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Time to Cash In: the Economic Returns of Patents

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Abstract

This study examines the impact of the Italian public program *Brevetti+* on the performance of small and medium-sized innovative enterprises, using a staggered Synthetic Difference-in-Differences methodology. The program offers financial aid to support the development of already existing patents. Initially, firms receiving financial assistance perform below comparable innovative companies but experience a significant improvement in their long-run performance in terms of return on assets, value added, and sales/assets ratio of respectively 0.65%, 24.59%, and 13.68%. The additional funds facilitate the commercial exploitation of patents, leading to increased expenses for services, materials, and labor. This study highlights the challenges faced by SMEs in acquiring complementary assets for successful technology implementation and emphasizes the importance of financial aid programs in enhancing SMEs' performance and innovation outcomes. The effectiveness of such initiatives may vary across contexts, warranting further research.

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Contents

1 Introduction

Innovation is as a crucial catalyst for the growth of businesses. Through it, companies can introduce novel technologies or processes into their production, leading to reduced operating costs or improved product quality. However, taking advantage of innovative activities necessitates the availability of complementary assets, which are crucial resources required for implementing new technology in a firm's production. Examples of these assets include financial capabilities, technological knowledge, and a highly skilled workforce, among others. Some firms may face challenges in acquiring these complementary assets, impeding their ability to innovate and reducing their incentives to exploit new technology. Small and medium enterprises (SMEs), in particular, are vulnerable to resource constraints and are more likely to lack these assets.

This study aims to provide insights into the role of complementary assets in fostering innovation while also highlighting the barriers that hinder the growth of innovative SMEs. To examine this, we take patents as a proxy for innovation and analyze an Italian public program called *Brevetti+*. Awarded firms received financial assistance to acquire specialized services that would further develop existing patents and enable their integration into production or realization of their full economic potential. The grants were specifically intended for purchasing the complementary assets whose lack was preventing SMEs from cashing in on their innovative ideas. To conduct our analysis, we utilize our knowledge of the evaluation criteria used to select the awarded firms and construct synthetic controls for each of them. We then employ multiple Difference-in-Differences (SDiD) with staggered treatment and aggregate the estimated coefficients using a measure of the synthetic controls' goodness of fit. This methodology allows us to address concerns related to both selection into patenting by comparing treated firms with other companies that hold patents, as well as selection into the treatment by matching on the evaluation criteria. Furthermore, it enables us to establish almost perfectly parallel pre-trends in the dependent variables by assigning higher weights to firms with better-fitting synthetic controls and to mitigate potential issues related to heterogeneity bias by aggregating firm- and time-specific treatment effects. Results can be informative for policy-making purposes by providing evidence on the barriers which hamper growth for innovative SMEs and estimating the causal effect of providing financial aid to improve already existing patents, rather than developing new ones, on performances.

Our findings indicate that, on average, treated firms experience growth of 0.65% on return on assets, 24.59% on value added, and 13.68% on revenues from sales over total assets in the years following the awarding of the grant. These results confirm that the treated firms were not fully capitalizing on the economic potential of their patents before receiving financial aid but were able to do so after acquiring additional complementary assets in the form of specialized services. Moreover, we examine the specific assets whose absence hindered the full technological exploitation of the treated firms by estimating the causal effect of receiving financial aid on various cost items. Our analysis reveals an average growth in the total cost of services, materials, and labor of 15.97%, 17.62%, and 13.03%, respectively. However, only the cost of services exhibits an immediate increase in the years following the treatment, suggesting that there was no parallel increase in other expenses accompanying the acquisition of specialized services. This finding indicates that having specific expertise within the labor force is a crucial complementary asset for innovation in Italian SMEs. These firms need to rely on external professional services to test or enhance specific aspects of their patents. In fact, innovation requires the availability of professionals with specialized skills (such as engineers or lawyers) who can be temporarily hired from third parties.

This study speaks to the strand of literature on the economic returns to innovation. It has already been shown how patenting can lead to economic growth, resource reallocation, and creative destruction for countries (Kogan et al., 2017), and, at a more granular level, to an increase in firm size, scope, and skill and capital intensity (Balasubramanian and Sivadasan, 2011). Such economic returns are heterogeneous among firms and tend to be positively correlated with company size (Argente et al., 2020). Santoleri et al. (2022) provide quasi-experimental evidence on the effect of R&D grants on a wide range of firm-level outcomes, finding a positive effect on patents, investment, and firm growth and survival, due to the alleviation of financial constraints that typically hamper innovation.

Moreover, we contribute to the economic literature on firms' absorptive capacity, focusing specifically on innovation. Cohen and Levinthal (1989; 1990) define absorptive capacity as a firm's ability to assimilate the value of new information and apply it for commercial purposes. It is influenced by a firm's prior knowledge, which accumulates through research and development (R&D) efforts and investments in complementary assets. Cohen and Levinthal (1989) discuss the dual role of R&D, which generates new information while also enhancing a firm's ability to assimilate new knowledge by building upon existing knowledge stocks. They develop a theoretical model and test it using survey data on technological opportunities and R&D expenditures. In a similar vein, Cohen and Levinthal (1990) focus on the impact of absorptive capacity on R&D-related innovative activities, including basic research and the adoption of innovations, and arrive at similar conclusions.

The economic literature extensively examined the determinants of technology adoption, particularly for SMEs. It has been demonstrated that innovation relies on the availability of a wide range of complementary assets necessary for firms to adopt new technologies and reap their economic benefits. Factors such as decentralized decision-making, a highly skilled workforce (Zahra and Nielsen, 2002; Giotopoulos et al., 2017), networking opportunities, low adoption costs, and effective marketing strategies (Hewitt-Dundas, 2006) have been found to increase the likelihood of technology adoption. Jansen et al. (2005) investigate the impact of organizational antecedents on potential (knowledge acquisition and assimilation) and realized (knowledge transformation and exploitation) absorptive capacity, finding a positive effect of coordination capabilities on the former and socialization capabilities on the latter. Additionally, innovation networks play a crucial role by facilitating the combination of inter-firm complementary resources or relation-specific assets, alleviating resource availability constraints and enabling firms to achieve gains through cooperative efforts (Dyer and Singh, 1998; Acemoglu et al., 2016a). Nevertheless, one of the most common constraints to innovation, particularly for SMEs, is the difficulty in obtaining external capital to finance innovative activities, making them highly reliant on internal cash flows (Canepa and Stoneman, 2008; Mohnen et al., 2008; Ughetto, 2008). Limited financial development can, in fact, significantly impede domestic firms' innovation capabilities, preventing them from catching up to the technological frontier (Gorodnichenko and Schnitzer, 2013). Pellegrino and Savona (2017), on the other hand, shift the focus from financial barriers to the lack of potential economic returns, emphasizing the critical role of demand-side factors in translating innovation into new products or processes.

The rest of the paper is organized as follows: in Section 2, we introduce the analyzed policy and the economic mechanism driving our results. In Section 3, we present the datasets used for the empirical analysis. In Sections 4 and 5, we describe the employed empirical strategy and the results. In Section 6, we conclude and discuss the implications of our results.

2 Theoretical framework

2.1 Policy background

Brevetti+ is an Italian public program initiated in 2011 by the Italian Ministry for Business and Made in Italy (MiSE) and administered by Invitalia, a national agency responsible for supporting economic growth in Italy. The program aims to enhance the competitive power of SMEs by promoting patenting strategies. Invitalia has been actively involved in managing various public grants to facilitate the establishment of new companies and foster the growth of innovative firms. Their initiatives have included funding 'development contracts' for major investments in industrial, agro-industrial, touristic, and environmental sectors, as well as supporting innovative startups and SMEs. These efforts have been facilitated through the utilization of national and European funds and providing services to the public administration.

For this study, our focus is on the first two calls of the *Brevetti+* program, implemented in 2011 and 2015. Both calls aimed to stimulate SMEs' patenting strategies and enhance their competitive position. The first call (Ufficio Italiano Brevetti e Marchi, 2011) consisted of two interventions: 'premi' (prizes) and 'incentivi' (incentives). The 'premi' involved monetary disbursements to Italian SMEs that filed new patents or extended existing ones with the European Patent Office (EPO) or the World Intellectual Property Organization (WIPO). The amount of the prize varied based on the specific action taken, and firms could accumulate up to five prizes, with a maximum total of €30,000. The specific amounts and requirements can be found in Table A.1 of the Appendix. On the other hand, the 'incentivi' offered grants to all SMEs in Italy that owned patents, filed patent applications (with positive research reports for national patents or requests for examination for European and international ones), or held options or preliminary agreements to acquire patents (including those from foreign owners). These firms could apply for a grant to fund specialized services that aimed to improve and develop existing patents, integrating them into the firms' production cycles or enhancing their economic value. The eligible expenses fell into three categories: industrialization and development, organization and development, and technological transfer. The complete list of allowed expenses can be found in Table A.2 of the Appendix. Notably, firms were prohibited from seeking grants to cover expenses incurred before the application or for services provided by individuals connected to the firm (e.g., managers, shareholders, workers, relatives, or other companies associated with the firm's managers or shareholders). Each firm could receive a maximum grant of €70,000, covering up to 80% of the expenses within the limits set by the *de minimis* regime[1]. The grants could not be accumulated with others covering the same expenses. The program did not apply to firms excluded by the *de minimis* regime[2] or those undergoing administrative

[1]A fiscal policy regime set forth in European Regulation No 1998/2006, whereby small amounts of State aid to firms do not have to be notified to the European Commission by the member state. The maximum amount of exempted aids is €200,000 over a 3 years period, with the exception of the road freight transport for hire or reward sector, which has a limit of €100,000.

[2]Firms operating in primary production of agricultural products, fishing, or aquaculture. Moreover, the regulation does not apply to the processing and marketing of agricultural products (conditional on the amount being fixed on the basis of the price or quantity of products purchased or put on

procedures for the inappropriate receipt of public funds.

The second call (Ufficio Italiano Brevetti e Marchi, 2015), issued in 2015, presented some minor differences. It eliminated the prizes and increased the maximum incentives to €140,000, covering up to 80% (or 100% for university/academic spin-offs) of the expenses within the *de minimis* limits. In addition to the previous requisites, eligible firms were required to own patents, file patent applications, or have options or preliminary agreements to acquire patents filed after the beginning of 2013. Newly established university/academic spin-offs were also eligible, provided that at least 10% of equity participation was owned by the university/research center and they had ownership, application, or preliminary acquisition agreements for patents filed after the beginning of 2012.

To participate in either of the two calls, firms had to submit an online project plan outlining how they intended to improve one or more of their patents and how the projected expenses would contribute to this goal. Project plans were reviewed on a first-come, first-served basis until funds were exhausted. The evaluation criteria included the credibility and potential impact of the project on the firm's profitability or leverage, as well as the coherence between the proposed expenses and suppliers. Additionally, an in-person meeting was required to gather more precise information about the project. Grants could be revoked if a firm declined the grant, provided false information, or failed to comply with obligations. The grants were disbursed in two installments: between 30% and 50% after the contract signing (if the firm presented a bank guarantee or insurance policy in favor of Invitalia) or during the project's progress (not exceeding the fraction of the project already completed). The remaining grant was paid after all services were provided, subject to on-site control. Firms had a maximum of 18 months to complete the entire process once the grant was awarded.

While subsequent calls and additional funds were made available by MiSE in the following years, this study focuses solely on the first two calls due to the lack of current data. In total, the first two calls granted €4 million in prizes and €31.7 million in incentives[3].

2.2 Economic mechanism

The goal of this study is to estimate the causal effect of the incentives from the *Brevetti+* program on the performance of treated firms. We examine three perfor-

the market, or being linked to an obligation to share the aid with primary producers) and to export or aid contingent upon the use of domestic over imported products (European Commission, 2013).

[3] https://www.invitalia.it/cosa-facciamo/rafforziamo-le-imprese/brevetti-vecchia-edizione/risultati

mance measures: value added, return on assets (ROA), and the sales-to-assets ratio (sales/assets). We expect value added and ROA to decrease in the first years following the treatment due to the additional expenses incurred by firms upon joining the program. The grants were only partially allocated to firms during the treatment year, with the remaining payment postponed until the project's completion. Consequently, treated firms face initial expenses that reduce their value added (revenues from sales minus expenses for materials and services) and ROA (net income reduction). However, we do not expect the same effect on the sales/assets ratio since the numerator (revenues from sales) is not influenced by costs. In the long run, instead, we expect an overall increase in all performance measures. As the projects conclude, firms acquire the complementary assets needed for technology adoption and are able to fully exploit their innovation, potentially raising product prices through improved quality or reducing production costs through the implementation of unique and efficient technologies. A similar pattern has been observed by Dranove et al. (2014) in the US health industry, where the adoption of electronic medical records initially increased expenses but resulted in long-term cost reductions. The initial rise in expenses can be attributed to the costly adjustments required for successful technology implementation.

Furthermore, we aim to analyze the potential channels through which this public program may have assisted innovative SMEs in overcoming their lack of complementary assets. In the short run, we expect to observe an increase in the cost of labor, cost of materials, or cost of services. SMEs, especially, may face difficulties in obtaining loans for expenses unrelated to tangible assets due to the inability to provide collateral. By receiving financial aid through these grants, firms can acquire the necessary complementary assets, enabling them to overcome this obstacle and capitalize on the financial returns from their innovation. In the long run, we still expect these costs to increase. The adoption of new and improved technologies prompts firms to undergo a process of technological change, shifting toward more skill-intensive operations that require skilled workers. Consequently, the cost of labor is expected to rise. The same principle applies to the cost of materials and services, which increase in quality and subsequently in cost. Additionally, increased productivity resulting from technological innovation should incentivize firms to produce more, further amplifying these effects.

3 Data and descriptive statistics

This section provides a description of the three main datasets utilized in this study, which include yearly balance sheet and patent information of Italian incorporated companies.

3.1 Patent data

The first dataset, obtained from UIBM, contains information on Italian patent filings spanning from 2007 to 2019. Figure 1 illustrates the temporal evolution of the total number of patents filed at UIBM, both for the entire sample and exclusively for Italian firms[4]. The complete sample series reaches its peak in 2008, with 4,871 patents filed, followed by a steady decline until 2015, when it hits its lowest point of 4,017. On average, Italian firms account for 79% of the filed patents. We use the year of publication of each patent to identify eligible firms for the two calls of the program. For example, firms that filed patents between 2007 and 2015 are considered eligible for the first call of *Brevetti+* during the years they qualify as SMEs[5]. We consider these firms as potential controls for the SDiD analysis.

The second dataset is sourced from Invitalia[6] and provides a list of firms that received a *Brevetti+* grant, either in the form of a prize or an incentive, along with the grant size. We merge this dataset with the patent data using a unique firm identifier (*codice fiscale*) and employ it to define our treatment group of firms that received an incentive. Overall, there were 1,347 applications for incentives and 2,930 for prizes[7], out of which 556 and 1,871 were granted, respectively. The average grant size amounts to €54,067.17 for incentives and €2,136.71 for prizes.

