small subsidies	Large subsidies
Panel A: Small SMEs (firm size under the median)			
Treatment year	- 0.006 (0.020)	0.014 (0.019)	- 0.012 (0.025)
T + 1	- 0.031 (0.023)	0.005 (0.024)	- 0.043 (0.033)
T + 2	- 0.032 (0.026)	0.018 (0.041)	0.008(0.039)
T + 3	- 0.024 (0.025)	0.016 (0.025)	0.006 (0.034)
T + 4	- 0.031 (0.028)	0.016 (0.030)	0.011 (0.037)
T + 5	- 0.024 (0.026)	0.042 (0.034)	- 0.002 (0.039)
Treated (off support):	583 (3)	245	340 (1)
Control (all):	929 (22,515)	442 (22,515)	527 (22,515)
Panel B: Large SMEs (median sized firm or above)			
Treatment year	- 0.011 (0.014)	- 0.010 (0.014)	- 0.032 (0.023)
T + 1	- 0.019 (0.016)	- 0.008 (0.015)	- 0.050 (0.028)*
T + 2	- 0.003 (0.018)	- 0.007(0.018)	0.003 (0.033)
T + 3	0.005 (0.019)	0.007 (0.020)	0.020 (0.032)
T + 4	0.024 (0.020)	0.005 (0.022)	0.040 (0.032)
T + 5	0.032 (0.021)	- 0.003 (0.021)	0.057 (0.046)
Treated (off support):	633 (1)	379	252 (3)
Control (all):	946 (10,045)	652 (10,045)	408 (10,045)

Significance: 10 % level (*), 5 % level (**) and 1 % level (***). Robust standard errors are in parentheses (Abadie and Imbens, 2009). Note: the median size of the subsidised firms in our sample is 33.1 employees in the year before the subsidy is granted.

TABLE W6 R&D subsidy effect (ATT) on the share of workers by skill level with different cut-off points (re-estimation of Table 5)

Dependent variable: Percentage of workers at different levels/fields of education			
	Higher tertiary education		Less than higher tertiary education
	Natural science and technology	Other fields	
Panel A: Low-skill firms (share of workers with tertiary education under the 40th percentile)			
Treatment year	0.100 (0.056)	0.002 (0.042)	-0.001 (0.049)
T + 1	0.186 (0.071)***	0.163 (0.068)**	-0.104 (0.090)
T + 2	0.114 (0.077)	0.255 (0.082)***	-0.361 (0.115)***
T + 3	0.111 (0.084)	0.257 (0.085)***	-0.318 (0.131)**
Average share (%)	0.44	0.41	99.2
Treated (off): 485 (1) Control (all): 836 (22,381)			
Panel B: High-skill firms (share of workers with tertiary education above the 60th percentile)			
Treatment year	0.510 (0.266)*	-0.170 (0.225)	0.043 (0.321)
T + 1	0.664 (0.375)*	-0.376 (0.275)	-0.227 (0.441)
T + 2	0.355 (0.425)	-0.307 (0.289)	-0.367 (0.518)
T + 3	0.182 (0.478)	-0.601 (0.335)	-0.174 (0.543)
Average share (%)	19.6	8.2	72.2
Treated (off): 471 (6) Control (all): 623 (5,731)			

Significance: 10 % level (*), 5 % level (**) and 1 % level (***). Robust standard errors are in parentheses (Abadie and Imbens, 2009). Note 1: Higher tertiary education comprises workers with master's, licentiate or doctoral degrees.