An issue that may affect our identification strategy is the possibility that the availability of grants incentivized firms to pursue patenting, thus complicating the isolation of the causal effect of incentives on firm performance. This arises from the consideration of not only firms that already possessed patents (and sought services to further develop them) but also companies that decided to file or acquire new patents in order to obtain the aid. Consequently, this confounds the desired causal effect with the mere effect of patenting, resulting in biased estimates. To address this, we exclude firms that received both a prize and an incentive, ensuring the

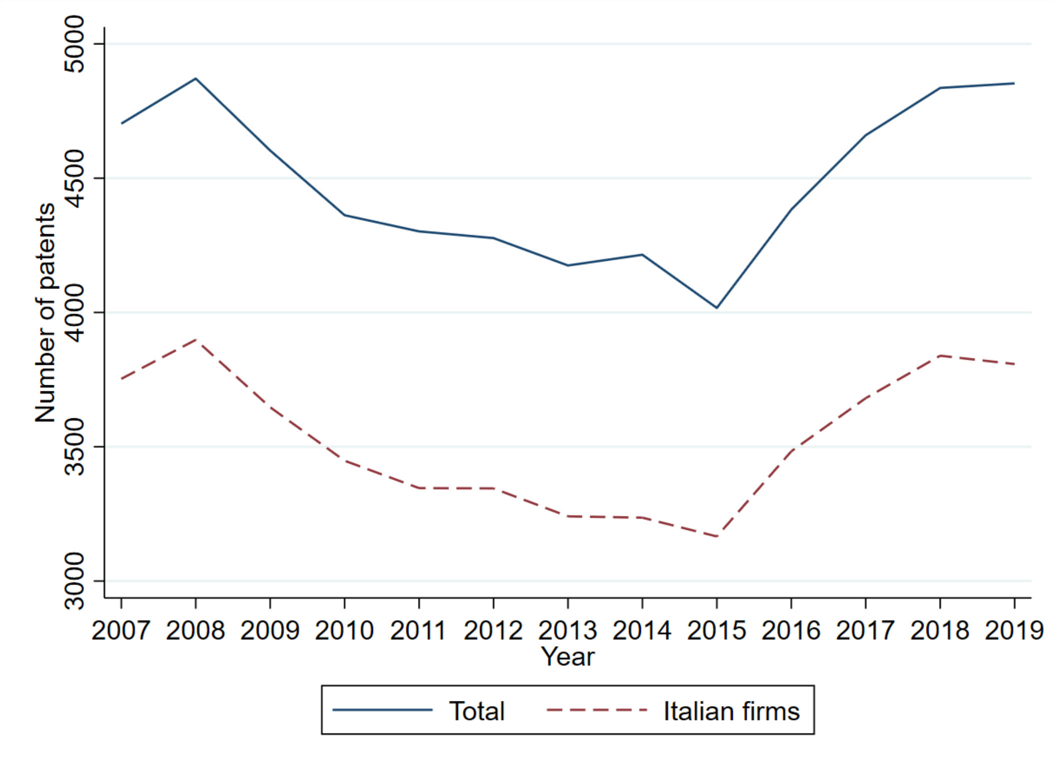
[4] It is important to note that patents can also be filed by individuals, universities or research institutes, and foreign firms.

[5] We determine SMEs using CERVED, where they are defined as firms with 250 employees or less, and less than either €50 million in sales or €43 million in total assets.

[6] https://www.invitalia.it/trasparenza/sovvenzioni-contributi-sussidi

[7] https://www.invitalia.it/cosa-facciamo/rafforziamo-le-imprese/brevetti-vecchia-edizione/risultati

Figure 1: Number of patents filed at UIBM from 2007 to 2019



exclusion of companies that filed or acquired a patent after the program's initiation.

3.2 Balance sheet data

The final dataset, obtained from CERVED, includes balance sheet information for the entire population of Italian incorporated companies spanning from 1999 to 2019. Once again, we use the *codice fiscale* to merge this dataset with the others and extract the variables of interest. Regarding performance measures, we consider operating income as value added, net income divided by total assets as return on assets, and revenues from sales divided by total assets as a third indicator. Additionally, we analyze the total costs of labor, materials, and services to investigate potential channels through which *Brevetti+* may have assisted SMEs in overcoming their lack of complementary assets. Furthermore, we construct a leverage measure, defined as total debt divided by total assets. Information on the industry (*ATECO 2007* code) and the province of operation is also available. We exclude firms operating in certain atypical industries[8].

[8]Agriculture, forestry and fishing (firms in these industries are ineligible for *de minimis* aids), mining and quarrying products, coke and refined petroleum products, financial and insurance activ-

Table 1: Descriptive statistics for the full sample

Panel A:	**Balance sheet variables**		
	Full sample		
	Mean	Std. Dev.	N
Value added	1,063.87	25,839.41	7,373,279
Return on assets	0.01	0.58	7,373,279
Sales/assets	1.50	1.90	7,373,279
Cost of labor	670.63	11,688.94	7,373,279
Cost of materials	2,556.40	54,778.94	7,373,279
Cost of services	1,203.22	19,625.13	7,373,279
Leverage	0.72	2.84	7,373,279
Total assets	5,134.24	181,984.09	7,373,279
Employees	19.77	299.10	5,130,135
Panel B:	**Location and Industry shares**		
	Full sample		
North	0.529		
Center	0.231		
South and Islands	0.240		
Manufacturing	0.276		

Note: Nominal values are in thousand euros and deflated using the Italian CPI index from OECD[9]. We exclude all firms with zero or missing fixed assets or total cost of labor, or with weakly negative or missing value added. We have information on the number of employees only between 2005 and 2018.

Descriptive statistics are provided for the entire set of remaining firms, as well as for three distinct groups: treated, eligible[10], and never-patenting[11] firms. As shown in Table 1, Italian firms tend to be small, with an average total asset value of €5.13 million and 20 employees. They primarily finance their operations through debt, with an average leverage ratio of 72%. Among the three analyzed expense categories, materials account for the highest average value (€2.56 million), followed by services (€1.20 million) and labor compensation (€0.67 million). In terms of performance, the average sales/assets ratio is 1.5, and the ROA stands at 1%. More than half of the firms are located in northern Italy, while the rest are almost evenly distributed between central Italy and southern Italy/the Islands. Additionally, 27.6%

ities, public administration and defense, compulsory social security, education, human health and social work activities, arts, entertainment and recreation, other service activities, activities of households as employers, and undifferentiated goods- and services-producing activities of households for own use. *ATECO 2007* codes are listed in Table A.3 of the Appendix.

[9] https://stats.oecd.org/index.aspx?DataSetCode=PRICES_CPI#

[10] Referring to any of the two calls.

[11] Firms that do not appear in any of our patent datasets.

Table 2: Descriptive statistics for subgroups

Panel A:	**Balance sheet variables**								
	Treated			Eligible			Non-patenting		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N
Value added	2,209.83	3,461.07	2,628	13,339.92	154,500.36	111,991	844.77	13,678.14	7,243,298
Return on assets	0.03	0.08	2,628	0.02	0.13	111,991	0.01	0.59	7,243,298
Sales/assets	1.11	0.54	2,628	1.11	0.55	111,991	1.51	1.92	7,243,298
Cost of labor	1,399.88	1,995.80	2,628	7,276.85	47,657.13	111,991	547.73	5,704.89	7,243,298
Cost of materials	3,850.20	6,192.64	2,628	24,229.51	265,578.50	111,991	2,205.79	45,446.88	7,243,298
Cost of services	2,007.75	2,692.31	2,628	12,015.52	98,262.06	111,991	1,019.67	14,936.34	7,243,298
Leverage	0.61	0.21	2,628	0.62	0.25	111,991	0.72	2.87	7,243,298
Total assets	7,470.65	10,921.16	2,628	72,966.79	1,010,625.50	111,991	3,893.62	95,397.50	7,243,298
Employees	34.31	38.53	1,967	158.11	951.02	78,996	17.09	176.66	5,038,647
Panel B:	**Location and Industry shares**								
	Treated			Eligible			Non-patenting		
North	0.763			0.827			0.524		
Center	0.201			0.127			0.233		
South and Islands	0.036			0.046			0.243		
Manufacturing	0.837			0.795			0.267		

Note: Nominal values are in thousand euros and deflated using the Italian CPI index from OECD. We exclude all firms with zero or missing fixed assets or total cost of labor, or with weakly negative or missing value added. We have information on the number of employees only between 2005 and 2018.

of the firms operate in the manufacturing sector. When focusing on the three subgroups (Table 2), treated and eligible firms exhibit higher ROA but lower sales/assets ratios compared to the overall average, with sales/assets ratios of 1.11 and ROA values of 3% and 2%, respectively. Both treated and eligible firms are larger and have higher expenses than the average company. However, treated firms tend to be smaller, with total assets averaging €7.47 million and 34 employees, while eligible firms have average total assets of €72.97 million and 158 employees. Similarly, expenses are higher for both groups, with eligible firms having higher values overall (€24.23 million for materials, €12.02 million for services, and €7.27 million for labor compensation). On the other hand, never-patenting firms are smaller than the average, with total assets averaging €3.89 million and 17 employees. As a result, their expenses are lower as well. The performance indicators for never-patenting firms are very similar to those of the entire sample, with a ROA of 1% and a sales/assets ratio of 1.51. The majority of treated and eligible firms are located in northern Italy (76.3% and 82.7%), and a large proportion operates in the manufacturing sector (83.7% and 79.5%), while only a small percentage is based in southern Italy or the Islands (3.6% and 4.6%). Notably, the location and industry shares for never-patenting firms closely mirror those of the overall sample.

4 Empirical strategy

This section outlines the empirical strategy employed in the study and discusses its potential limitations. Estimating the causal effect of the policy on firms' performance presents challenges due to the non-random allocation of grants. The selection process for granting funds is based on a first-come, first-served basis, following an evaluation of the project's potential impact on the firm's profitability and leverage. Consequently, the firms receiving aid may inherently differ from the others, leading to biased coefficients when using a simple ordinary least squares (OLS) regression. To address this issue, we adopt a Synthetic Difference-in-Differences with staggered treatment methodology. This approach allows us to compare each treated firm with a weighted average of eligible companies (which did not receive the grant) that closely resemble it in terms of industry, geographical area, and relevant variables such as ROA, leverage, and total assets. We estimate the treatment effect independently for each treated firm and aggregate the coefficients using a measure of goodness of fit of the synthetic control. We assess the statistical significance of our results through a permutation exercise.

4.1 Synthetic DiD with staggered treatment

To mitigate potential problems of omitted variable bias, we employ a staggered Difference-in-Differences approach, leveraging the methodology proposed by Abadie and Gardeazabal (2003) and Abadie et al. (2010) to create a synthetic control for each treated firm. We assign weights to firms in the set of potential controls (donor group) to closely resemble the pre-treatment condition and potential evolution of each treated firm in the absence of the treatment. The coefficients we aim to estimate correspond to the classical DiD framework:

$$\hat{\beta}_{i,t} = (Y_{i,t} - Y_{i,-1}) - (\hat{Y}_{i,t} - \hat{Y}_{i,-1}), \quad \forall i, \quad \forall t \neq -1 \tag{1}$$

where $Y_{i,t}$ denotes the outcome variable for treated firm i at time t, and $\hat{Y}i,t$ represents its counterfactual value in the absence of the treatment, estimated based on the control group. To address collinearity, we normalize one of the coefficients to 0, choosing year -1 as the reference point. Thus, all estimated coefficients $\hat{\beta}i,t$ are interpreted as deviations from the immediate pre-treatment period. We consider as treatment year the one in which the firm received the grant in case the awarding happened in the first half of the year, and the following one otherwise. We define the counterfactual outcome as:

$$\hat{Y}_{i,t} = \sum_{j=1}^{J} w_j^{(i)} Y_{j,t}, \quad \forall i \tag{2}$$

where $\mathbf{W^{(i)}} = (w_1^{(i)}, ..., w_J^{(i)})$ is a $J \times 1$ vector of weights assigned to firms j in the donor pool to construct a synthetic control for treated firms i. These weights minimize the distance between the treated and control units concerning pre-treatment outcomes and relevant predictors:

$$||\mathbf{X_i} - \mathbf{X_j}\mathbf{W^{(i)}}|| = \left(\sum_{h=1}^{k} v_h^{(i)} (X_{h,i} - w_1^{(i)} X_{h,1} - ... - w_J^{(i)} X_{h,J})^2 \right)^{1/2}, \quad \forall i \tag{3}$$

In the above equation, $\mathbf{X_i}$ and $\mathbf{X_j}$ represent vectors of the dependent variable and other controls affecting it for the treated firm and firms in the donor pool, respectively. The weights are subject to non-negativity constraints and sum to one. We solve the minimization problem using a two-step procedure. First, we determine the weights $\mathbf{W}^{(i)}$ that minimize the squared distance:

$$(\mathbf{X_i} - w_1^{(i)}\mathbf{X_1} - ... - w_J^{(i)}\mathbf{X_J})\mathbf{V}^{(i)\intercal}(\mathbf{X_i} - w_1^{(i)}\mathbf{X_1} - ... - w_J^{(i)}\mathbf{X_J}), \quad \forall i \tag{4}$$

Then, we assign weights $\mathbf{V}^{(i)}$ that define the relative importance of each predictor.

We match each treated firm with other companies operating in the same industry and geographical area[12]. These matched firms were eligible for the same call in the corresponding year but did not receive financial aid. Following Angrist (1998), we utilize knowledge of the evaluation criteria for grant awards to define our predictors. We match based on the dependent variable, ROA (which proxies for profitability), leverage, and total assets (which proxies for size). This matching approach reduces the scope for both problems of selection into patenting, given that all eligible firms filed a patent in the past, and selection into the program, as we match for the evaluation criteria.

4.2 Aggregation

After performing the SDiD analysis independently for each treated firm, we aggregate the firm- and time-specific treatment effects into event-time treatment effects, which we call dynamic ATTs. This aggregation procedure takes into account a measure of the synthetic control's goodness of fit. Following the approach of Acemoglu et al. (2016b), we aggregate the estimated coefficients as follows:

$$\hat{\phi}_t = \frac{\sum_{i \in Treat.group} \frac{\hat{\beta}_{it}}{\hat{\sigma}_i}}{\sum_{i \in Treat.group} \frac{1}{\hat{\sigma}_i}} \tag{5}$$

where $\hat{\sigma}_i$ is defined as:

$$\hat{\sigma}_i = \sqrt{\frac{\sum_{t \in Estim.window} \hat{\beta}_{it}^2}{T_i}} \tag{6}$$

T_i represents the length of the estimation window (i.e., the pre-treatment period). The coefficient $\hat{\phi}_t$ captures the causal effect of the treatment at event time t, and $1/\hat{\sigma}_i$ serves as a measure of the synthetic control's goodness of fit. Thus, for each event year, we calculate a weighted average of all estimated coefficients, giving higher weights to firms with a better synthetic control, which implies a smaller difference in pre-treatment outcomes of the dependent variable and a longer availability of data.

[12] North, Center, or South and Islands. The official ISTAT classification of Italian regions into these three areas is reported in Table A.4 of the Appendix.

We also take an average of all post-treatment dynamic ATTs to estimate overall treatment effects.

This methodology allows us to achieve almost perfectly parallel pre-trends by assigning higher weights to firms with smaller differences with respect to their synthetic control in pre-treatment outcomes of the dependent variable. Additionally, it helps mitigate potential problems of heterogeneity bias by aggregating firm- and time-specific treatment effects.

4.3 Permutation

To assess the statistical significance of our results, we conduct a permutation exercise. We randomly assign a treatment year to each firm in the donor pool[13], construct synthetic controls, and estimate firm- and time-specific treatment effects. For each firm, we match based on the same variables as in our main specification and assign positive weights exclusively to companies operating in the same industry and geographical area as the artificially treated ones, eligible for the assigned call and treatment year. Subsequently, we randomly draw the estimated coefficients while maintaining the exact distribution of treatment years as in the actual data. We then aggregate these coefficients using the measure of goodness of fit mentioned earlier. We repeat this exercise for 5,000 placebo treatment groups and obtain a distribution of coefficients for each event year. Finally, we utilize these distributions to obtain p-values for two-tailed hypothesis testing of whether the estimated coefficient differs from zero. The p-values are calculated as the share of placebo ATTs higher (or lower) than the true one. For example, an estimated coefficient is statistically significant at the 5% level if it ranks in the top (or bottom) 5% of the distribution of placebo ATTs. Similarly, we take an average of all placebo dynamic ATTs for all 5,000 placebo treatment groups and use the resulting distributions to retain p-values for the overall post-treatment ATTs.

5 Empirical results

This section presents the empirical findings of our study. Before going to the main estimates, we perform the SDiD using the most recent patent filing of firms that received *Brevetti+* aid as treatment, rather than focusing on the grant award itself. The goal of this preliminary analysis is to estimate the impact that such patents had on the performances of treated firms, to understand whether they initially faced

[13] We drop firms that are assigned the treatment in a year in which they were not SMEs, given that they could not have been eligible for any of the calls.

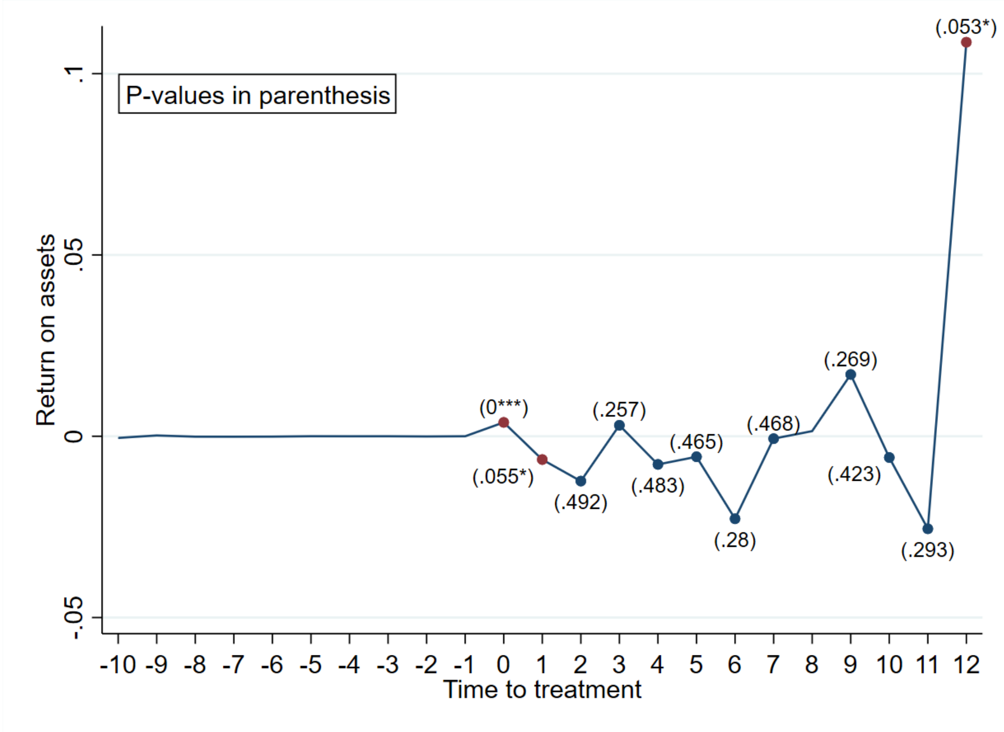
difficulties in appropriating the economic benefits of their innovations due a lack of complementary assets. We then examine the effect of receiving a *Brevetti+* grant on firm performance, allowing us to estimate the causal effect of full patent exploitation on economic returns. Additionally, we investigate the main obstacles hindering technological adoption for these firms by analyzing the effect of the treatment on various potential expenses. By doing so, we contribute to the understanding of the constraints that impede innovation and growth for SMEs. All coefficient estimations are based on the SDiD methodology described in the previous Section.

5.1 Barriers to innovation

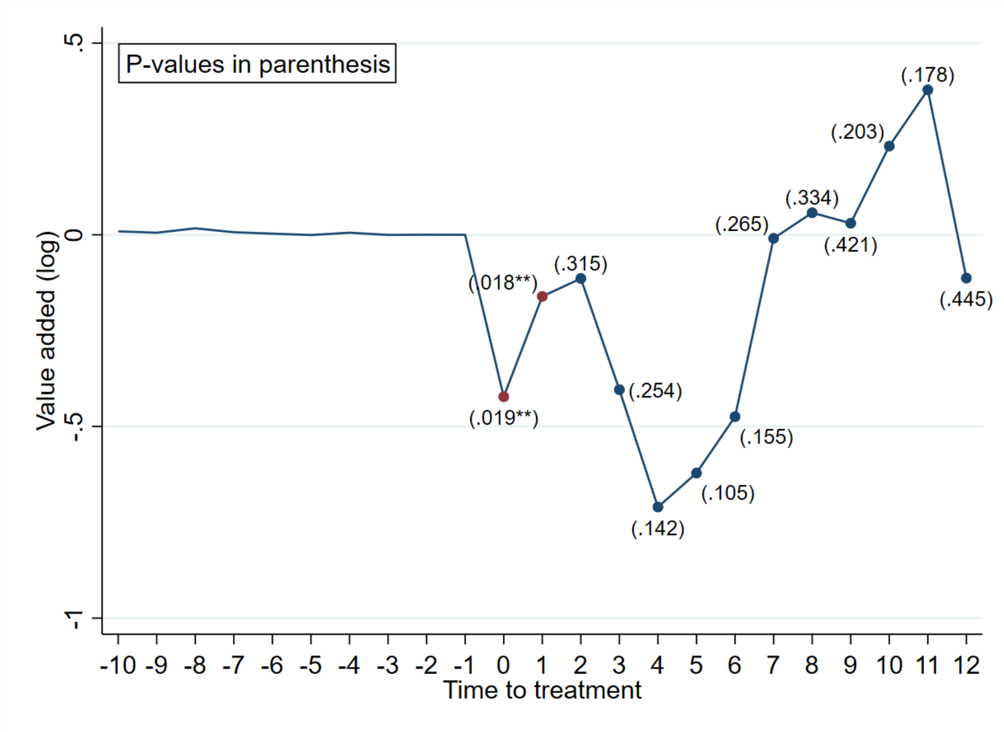
We begin by providing evidence of the initial difficulties faced by SMEs in appropriating the economic returns of their patents. Using the staggered SDiD estimation, we analyze two common measures of firm performance—value added and return on assets—using the last published patent as treatment for firms receiving a *Brevetti+* financial aid. Assuming they used the granted funding for their latest patent, we aim to investigate the subsequent impact on their performance in the immediate years following the patent filing. This allows us to explore potential hurdles in earning rental income from their innovative endeavors due to the lack of complementary assets prior to receiving the grant. Treated firms are matched with other companies in the same industry and geographical area that filed a patent in the same year. For simplicity, from now on we report p-values computed with the permutation exercises alongside the point estimates. Regression tables and figures depicting the densities of the placebo ATTs and the real ATT of treated firms can be found in Tables B.1 to B.9 and Figures B.1b to B.9b of the Appendix.

Figure 2 shows that treated firms exhibit similar ROA but lower value added compared to their synthetic controls after filing their last patent before receiving the *Brevetti+* grant. Throughout the post-patent period, they experience a 17.94% decrease in value added compared to their counterparts. While they achieve a 0.36% higher ROA, this result is heavily influenced by the last event-time estimate, which has only two available observations compared to 118 in the first one. Excluding it, we observe a 0.51% lower ROA for treated firms, which is 45.74% less than their pre-treatment (event-time -1) average. Hence, treated firms perform worse than their synthetic controls in the years following their last patent filing. This may be due to the challenges that such firms encountered in implementing the new technology within their production processes. The grants were, in fact, awarded to firms that did not succeed in adopting or economically exploiting existing patents. Other firms in the donor pool, instead, were able to appropriate the economic returns

Figure 2: Performance measures using last patent's publication before receiving the grant as treatment



(a) Return on assets



(b) Value added

Note: Dynamic SDiD estimates after aggregating as in equation (5). P-values estimated with the permutation exercise are in parenthesis.

of their innovations, outperforming companies which would later receive a *Brevetti+* financial aid.

These preliminary findings are based on the assumption that grants were used for the most recently filed patents, although they could have been allocated to older or acquired ones instead. Such an assumption cannot be tested, so the results should be interpreted with caution. However, they suggest the possibility that treated firms faced difficulties in economically exploiting their innovations, leading to underperformance compared to similar innovative companies. This conclusion would be further strengthened if opposite results were observed when grants' awardings are used as treatment, indicating that such firms were unable to fully exploit their innovations until they received financial aid. Additionally, these figures already demonstrate how the employed methodology enables us to estimate nearly parallel pre-trends by assigning higher weights to firms with better synthetic controls in terms of pre-treatment differences in the dependent variable.

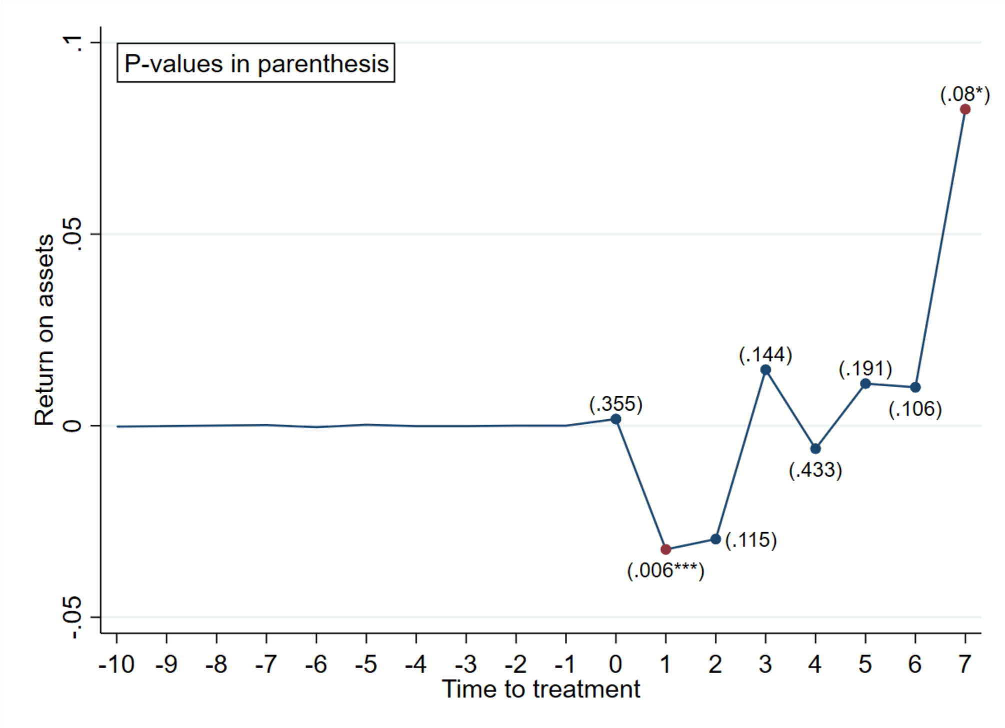
5.2 Performance measures

We now proceed to estimate the main results of this study, focusing on the causal effect of receiving *Brevetti+* financial aid on firm performance, using ROA and value added as proxies.

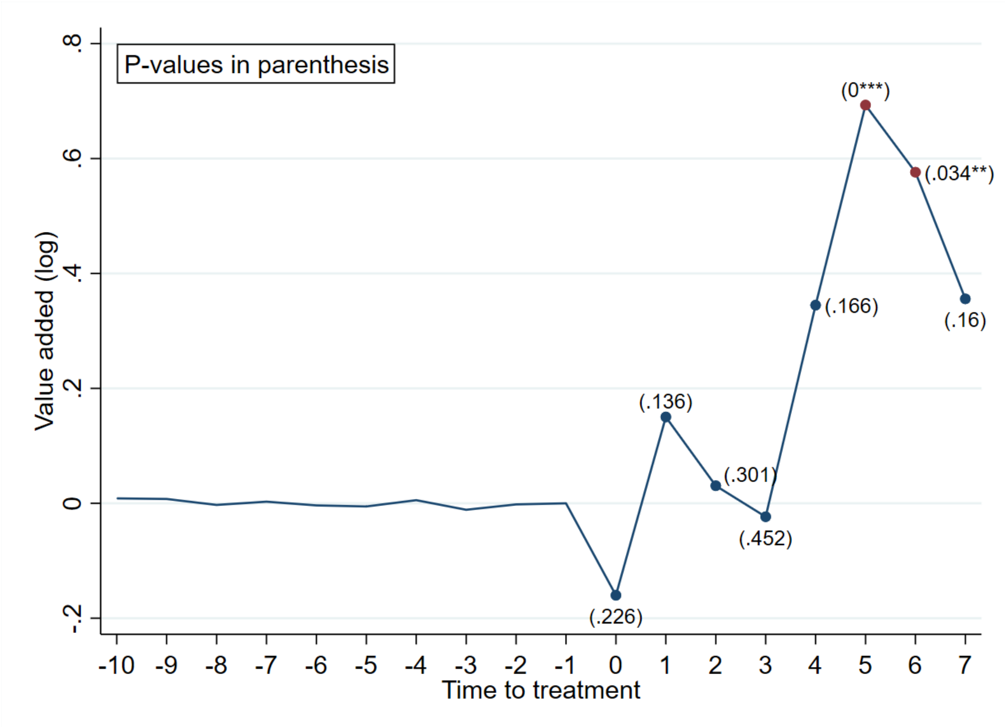
Figure 3 illustrates that, for both ROA and value added, treated firms demonstrate superior performance in the long run compared to their respective synthetic controls. The most substantial increase in ROA is observed in the final year of treatment, reaching 8.26%. Conversely, for value added, consistently better performance among treated firms becomes evident from the fourth period, with a maximum increase of 69.31% occurring in the subsequent event year. Overall, treated firms achieve a post-treatment period increase of 0.65% in ROA and 24.59% in value added. These findings provide further evidence that such firms faced previous barriers in implementing their new innovations and were unable to fully exploit their economic potential. However, after receiving financial aid for their development, these firms successfully undergo a process of technological adoption, thereby reaping the benefits of their innovation.

Turning to the short-run effects of the treatment, we observe initial poor performance among treated firms in terms of both ROA and value added. The most significant decline in value added, estimated at 16.01%, occurs during the treatment year, while for ROA, the ratio decreases by up to 3.23% in the following one. These initial performance drops among firms awarded financial aid can be explained by the implementation process of the public program. Treated firms were initially required

Figure 3: Performance measures



(a) Return on assets



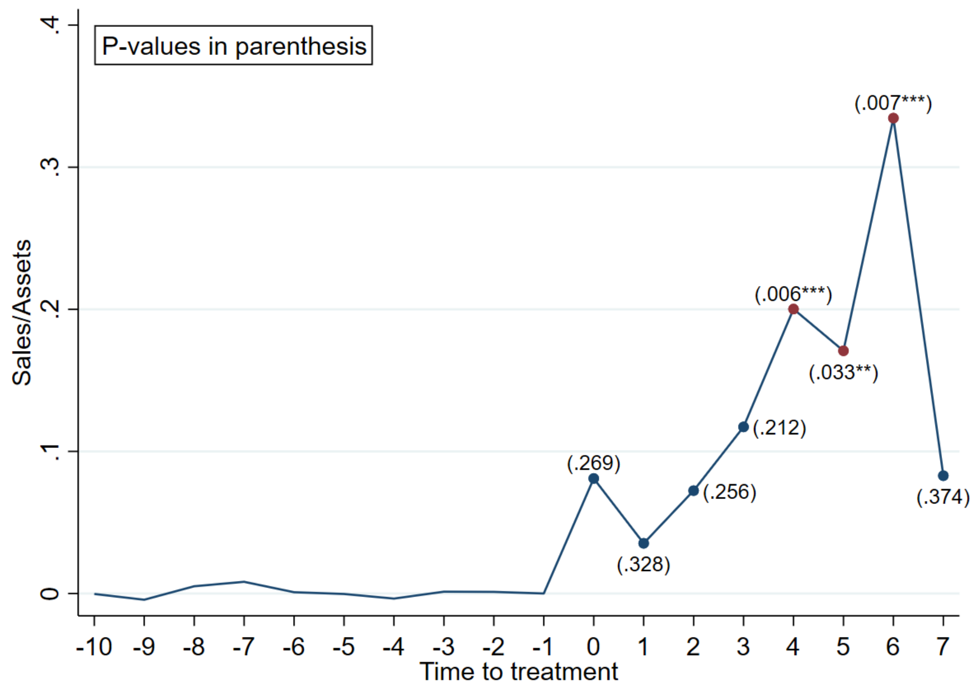
(b) Value added

Note: Dynamic SDiD estimates after aggregating as in equation (5). P-values estimated with the permutation exercise are in parenthesis.

to bear the planned expenses themselves, with the possibility of receiving only a fraction of the total amount granted either at the beginning or during the provision of specialized services. The remaining financial aid was to be granted to companies at a later stage once the project was completed. Consequently, treated firms initially underperform in comparison to similar companies due to the increased expenses they face in the initial years of treatment.