TABLE W7 Placebo effects – R&D subsidy effect (ATT) on share of workers by education level. Sample is constrained (subsidy years 2004–2007) to show possible placebo effects before actual treatment year

Dependent variable: Percentage of workers at different levels/fields of education			
	Higher tertiary education		Less than higher tertiary education
	Natural science and technology	Other fields	
Panel A: All firms			
T - 2	-0.180 (0.143)	0.145 (0.191)	-0.170 (0.163)
T - 1	0.120 (0.140)	-0.016 (0.037)	-0.130 (0.156)
Treatment year	0.439 (0.132)***	-0.059 (0.097)	-0.205 (0.160)
T + 1	0.501 (0.184)***	0.020 (0.137)	-0.334 (0.203)*
T + 2	0.469 (0.214)**	0.002 (0.149)	-0.295 (0.226)
T + 3	0.586 (0.238)**	-0.058 (0.167)	-0.124 (0.267)
Average share (%)	8.16	3.81	88.03
Treated (off support): 761 (3)	Control (all): 1,188 (19,871)		
Panel B: Low-skill firms (share of workers with tertiary education under the median)			
T - 2	-0.078 (0.078)	-0.001 (0.043)	0.050 (0.081)
T - 1	-0.033 (0.048)	-0.039 (0.042)	0.005 (0.075)
Treatment year	0.188 (0.061)***	0.081 (0.050)	0.028 (0.070)
T + 1	0.288 (0.088)***	0.346(0.075)***	-0.162 (0.106)**
T + 2	0.272 (0.097)***	0.429(0.096)***	-0.403 (0.136)***
T + 3	0.212 (0.109)*	0.413(0.095)***	-0.584 (0.150)***
Average share (%)	0.51	0.50	98.99
Treated (off support): 386 (1)	Control (all): 642 (15,009)		
Panel C: High-skill firms (share of workers with tertiary education above the median)			
T - 2	-0.089 (0.281)	0.334 (0.198)*	-0.396 (0.319)
T - 1	-0.015 (0.284)	-0.092 (0.109)	-0.286 (0.299)
Treatment year	0.506 (0.287)*	-0.067(0.232)	-0.049 (0.310)
T + 1	0.474 (0.336)	-0.226 (0.245)	-0.370 (0.417)
T + 2	0.251 (0.388)	-0.497 (0.282)*	-0.425 (0.465)
T + 3	0.339 (0.450)	-0.678 (0.322)**	-0.158 (0.514)
Average share (%)	15.76	7.16	77.08
Treated (off support): 370 (7)	Control (all): 520 (4,834)		

Significance: 10 % level (*), 5 % level (**) and 1 % level (***). Robust standard errors are in parentheses (Abadie and Imbens, 2009). Note 1: Higher tertiary education comprises workers with master's, licentiate or doctoral degrees. Note 2: Periods (t-1) and (t-2) show the possible placebo effects before matching; data on education were not available for early periods.

TABLE W8 Impact of R&D subsidies on labour productivity over one year and three years (CDID).

Dependent variable: log (Productivity)				
	Sample 1		Sample 2	
	ATT	(s.e.)	ATT	(s.e.)
Treatment year	- 0.021	(0.012)*	- 0.020	(0.012)
T + 1	- 0.039	(0.015)***	- 0.036	(0.015)***
T + 2			- 0.019	(0.016)
T + 3			- 0.007	(0.017)
Treated (off support):	1,798 (1)		1,638 (2)	
Control group (all):	2,828 (50,611)		2,370 (44,213)	

Significance: 10 % level (*), 5 % level (**) and 1 % level (***). Robust standard errors are in parentheses (Abadie and Imbens, 2009).

TABLE W9 R&D subsidy effect on labour productivity (only direct subsidies).

Dependent variable: log (productivity)		
	Relative size of the subsidy	
	All subsidies	Large subsidies
Treatment year	0.006 (0.013)	- 0.024 (0.022)
T + 1	- 0.022 (0.013)*	- 0.050 (0.027)*
T + 2	- 0.023 (0.017)	- 0.059 (0.026)**
T + 3	- 0.022 (0.015)	- 0.045 (0.026)*
T + 4	- 0.020 (0.016)	- 0.067 (0.029)**
T + 5	- 0.001 (0.018)	- 0.035 (0.032)
Treated (off support):	898 (1)	304 (1)
Control (all):	1,500 (32,590)	534 (32,590)

Significance: 10 % level (*), 5 % level (**) and 1 % level (***).
Robust standard errors are in parentheses (Abadie and Imbens, 2009).