To ascertain the validity of this explanation, we examine whether a similar immediate drop in performance is observed using a measure independent of operating costs. To this end, we repeat the analysis using sales/assets as the dependent variable. Our results, presented in Figure 4, consistently support our prior expectations, as all post-treatment estimates are positive. On average, we observe a positive causal effect of 13.68% on sales/assets for treated firms, with the highest estimates occurring in later periods[14].

Figure 4: Sales/Assets



Note: Dynamic SDiD estimates after aggregating as in equation (5). P-values estimated with the permutation exercise are in parenthesis.

In summary, we consistently find a positive causal effect of receiving financial aid aimed at improving existing patents across three different performance mea-

[14]Another explanation could be a simple increase in total assets, resulting in a mechanical decrease in ROA. However, this would not explain the negative impact on value added and the absence of such effect in sales/assets.

sures. While the overall ATT is not statistically significant for any of them, we observe positive and statistically significant dynamic ATTs, particularly in later periods. These positive effects are accompanied by immediate negative performance impacts for ROA and value added, driven by the initial expenses required to initiate the projects. The treated firms in our study are innovative SMEs that have previously filed or acquired patents but have struggled to implement them in their production or to fully capitalize on their economic value. The reason behind this limitation may be the lack of certain complementary assets necessary for the adoption of new technologies. However, the *Brevetti+* grants have made such assets available to these firms, enabling them to acquire specialized services for the development of their patents.

One limitation of our study is the absence of information regarding how winning firms allocated the grants, preventing us from precisely identifying the complementary assets that were lacking and impeding technology adoption. To address this issue, we re-estimate our SDiD model, employing various cost items as dependent variables in an attempt to identify the allocation of the grants. Additionally, this allows us to observe how these expenses evolve in the long run for treated firms following the implementation of new technologies in their production.

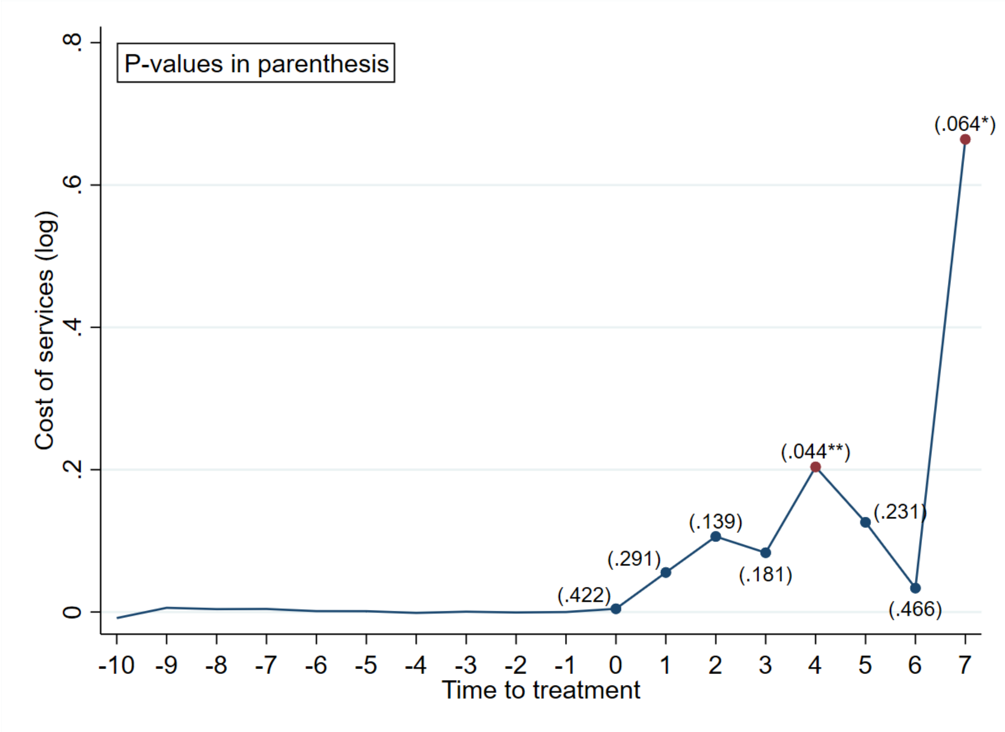
5.3 Channels

We analyze three distinct cost items: cost of services, cost of materials, and cost of labor. These three items are selected because financing such expenses can be particularly challenging for SMEs. Due to their high liquidity constraints and the inability to use these assets as collateral, securing loans for these purchases becomes difficult. Consequently, we expect to observe an effect of the treatment on them, attributed to the availability of a new flow of liquidity for treated firms, enabling them to overcome these constraints.

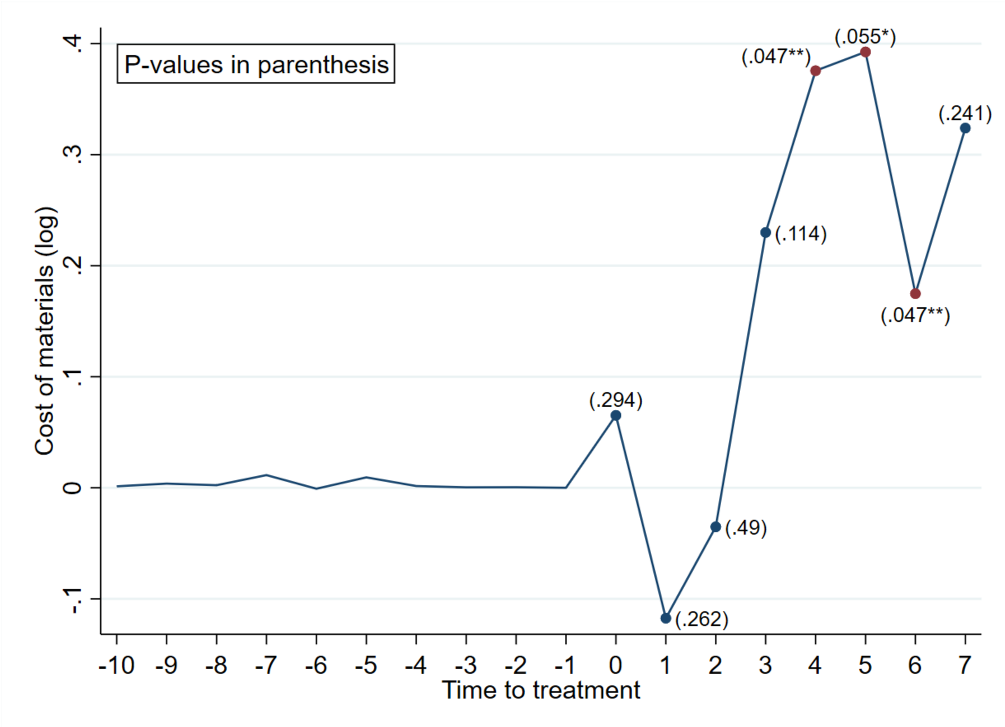
We commence by examining the total costs of services and materials, depicted in Figure 5. In the initial treatment years, we observe a positive trend for the cost of services, although it is not statistically significant. By the second event year, there is already a 10.61% increase for treated firms. Conversely, we do not find a clear trend for the cost of materials in the immediate post-treatment periods. However, in the long run, both cost items display an overall increase, resulting in a statistically significant post-treatment ATT of 15.97% for the cost of services and 17.62% for the cost of materials at a significance level of 10%.

The results for the total cost of labor, presented together with the effect on the total number of employees, are shown in Figure 6. In the first three treatment years,

Figure 5: Materials and services expenses



(a) Cost of services (log)



(b) Cost of materials (log)

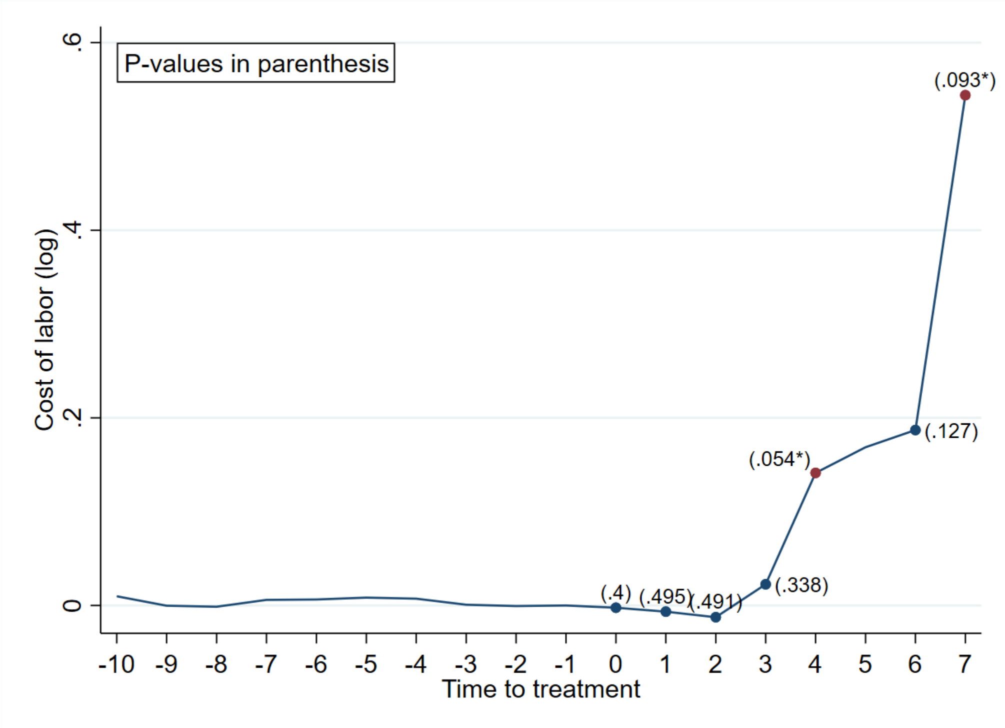
Note: Dynamic SDiD estimates after aggregating as in equation (5). P-values estimated with the permutation exercise are in parenthesis.

both variables exhibit slightly negative coefficients, which are statistically and economically insignificant. This indicates that treated firms did not need to hire new employees or provide higher wages during this period. However, in the long run, there is a substantial increase in both variables. The overall ATT is 13.03% for the cost of labor and 0.3474 for the number of employees. However, only the former is statistically significant at the 10% level.

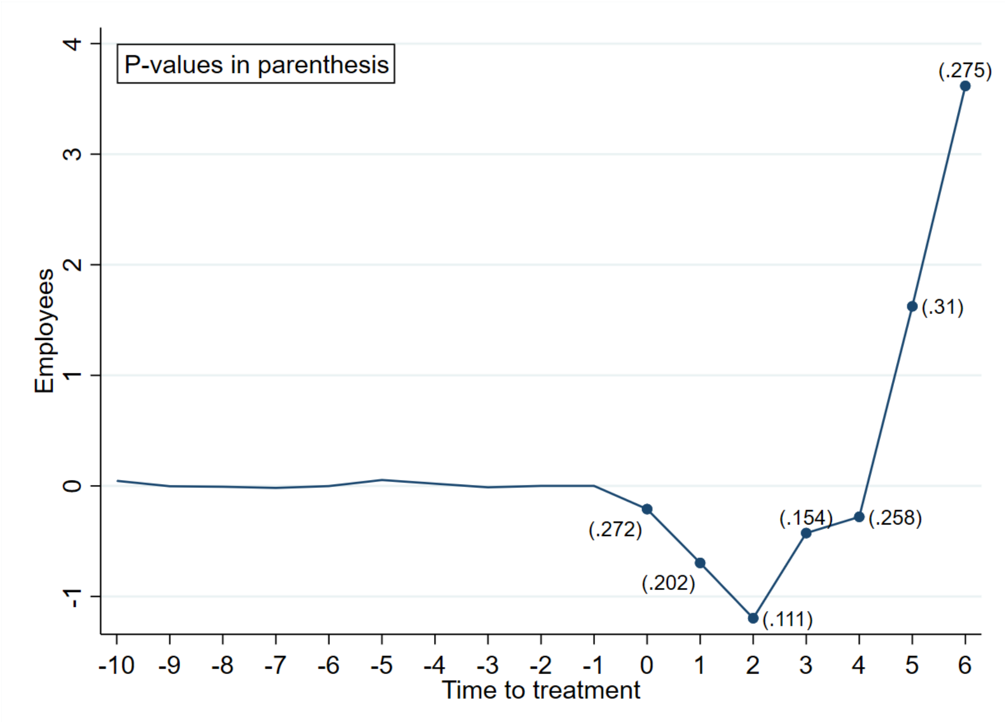
It is worth noting that the largest increases in most analyzed dependent variables tend to occur in the last year of treatment. However, during this period, we have fewer treated firms available, which may result in our results being driven by a few outliers that received the treatment in the first available year and achieved exceptional performance. While synthetic controls are designed to address small sample issues, there could still be concerns related to sample composition due to the subsequent aggregation. The number of observations available for each dynamic estimate is provided in the regression Tables B.1 to B.9 of the Appendix.

In summary, we observe a short-term increase in expenses solely for the cost of services, aligning with the fact that grants were allocated for the procurement of specialized services. This payment was not accompanied by the hiring of new employees or increased purchases of materials, suggesting that the immediate drop in performance for treated firms was primarily driven by this cost item. Thus, the availability of external specialized services appears to play a significant role in innovation adoption for Italian SMEs, allowing them to earn a return on their new technologies. Unfortunately, due to the lack of information on the specific services provided to firms, we are unable to identify the precise constraints that hindered innovation for these companies. However, we find that there was no simultaneous increase in other significant cost items. The absence of specialized expertise within the labor force seems to be a significant barrier to innovation for smaller firms, as they are unable to access the necessary external specialized services for testing or improving specific aspects of the patent. Innovation requires various one-time expenses (e.g., engineers for feasibility studies, lawyers for due diligence, etc) that must be directed toward experienced and qualified professionals. In the long run, instead, all analyzed costs tend to increase. There could be two reasons for this: firstly, the need to undergo a process of technological adaptation toward more skill-intensive operations, which may necessitate higher-quality materials and a more skilled workforce, resulting in increased costs; secondly, these results may be driven by a simple increase in Total Factor Productivity (TFP) for treated firms. After adopting new technology, they may become more productive and choose to produce more, leading to the need for higher quantities of intermediate inputs. Unfortunately, we are unable to determine which channel is the primary driver of our

Figure 6: Labor expenses



(a) Cost of labor (log)



(b) Number of employees

Note: Dynamic SDiD estimates after aggregating as in equation (5). P-values estimated with the permutation exercise are in parenthesis.

results due to the empirical methodology employed and the available data. If we were to estimate TFP using a control function approach, for instance, we would end up with the same inputs' output elasticity coefficients for all firms operating in the same industry at any given year. Our firm-level data would only allow us to compute elasticities accurately at the two-digit industry level[15]. Therefore, we would implicitly assume that all firms within the same industry possess identical technology, with their inputs having the same output elasticity. Consequently, comparing a rescaled version of the difference between value added and input contributions rather than true productivities would be inevitable. We further elaborate on this concern in Appendix C[16].

In conclusion, we find that treated firms faced liquidity barriers to innovation, preventing them from purchasing the services required to implement their new technology in production. Following the receipt of *Brevetti+* grants, these firms were subsequently able to bear such costs, addressing the lack of complementary assets that had hindered their growth. We observe an initial decrease in performance due to the expenses incurred in procuring services necessary to initiate the projects, followed by a sharp increase in all performance measures and input costs. We are unable to determine whether the latter was driven by quantities (TFP increase) or prices (need for higher quality inputs).

5.4 Robustness checks

As a robustness check, we conduct a backdating exercise. Instead of using data up until the treatment year to construct our synthetic controls, we match firms only until three years prior. This approach allows us to examine whether the synthetic firms closely track the behavior of the treated units during the validation period from $t{=}-3$ to $t{=}-1$ and assess the robustness of our estimates to a different matching procedure. Similar to our main specification, we aggregate the firm and time-specific treatment effects using a measure of goodness of fit for the synthetic control. By doing that, we enhance the credibility of our causal estimates and demonstrate their sensitivity to a different estimation window. The results of this backdating exercise are presented in Figure B.10, and the specific point estimates can be found in Tables B.1 to B.9 of the Appendix.

[15] We do not have enough observations to do a more granular analysis. It would be possible if we had, for example, establishment-level data.

[16] Another possibility could be to look at the evolution of investments for treated firms to understand whether the increase in expenses is driven by the productivity channel. However, firms' investments tend to be spiky, making it difficult to find good synthetic controls when analyzing such dependent variable (they would have to both invest in similar magnitudes and in the same exact years of treated firms).

We find that for all variables we still observe almost perfectly parallel pre-treatment trends, even during the validation period. This provides further evidence that the synthetic controls effectively capture the characteristics of the treated units. In terms of performance measures, we observe similar trends but slightly different post-treatment ATTs. However, all the estimates maintain the same sign as the main ones. The analysis of cost items yields highly robust results, with both the dynamic and overall ATTs closely resembling those presented earlier. The only notable difference is observed in the number of employees, which presents an overall ATT of 6.5069, significantly higher than the main estimate. However, this discrepancy is primarily driven by the last dynamic ATT of the backdating exercise, which features an unrealistically high coefficient of 39.4276. This could be due to the presence of only two treated firms.

Additionally, in Tables B.1a to B.9a of the Appendix, we display the evolution of the outcome variables separately for the aggregated treated and synthetic control firms prior to taking the difference. This allows us to visualize the origin of the estimated differences between the two groups.

6 Conclusion

This paper investigates the economic returns and potential barriers to innovation faced by small and medium-sized innovative enterprises. It uses patents as a measure of innovative efforts and employs a staggered SDiD methodology to analyze the impact of the Italian public program *Brevetti+* on these firms. The program provided funds to SMEs for the acquisition of specialized services aimed at improving existing patents.

Our findings indicate that firms receiving financial assistance perform below comparable innovative companies after filing their latest patent. However, this situation is reversed once they receive the grants and manage to boost their long-run performance in terms of ROA, value added, and sales/assets ratio. This creates a noticeable gap of 0.65%, 24.59%, and 13.68%, respectively, between these firms and their synthetic controls. The highest gaps are observed in the latest event years after treated firms manage to upgrade their inputs. These results provide evidence of the challenges faced by treated companies in implementing or fully capitalizing on new technology. Only after receiving financial aid and acquiring specialized services to improve and adopt the new technology were they able to realize the economic benefits of their innovation. Disregarding it would lead to mismeasuring patents' value.

Additionally, we explore the mechanisms through which the additional funds may have assisted Italian SMEs in developing their patents. We examine three cost components: services, materials, and labor. We find a short-term increase only in service expenses, as the funds were specifically allocated for such purposes. However, in the long run, all three components experience significant increases, with respective ATTs of 15.97%, 17.62%, and 13.03%. These increases may be attributed to improved input quality and higher prices resulting from technological change, as well as increased productivity following technology adoption, leading to greater production and quantity of inputs.

Consequently, this study highlights the challenges faced by SMEs in acquiring the complementary assets necessary for implementing new technology in their production processes, ultimately resulting in diminished returns to innovation. Commercial exploitation of patents requires substantial upfront investments, which hampers the growth of companies that lack the required resources to compete with larger and less financially constrained firms. Such a conclusion bears relevance for policymakers, given the substantial amount of government funds typically allocated to support innovative activities. The provision of financial aid for the acquisition of specialized services has proven effective for Italian SMEs, enabling them to significantly improve their performance after participating in the program. This policy tool may yield similar results for firms that have already patented while also enhancing incentives for other companies to innovate by providing them with the resources needed to fully exploit their new technologies. However, its effectiveness may vary across different contexts. In financially developed countries where SMEs are less credit constrained, the impact of such initiatives may be comparatively less pronounced. Therefore, further research is needed to explore their potential applicability and effectiveness in different economic environments.

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Appendix A

Table A.1: List of allowed prizes with respective requirements from Ufficio Italiano Brevetti e Marchi (2011)

Patent proceeding	**Result achieved**	**Verification elements**	**Prize**
Patent application filing at UIBM	Non negative research report released by EPO regarding: novelty, innovative activity, industrial application	- Proof of application deposit - Non negative research report for two out of three elements	1,500 €
Patent application for extension at EPO	Request for examination	- Proof of application deposit - Payment receipt	3,000 €
Patent application for extension at WIPO	Request for international international	- Proof of application deposit - Payment receipt	4,000 €
Patent application for extension to countries participating in PCT (additional bonus): a. 3 to 5 countries b. more than 5 countries	Request to the participating countries	- Proof of application deposit	 a. 3,000 € b. 6,000 €
Patent application for extension to the following countries (additional bonus): a. China and India b. USA, Brasil and Russia	Request to the participating countries	- Proof of application deposit	 a. 1,500 € b. 1,000 €

Table A.2: List of allowed services from Ufficio Italiano Brevetti e Marchi (2015)

Allowed services	Allowed sub-services
Industrialization and development	✓ Feasibility studies ✓ Productive design ✓ Study, design and engineering of the prototype ✓ Firmware design ✓ Software design and production ✓ Product tests ✓ Pre-production ✓ Issuing of product and process certifications
Organization and development	✓ IT Governance services ✓ Analyses and studies for the development of new geographical or industrial markets ✓ Organizational design services ✓ Production process services ✓ Communication, promotion and distribution channels strategies
Technological transfer	✓ Proof of concept ✓ Due diligence ✓ Non disclosure agreements' arrangement ✓ Patent licensing agreements' arrangement ✓ Costs for cooperation agreements with research institutes/universities ✓ Patent acquisition (only for spin-offs)

Table A.3: List of excluded industries

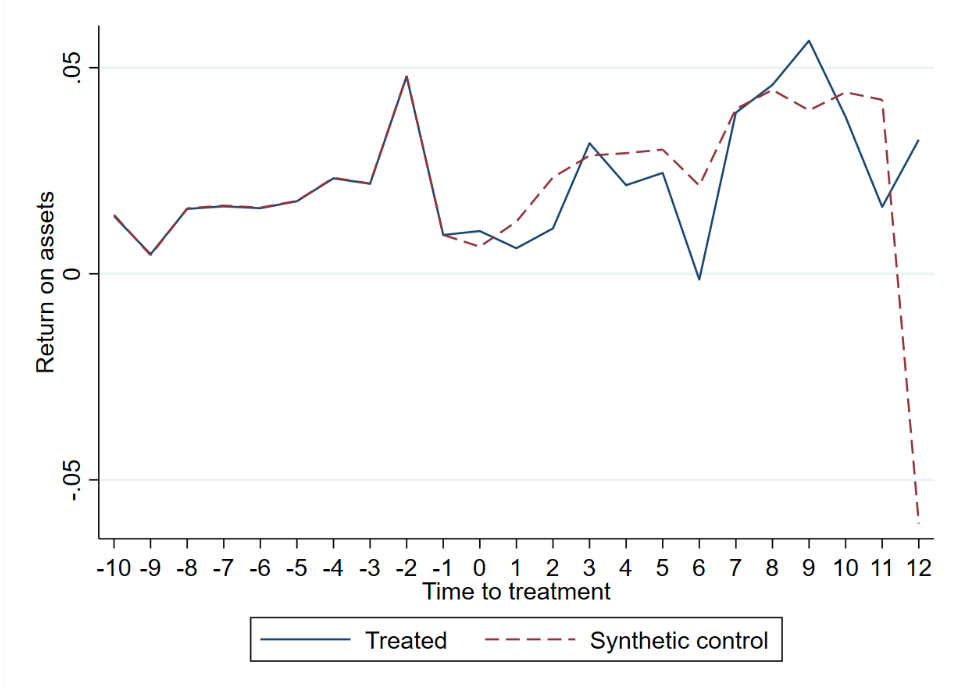
ATECO 2007	Description
01	Crop and animal production, hunting and related service activities
02	Forestry and logging
03	Fishing and aquaculture
05	Mining of coal and lignite
06	Extraction of crude petroleum and natural gas
07	Mining of iron ores
08	Other mining and quarrying
09	Mining support service activities
19	Manufacture of coke and refined petroleum products
64	Financial service activities, except insurance and pension funding
65	Insurance, reinsurance and pension funding, except compulsory social security
66	Activities auxiliary to financial services and insurance activities
84	Public administration and defence; compulsory social security
85	Education
86	Human health activities
87	Residential care activities
88	Social work activities without accommodation
90	Creative, arts and entertainment activities
91	Libraries, archives, museums and other cultural activities
92	Gambling and betting activities
93	Sports activities and amusement and recreation activities
94	Activities of membership organisations
95	Repair of computers and personal and household goods
96	Other personal service activities
97	Activities of households as employers of domestic personnel

Table A.4: Division of regions in geographical area

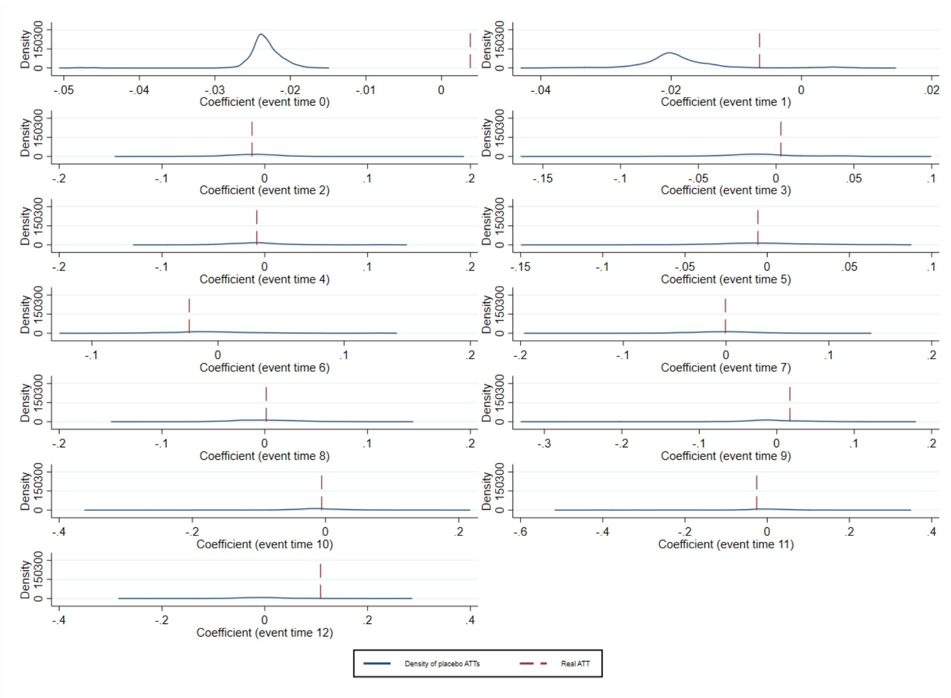
Geographical area	**Regions**
North	Emilia-Romagna
	Friuli-Venezia Giulia
	Liguria
	Lombardia
	Piemonte
	Trentino-Alto Adige/Südtirol
	Valle d'Aosta/Vallée d'Aoste
	Veneto
Center	Lazio
	Marche
	Toscana
	Umbria
South and Islands	Abruzzo
	Basilicata
	Calabria
	Campania
	Molise
	Puglia
	Sardegna
	Sicilia

Appendix B

Figure B.1: Return on assets using last patent's publication before receiving the grant as treatment



(a) Treated and synthetic control separately



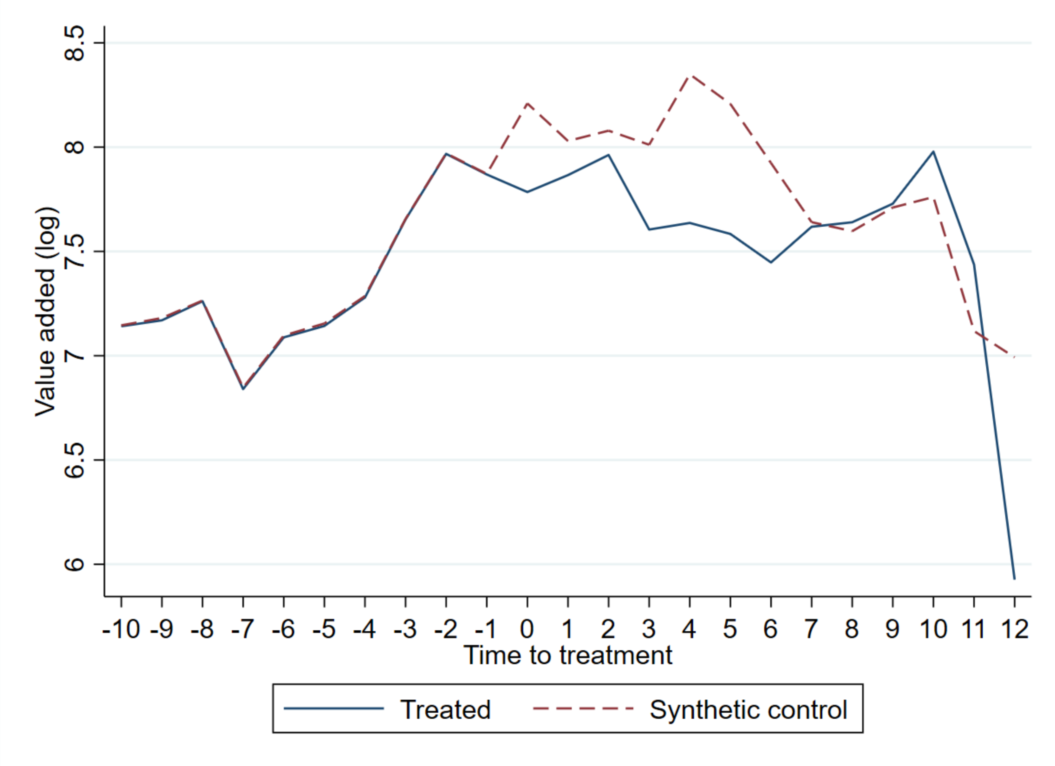
(b) Real ATT and density of placebo ATTs used for permuation

Table B.1: Return on assets using last patent's publication before receiving the grant as treatment