TABLE W10 Heterogeneity by sector - Industrial and service sector

Dependent variable: log (productivity)		
	Industrial sector	Service sector
Treatment year	- 0.012 (0.015)	- 0.028 (0.024)
T + 1	- 0.036 (0.018)**	- 0.011 (0.030)
T + 2	- 0.034 (0.020)*	- 0.018 (0.030)
T + 3	- 0.025 (0.020)	0.036 (0.029)
T + 4	- 0.027 (0.022)	0.034 (0.029)
T + 5	- 0.010 (0.023)	0.043 (0.035)
Treated (off support):	790 (3)	380 (2)
Control (all):	1,194 (10,101)	512 (17,370)

Significance: 10 % level (*), 5 % level (**) and 1 % level (***). Robust standard errors are in parentheses (Abadie and Imbens, 2009). Industrial sector: food, textile, wood, paper, chemical, metal, and machinery, electronic and other industries. Service sector: sales, business services and other services. Note: Utility and construction sectors are excluded from both groups.

TABLE W11 Descriptive survival rate cross tabulations by initial (subsidy year) productivity level and treatment status

	Survival rate (T relative to period T+5)	
	Subsidized firms	Unsubsidized similar firms (by matching)
Under median (or median) productivity at period T	88.3 %	83.8 %
Above median productivity at period T	86.5 %	83.7 %

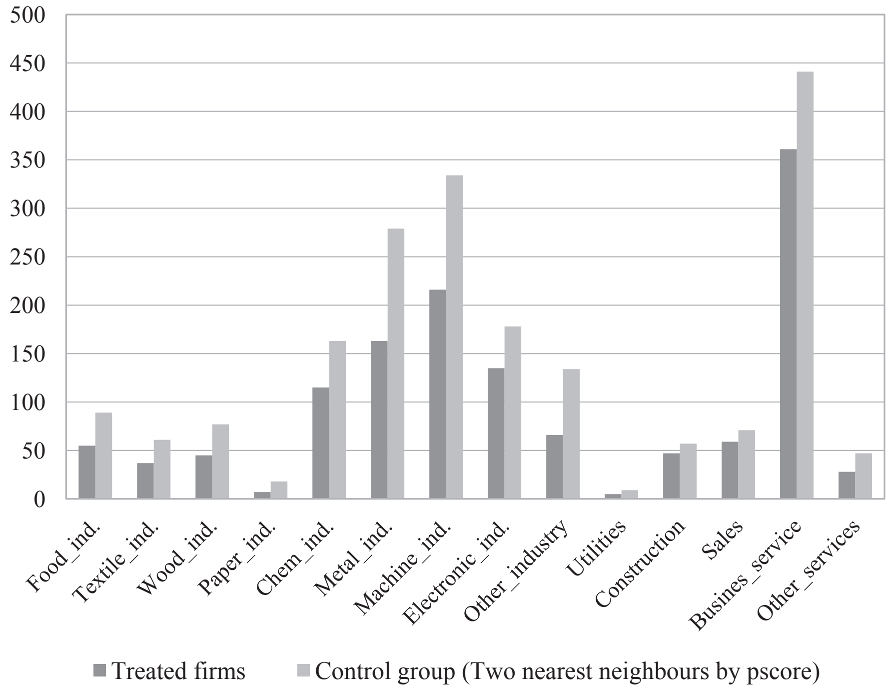

FIGURE W1 Industry distribution in the sample by treatment status.

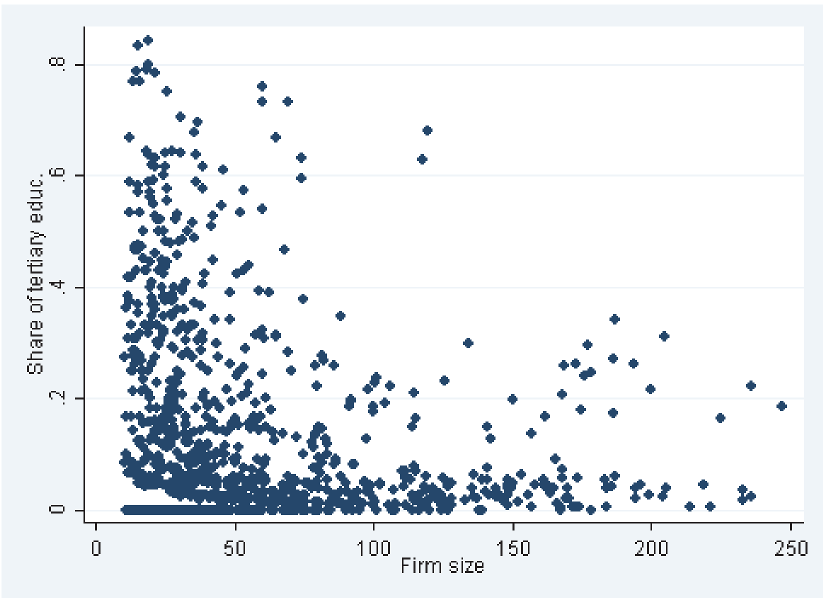

FIGURE W2 Firm size and share of employees with tertiary education.

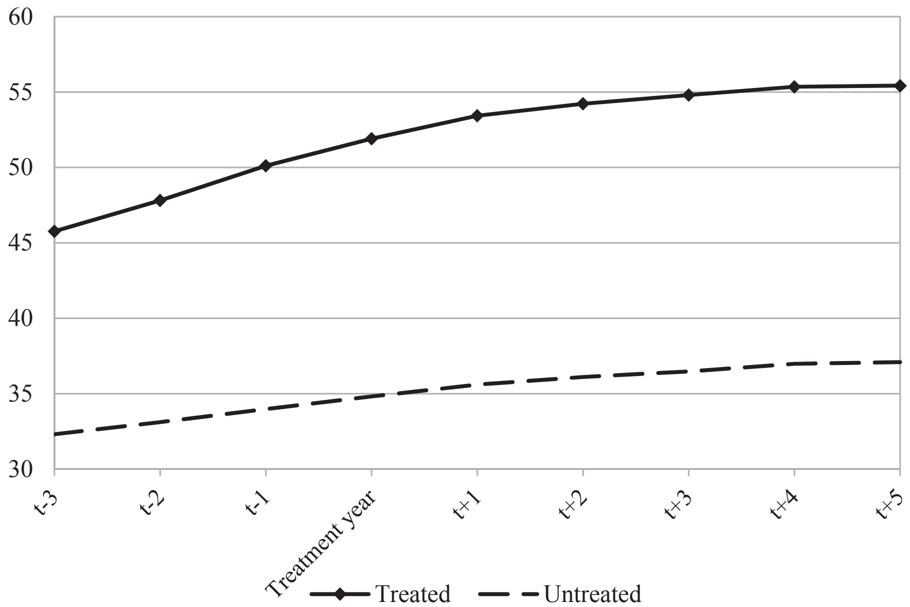

FIGURE W3.1 Average employment before matching.