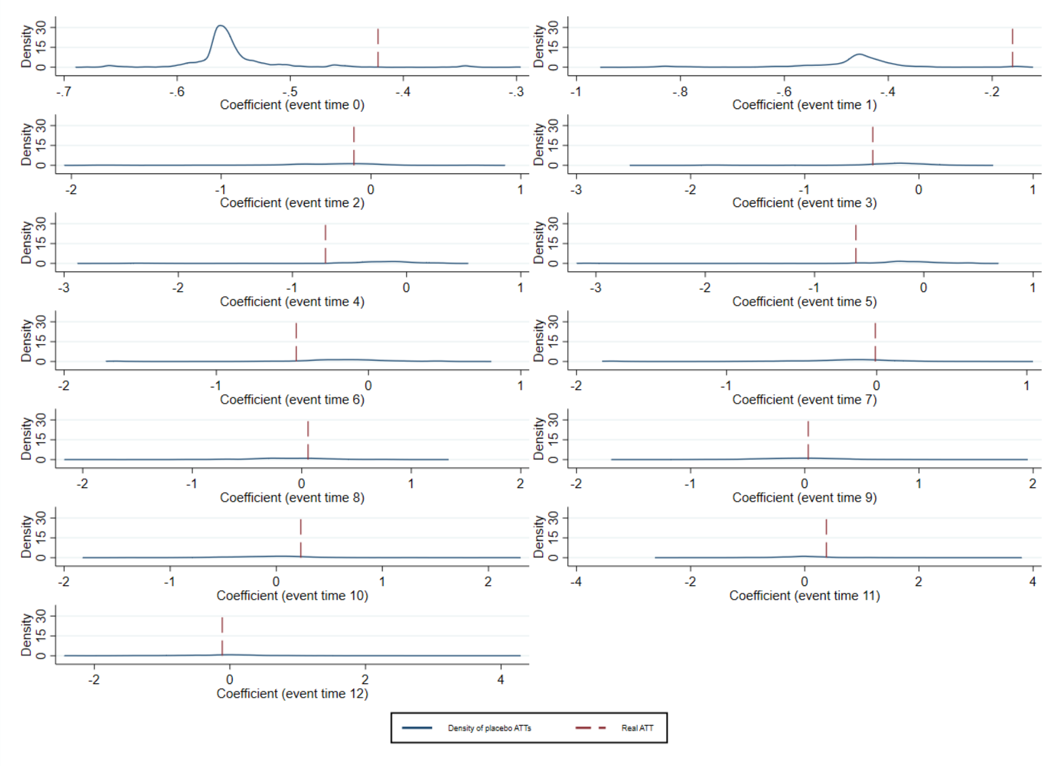
Pre-treatment			
Event time	SDiD (1)		
	Coefficient	P-value	Obs
β_{-18}	-0.0120***	0	4
β_{-17}	-0.0094***	0	6
β_{-16}	-0.0036***	0	16
β_{-15}	-0.0072***	0	27
β_{-14}	-0.0051***	0	34
β_{-13}	-0.0032***	0	43
β_{-12}	-0.0016***	0	51
β_{-11}	-0.0006***	0	58
β_{-10}	-0.0005***	0	64
β_{-9}	0.0002***	0	71
β_{-8}	-0.0001	0.167	79
β_{-7}	-0.0001***	0	84
β_{-6}	-0.0001	0.352	89
β_{-5}	0***	0	98
β_{-4}	0**	0.046	101
β_{-3}	0***	0	109
β_{-2}	-0.0001	0	115
Post-treatment			
Event time	SDiD (1)		
	Coefficient	P-value	Obs
β_{0}	0.0038***	0	118
β_{1}	-0.0064*	0.055	118
β_{2}	-0.0124	0.492	118
β_{3}	0.0030	0.257	108
β_{4}	-0.0078	0.483	104
β_{5}	-0.0057	0.465	89
β_{6}	-0.0228	0.280	70
β_{7}	-0.0007	0.468	48
β_{8}	0.0014	0.480	32
β_{9}	0.0170	0.269	22
β_{10}	-0.0059	0.423	16
β_{11}	-0.0255	0.293	8
β_{12}	0.1087*	0.053	2
Overall ATT			
Average	SDiD (1)		
	Coefficient	P-value	Obs
ϕ	0.0036	0.252	1

Note: We exclude all firms with zero or missing fixed assets or total cost of labor, or with weakly negative or missing value added. The dependent variable is trimmed at the 1st and 99th percentiles of its distribution, and treated firms which get an observation trimmed are dropped. For other treated firms, we interpolate linearly any missing values in the dependent variable and other variables used for the matching.

Figure B.2: Value added using last patent's publication before receiving the grant as treatment



(a) Treated and synthetic control separately



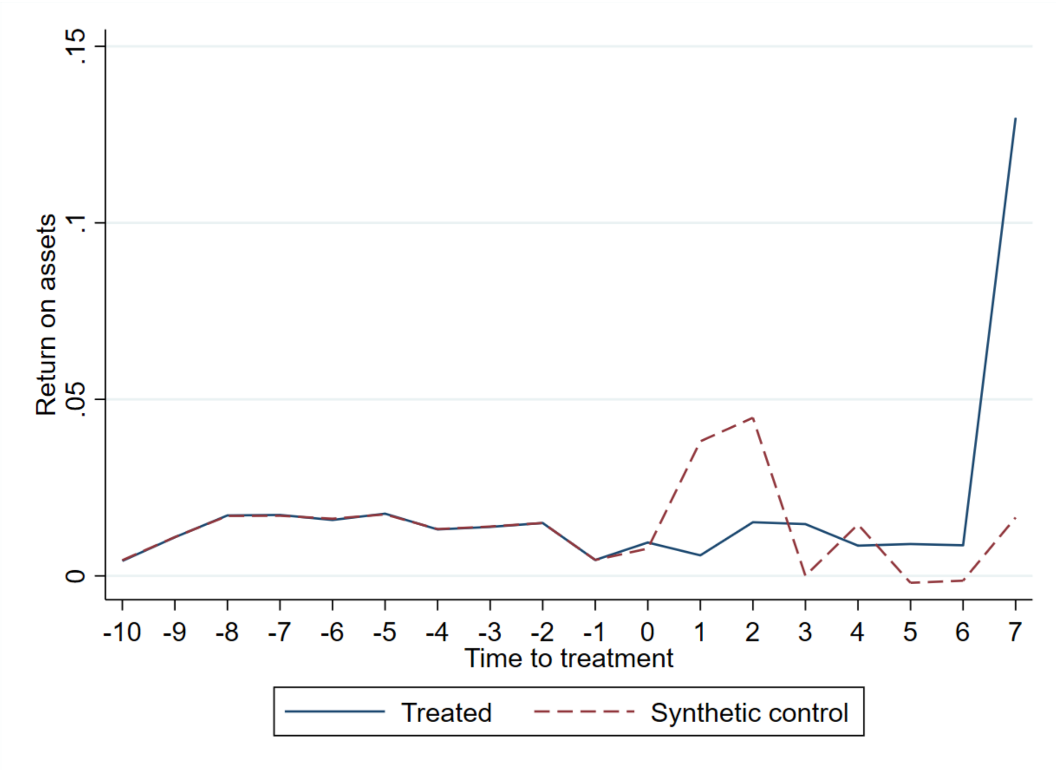
(b) Real ATT and density of placebo ATTs used for permuation

Table B.2: Value added using last patent's publication before receiving the grant as treatment

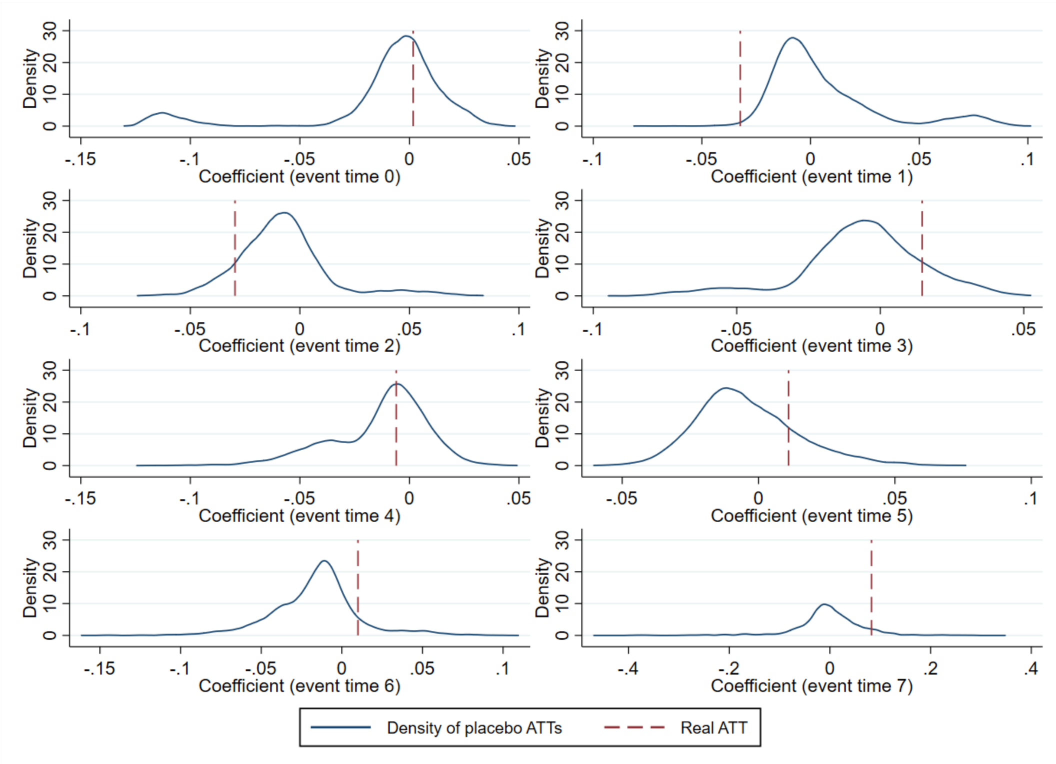
Pre-treatment			
Event time	SDiD (1)		
	Coefficient	P-value	Obs
β_{-18}	-0.0124***	0	4
β_{-17}	0.0788***	0	6
β_{-16}	0.0245***	0	16
β_{-15}	0.0054***	0	25
β_{-14}	-0.0503***	0	31
β_{-13}	-0.0155***	0	41
β_{-12}	0.0189***	0	49
β_{-11}	-0.0124***	0	53
β_{-10}	0.0090***	0	60
β_{-9}	0.0055***	0	66
β_{-8}	0.0170***	0	72
β_{-7}	0.0068***	0	78
β_{-6}	0.0031***	0	82
β_{-5}	-0.0006***	0	90
β_{-4}	0.0056***	0	92
β_{-3}	-0.0002***	0	100
β_{-2}	0.0002***	0	106
Post-treatment			
Event time	SDiD (1)		
	Coefficient	P-value	Obs
β_{0}	-0.4224**	0.019	109
β_{1}	-0.1607**	0.018	109
β_{2}	-0.1139	0.315	109
β_{3}	-0.4040	0.254	101
β_{4}	-0.7102	0.142	97
β_{5}	-0.6215	0.105	79
β_{6}	-0.4744	0.155	62
β_{7}	-0.0092	0.265	45
β_{8}	0.0575	0.334	29
β_{9}	0.0302	0.421	19
β_{10}	0.2314	0.203	16
β_{11}	0.3782	0.178	8
β_{12}	-0.1130	0.445	2
Overall ATT			
Average	SDiD (1)		
	Coefficient	P-value	Obs
ϕ	-0.1794	0.4272	1

Note: We exclude all firms with zero or missing fixed assets or total cost of labor, or with weakly negative or missing value added. The dependent variable is trimmed at the 1st and 99th percentiles of its distribution, and treated firms which get an observation trimmed are dropped. For other treated firms, we interpolate linearly any missing values in the dependent variable and other variables used for the matching.

Figure B.3: Return on assets



(a) Treated and synthetic control separately



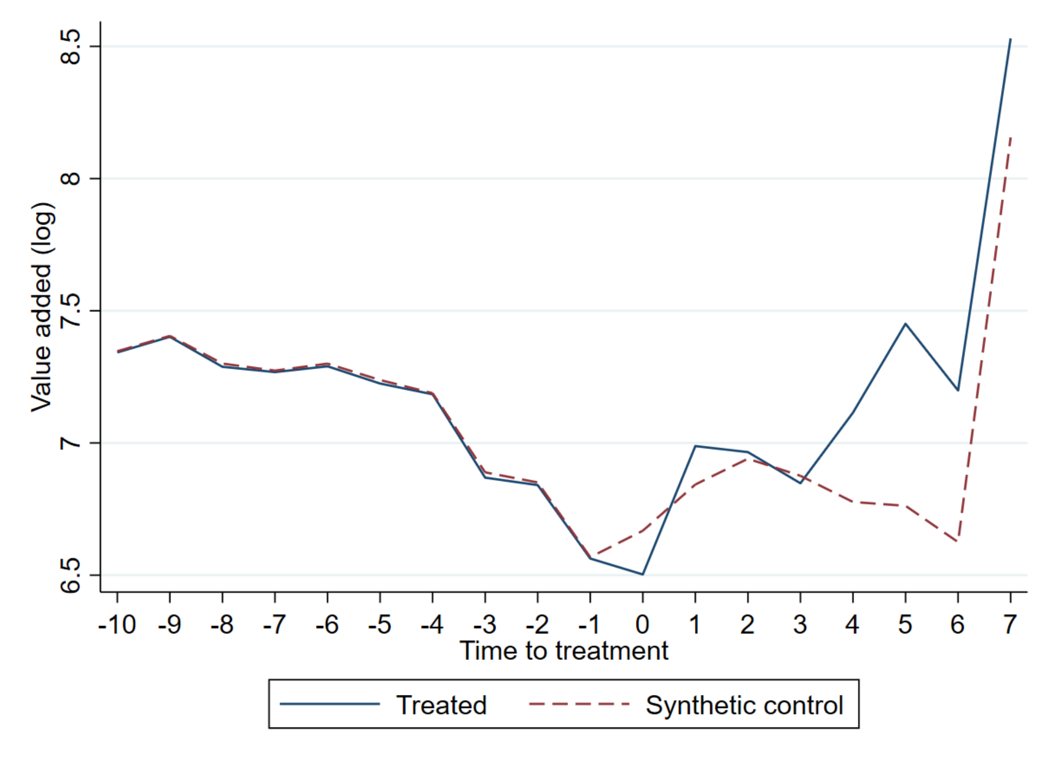
(b) Real ATT and density of placebo ATTs used for permuation

Table B.3: Return on assets

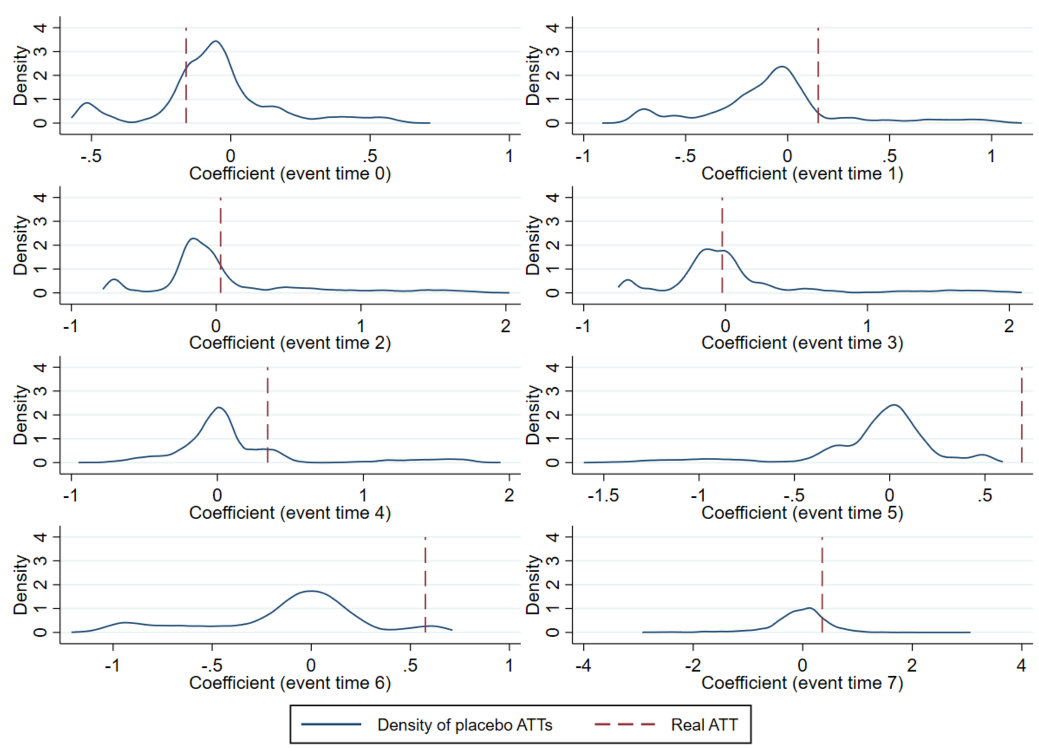
Pre-treatment					
Event time	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
β_{-19}	-0.0020	0.336	3	0.0008	3
β_{-18}	-0.0139***	0.003	13	-0.0222	13
β_{-17}	-0.0135***	0	31	-0.0213	31
β_{-16}	-0.0023***	0.001	66	-0.0067	66
β_{-15}	-0.0008	0.150	90	-0.0028	90
β_{-14}	0.0001	0.216	117	0.0018	117
β_{-13}	0	0.351	124	0.0022	124
β_{-12}	-0.0001	0.335	131	0.0021	131
β_{-11}	-0.0002	0.249	136	0.0013	136
β_{-10}	-0.0002	0.184	140	0.0017	140
β_{-9}	-0.0001	0.334	151	0.0011	151
β_{-8}	0	0.320	163	0.0029	163
β_{-7}	0.0002	0.254	172	0.0029	172
β_{-6}	-0.0004**	0.015	187	0.0007	187
β_{-5}	0.0002*	0.054	196	0.0040	196
β_{-4}	-0.0001*	0.074	211	0.0018	211
β_{-3}	-0.0001*	0.061	221	0.0014	221
β_{-2}	0	0.361	239	0.0002	221
Post-treatment					
Event time	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
β_0	0.0017	0.365	247	0.0106	221
β_1	-0.0323***	0.008	244	-0.0058	218
β_2	-0.0296	0.120	226	0.0014	202
β_3	0.0146	0.144	204	0.0157	183
β_4	-0.0060	0.432	156	0.0146	139
β_5	0.0110	0.202	90	0.0385	81
β_6	0.0100	0.117	49	0.0633	46
β_7	0.0826*	0.075	2	0.0406	1
Overall ATT					
Average	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
ϕ	0.0065	0.153	1	0.0224	1

Note: We exclude all firms with zero or missing fixed assets or total cost of labor, or with weakly negative or missing value added. The dependent variable is trimmed at the 1st and 99th percentiles of its distribution, and treated firms which get an observation trimmed are dropped. For other treated firms, we interpolate linearly any missing values in the dependent variable and other variables used for the matching.