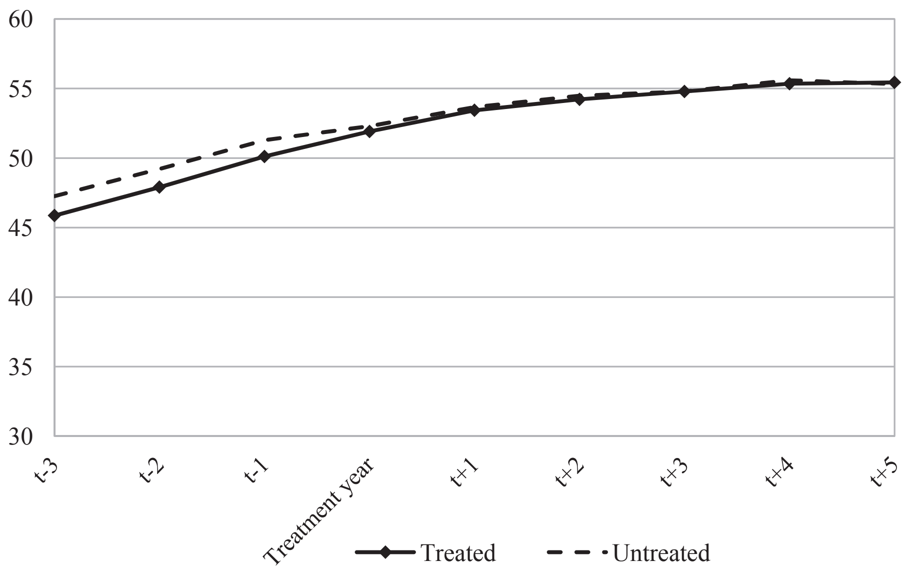

FIGURE W3.2 Average employment after matching.

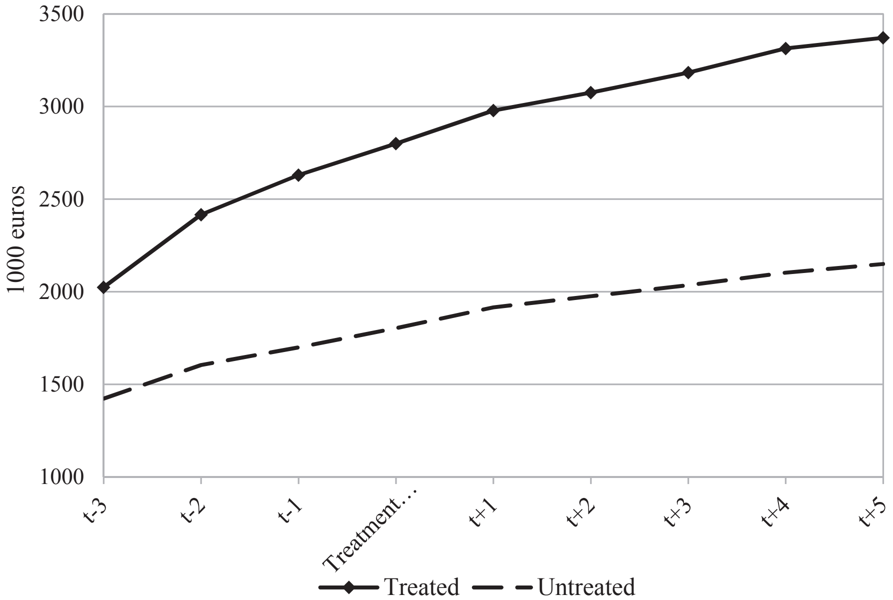

FIGURE W4.1 Average value added before matching.