Figure B.4: Value added (log)



(a) Treated and synthetic control separately



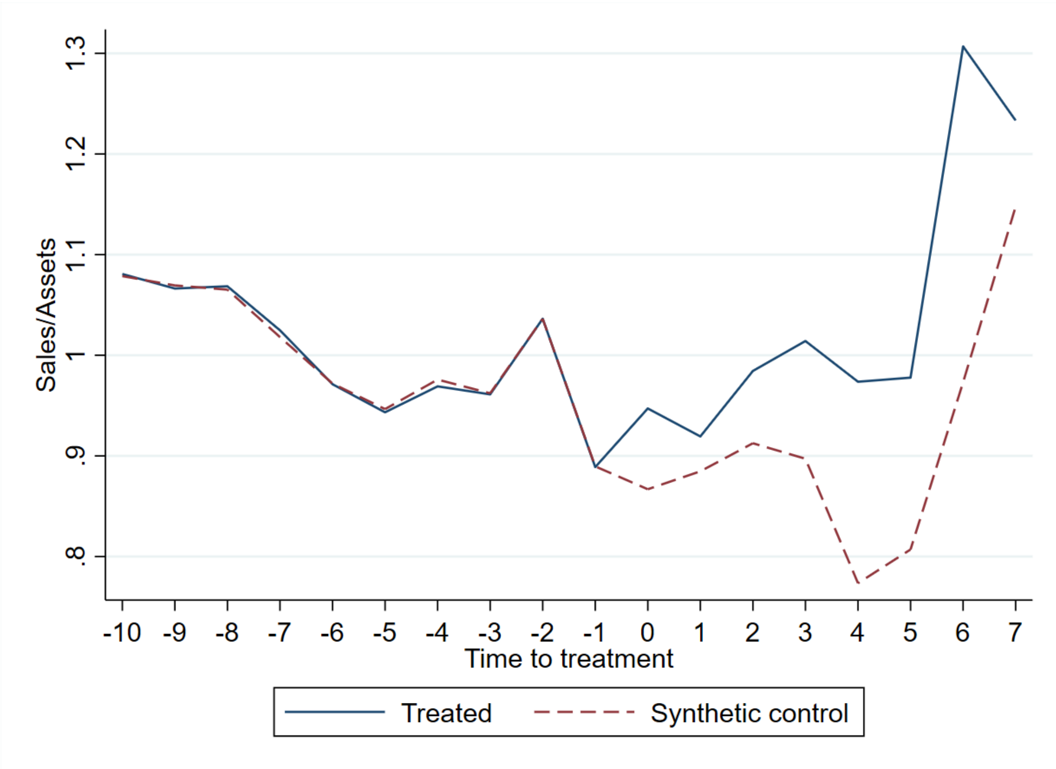
(b) Real ATT and density of placebo ATTs used for permuation

Table B.4: Value added (log)

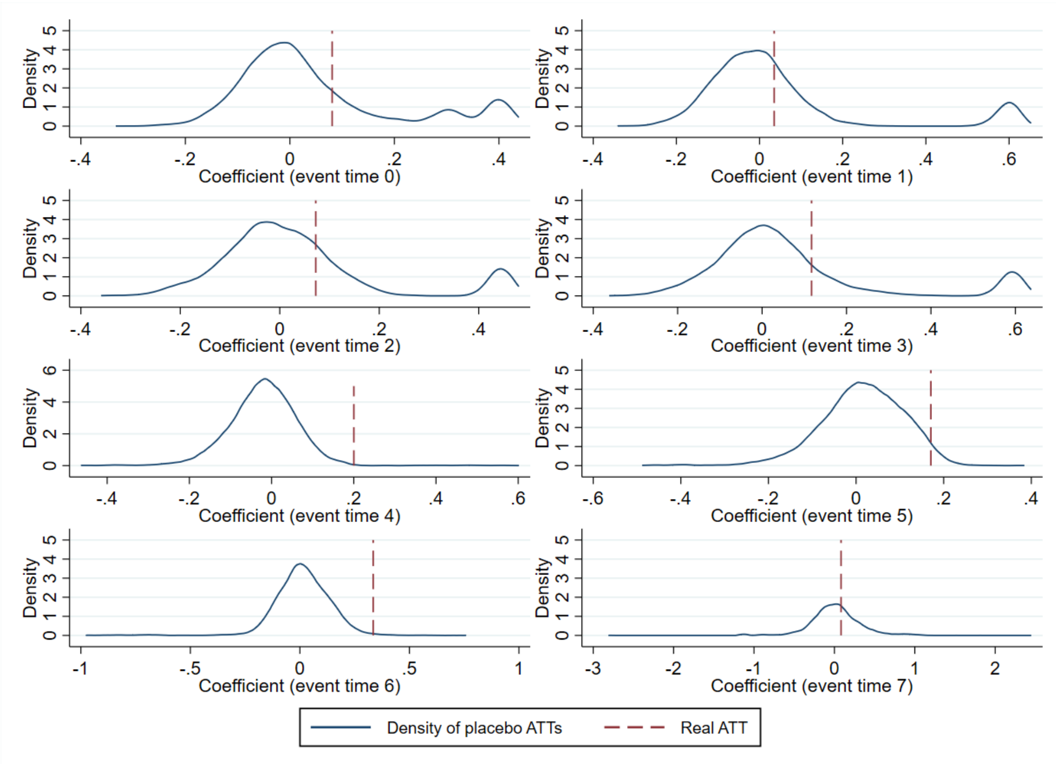
Pre-treatment					
Event time	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
β_{-19}	-0.0140	0.305	3	-0.0996	3
β_{-18}	-0.0259	0.277	12	-0.0409	12
β_{-17}	-0.0299*	0.064	30	-0.0952	30
β_{-16}	-0.0172*	0.072	64	-0.0548	64
β_{-15}	0.0062	0.182	88	-0.0122	88
β_{-14}	0.0091*	0.082	112	0.0201	112
β_{-13}	0.0141**	0.013	120	0.0277	120
β_{-12}	0.0097**	0.025	127	0.0125	127
β_{-11}	0.0065**	0.027	134	0.0096	134
β_{-10}	0.0086*	0.073	138	0.0156	138
β_{-9}	0.0075**	0.038	148	0.0013	148
β_{-8}	-0.0028	0.444	161	-0.0069	161
β_{-7}	0.0028	0.173	171	-0.0036	171
β_{-6}	-0.0036	0.442	184	-0.0178	184
β_{-5}	-0.0055	0.210	192	-0.0146	192
β_{-4}	0.0054**	0.045	210	0.0031	210
β_{-3}	-0.0113**	0.026	222	-0.0108	222
β_{-2}	-0.0019	0.327	241	-0.0047	222
Post-treatment					
Event time	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
β_0	-0.1601	0.226	249	0.0105	222
β_1	0.1502	0.136	249	-0.0349	220
β_2	0.0305	0.301	225	0.0041	200
β_3	-0.0234	0.452	203	0.0611	181
β_4	0.3448	0.166	153	0.1437	135
β_5	0.6931***	0	86	0.1373	76
β_6	0.5762**	0.034	48	0.0854	44
β_7	0.3558	0.160	3	0.3164	2
Overall ATT					
Average	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
ϕ	0.2459	0.119	1	0.0904	1

Note: We exclude all firms with zero or missing fixed assets or total cost of labor, or with weakly negative or missing value added. The dependent variable is trimmed at the 1st and 99th percentiles of its distribution, and treated firms which get an observation trimmed are dropped. For other treated firms, we interpolate linearly any missing values in the dependent variable and other variables used for the matching.

Figure B.5: Sales/Assets



(a) Treated and synthetic control separately



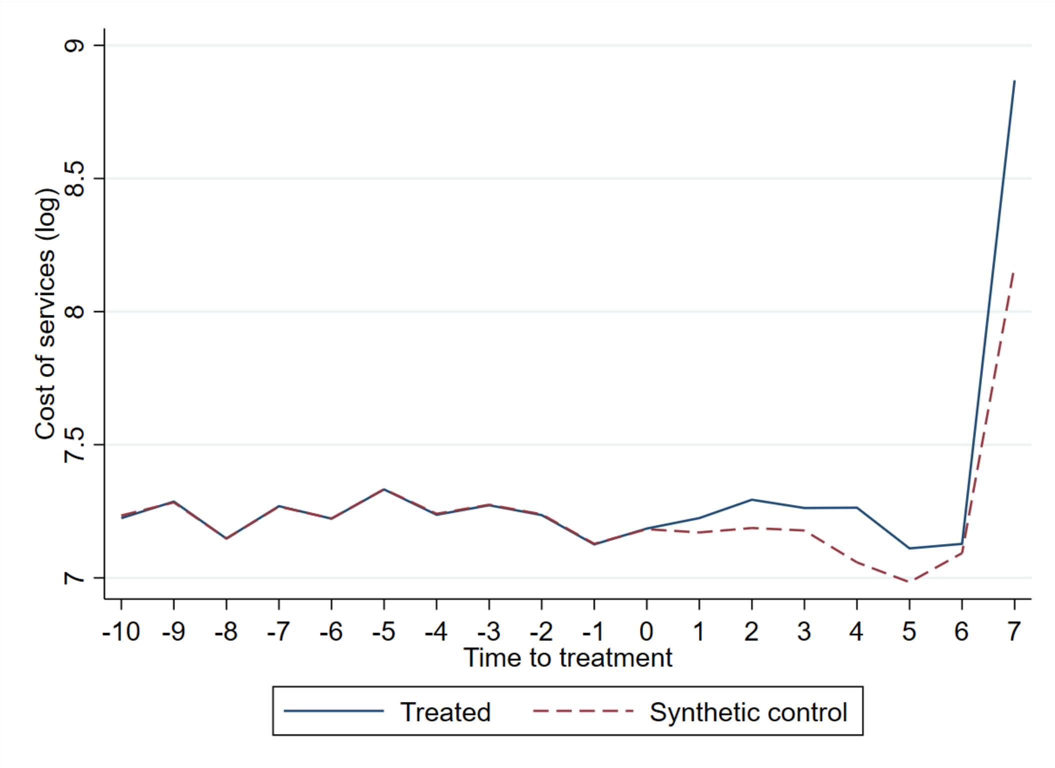
(b) Real ATT and density of placebo ATTs used for permuation

Table B.5: Sales/Assets

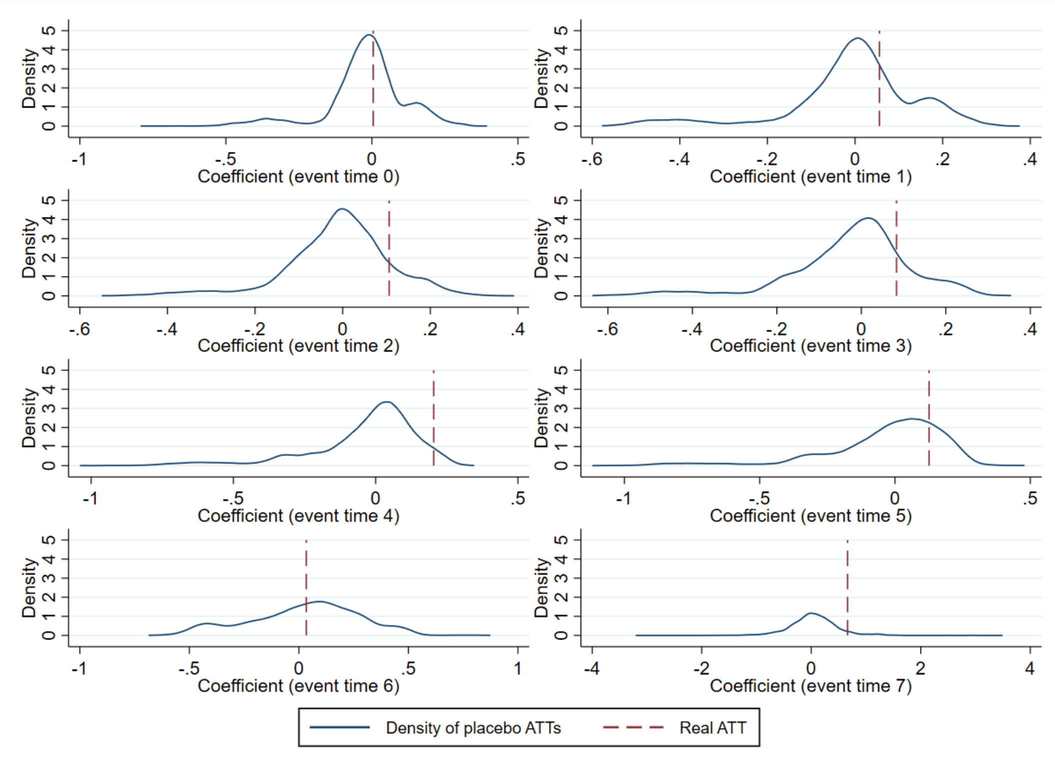
Pre-treatment					
Event time	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
β_{-19}	-0.0029	0.444	3	-0.0651	3
β_{-18}	-0.0028	0.433	13	-0.0710	13
β_{-17}	0.0011	0.462	32	-0.0301	32
β_{-16}	-0.0134*	0.085	69	-0.0598	69
β_{-15}	-0.0054	0.118	94	-0.0257	94
β_{-14}	-0.0005	0.365	122	-0.0042	122
β_{-13}	-0.0073**	0.019	130	-0.0201	130
β_{-12}	0	0.261	138	-0.0108	138
β_{-11}	-0.0068**	0.036	145	-0.0144	145
β_{-10}	-0.0003	0.428	148	-0.0063	148
β_{-9}	-0.0044	0.121	159	-0.0122	159
β_{-8}	0.0051	0.251	171	0.0037	171
β_{-7}	0.0082**	0.033	179	0.0103	179
β_{-6}	0.0009	0.483	192	0.0028	192
β_{-5}	-0.0003	0.473	201	0.0018	201
β_{-4}	-0.0036**	0.044	218	-0.0042	218
β_{-3}	0.0013	0.301	229	0.0083	229
β_{-2}	0.0011	0.181	247	0.0064	229
Post-treatment					
Event time	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
β_{0}	0.0810	0.269	253	0.0295	229
β_{1}	0.0353	0.328	250	0.0287	226
β_{2}	0.0724	0.256	230	0.0408	207
β_{3}	0.1172	0.212	208	0.0901	188
β_{4}	0.2002***	0.006	155	0.1026	139
β_{5}	0.1708**	0.033	91	0.1185	82
β_{6}	0.3346***	0.007	51	0.0562	48
β_{7}	0.0829	0.374	3	0.1083	2
Overall ATT					
Average	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
ϕ	0.1368	0.108	1	0.0718	1

Note: We exclude all firms with zero or missing fixed assets or total cost of labor, or with weakly negative or missing value added. The dependent variable is trimmed at the 1st and 99th percentiles of its distribution, and treated firms which get an observation trimmed are dropped. For other treated firms, we interpolate linearly any missing values in the dependent variable and other variables used for the matching.