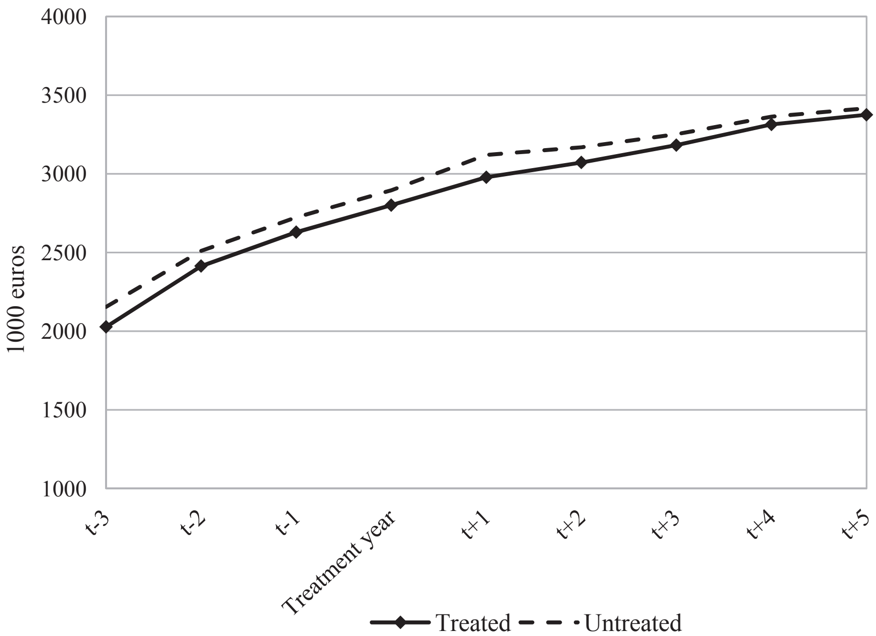

FIGURE W4.2 Average value added after matching.

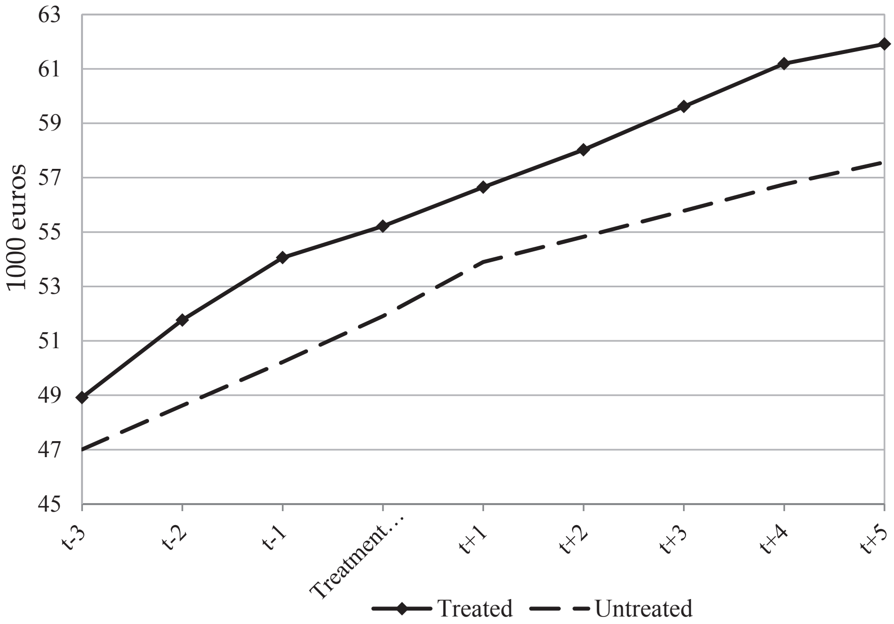

FIGURE W5.1 Average productivity before matching.

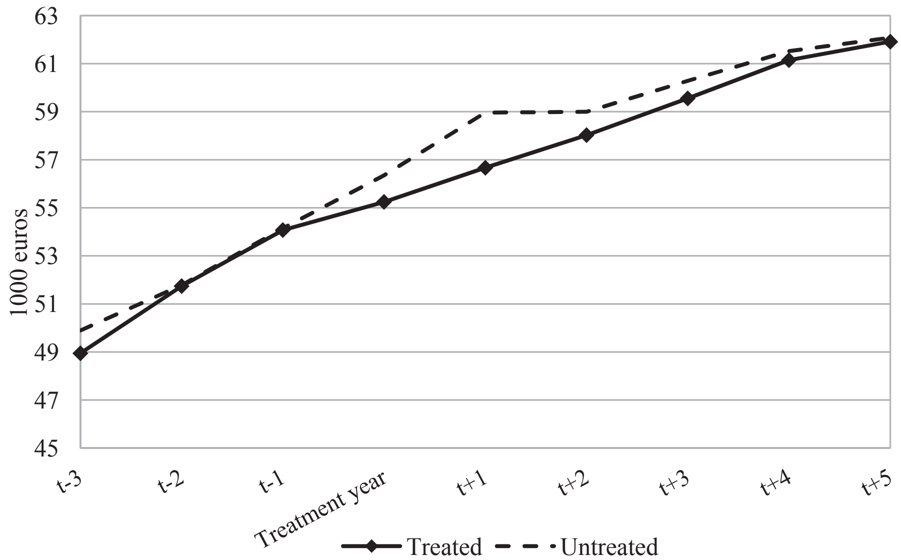

FIGURE W5.2 Average productivity after matching

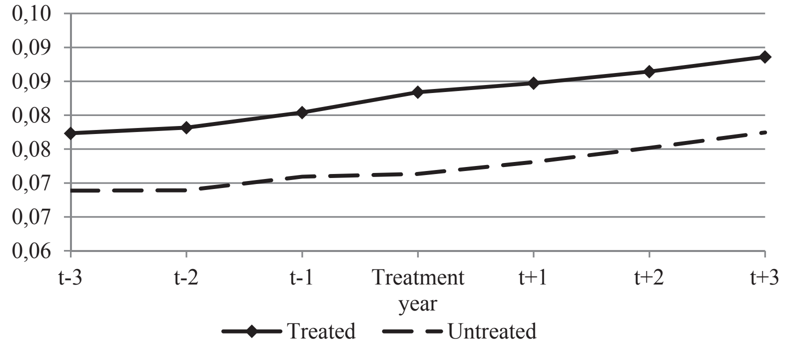

FIGURE W6.1 Percentage of workers with higher tertiary education (science and technology) after matching.

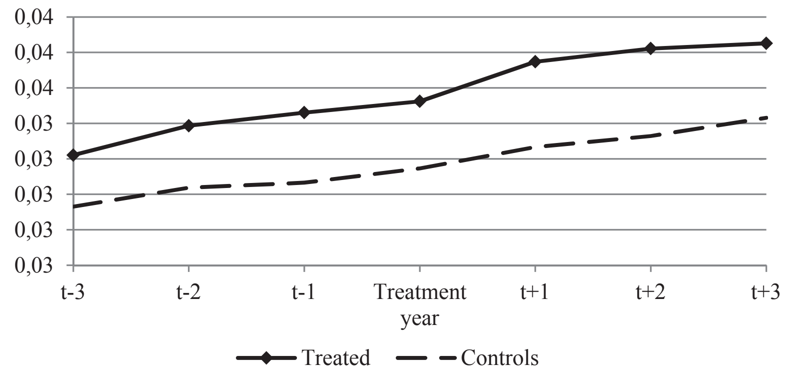

FIGURE W6.2 Percentage of workers with higher tertiary education (other than science and technology) after matching.

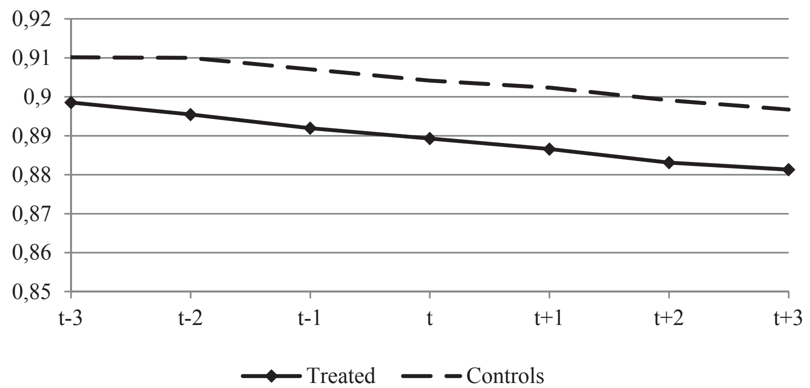

FIGURE W6.3 Percentage of workers with less than higher tertiary education after matching.