Figure B.6: Cost of services (log)



(a) Treated and synthetic control separately



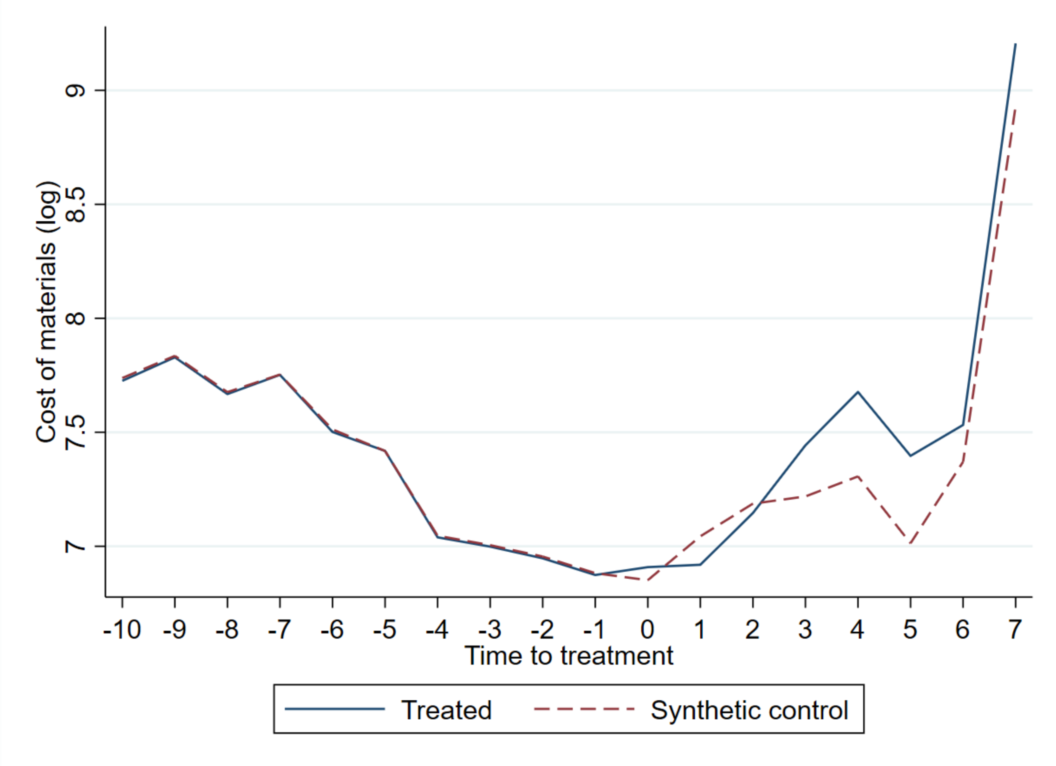
(b) Real ATT and density of placebo ATTs used for permuation

Table B.6: Cost of services (log)

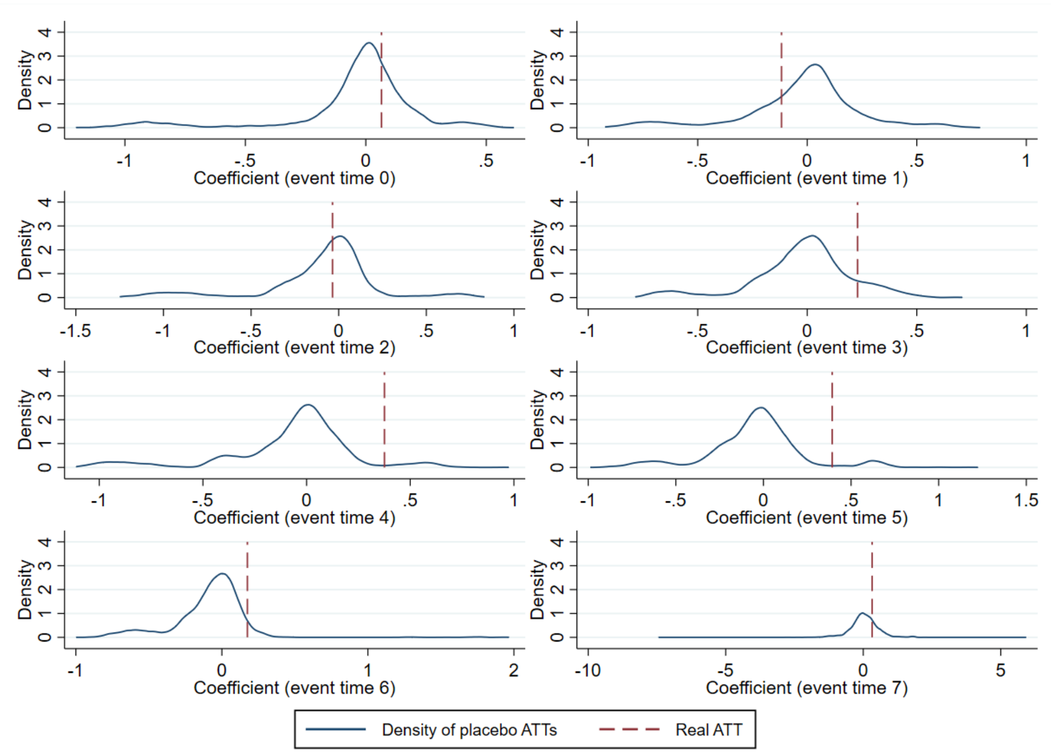
Pre-treatment					
Event time	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
β_{-19}	-0.0326	0.228	3	0.0259	3
β_{-18}	-0.0008	0.339	13	0.0346	13
β_{-17}	0.0201**	0.018	31	0.0427	31
β_{-16}	-0.0020	0.413	66	-0.0080	66
β_{-15}	-0.0001	0.376	92	0.0055	92
β_{-14}	0.0011	0.351	119	0.0097	119
β_{-13}	-0.0045	0.336	126	0.0028	126
β_{-12}	0.0036	0.120	134	0.0028	134
β_{-11}	-0.0033	0.319	141	-0.0029	141
β_{-10}	-0.0085*	0.066	144	-0.0078	144
β_{-9}	0.0059	0.113	155	0.0064	155
β_{-8}	0.0040	0.220	169	0.0022	169
β_{-7}	0.0043	0.141	179	0.0029	179
β_{-6}	0.0012	0.491	194	0.0029	194
β_{-5}	0.0012	0.372	203	0.0022	203
β_{-4}	-0.0012	0.317	221	0.0002	221
β_{-3}	0.0005	0.356	233	0.0081	233
β_{-2}	-0.0006	0.323	252	0.0083	233
Post-treatment					
Event time	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
β_0	0.0045	0.422	260	0.0165	233
β_1	0.0556	0.291	257	0.0270	230
β_2	0.1061	0.139	234	0.0343	209
β_3	0.0833	0.181	211	0.0670	189
β_4	0.2039**	0.044	159	0.1339	141
β_5	0.1261	0.231	92	0.1534	82
β_6	0.0336	0.466	52	0.0957	48
β_7	0.6642*	0.064	3	0.8368	2
Overall ATT					
Average	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
ϕ	0.1597*	0.079	1	0.1706	1

Note: We exclude all firms with zero or missing fixed assets or total cost of labor, or with weakly negative or missing value added. The dependent variable is trimmed at the 1st and 99th percentiles of its distribution, and treated firms which get an observation trimmed are dropped. For other treated firms, we interpolate linearly any missing values in the dependent variable and other variables used for the matching.

Figure B.7: Cost of materials (log)



(a) Treated and synthetic control separately



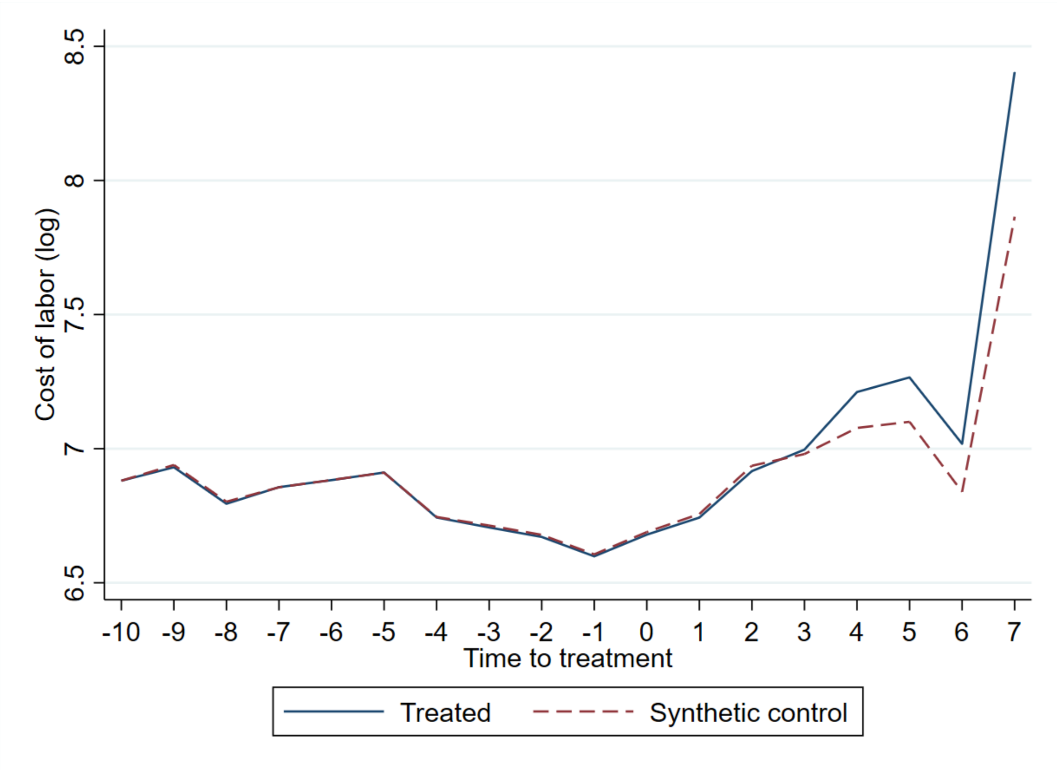
(b) Real ATT and density of placebo ATTs used for permuation

Table B.7: Cost of materials (log)

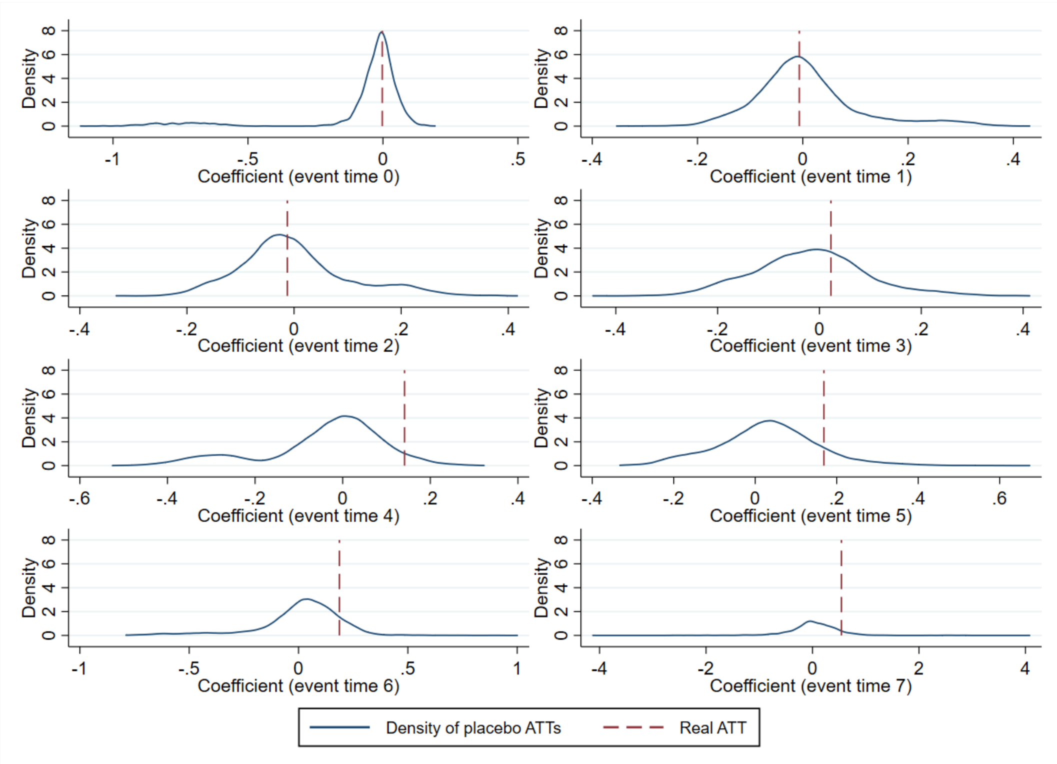
Pre-treatment					
Event time	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
β_{-19}	0.0527	0.208	3	0.1459	3
β_{-18}	0.0103	0.320	13	0.0332	13
β_{-17}	0.0405*	0.069	32	0.0593	32
β_{-16}	-0.0010	0.445	67	0.0126	67
β_{-15}	0.0125**	0.016	92	0.0390	92
β_{-14}	0.0268***	0.001	119	0.0530	119
β_{-13}	-0.0073	0.215	127	-0.0010	127
β_{-12}	0.0129**	0.017	135	0.0219	135
β_{-11}	0.0069*	0.079	142	0.0222	142
β_{-10}	0.0013	0.263	146	0.0162	146
β_{-9}	0.0038	0.169	155	0.0152	155
β_{-8}	0.0023	0.207	169	0.0104	169
β_{-7}	0.0114**	0.038	179	0.0183	179
β_{-6}	-0.0008	0.402	195	-0.0005	195
β_{-5}	0.0094**	0.014	203	0.0187	203
β_{-4}	0.0016	0.124	221	0.0107	221
β_{-3}	0.0004	0.302	233	0.0073	233
β_{-2}	0.0005	0.394	252	-0.0118	233
Post-treatment					
Event time	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
β_{0}	0.0652	0.294	259	0.0151	233
β_{1}	-0.1175	0.262	254	0.0541	228
β_{2}	-0.0352	0.490	232	0.1044	208
β_{3}	0.2299	0.114	207	0.1537	186
β_{4}	0.3756**	0.047	154	0.1941	137
β_{5}	0.3925*	0.055	90	0.2645	80
β_{6}	0.148**	0.047	50	0.2826	46
β_{7}	0.3239	0.241	3	0.1704	2
Overall ATT					
Average	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
ϕ	0.1762*	0.074	1	0.1549	1

Note: We exclude all firms with zero or missing fixed assets or total cost of labor, or with weakly negative or missing value added. The dependent variable is trimmed at the 1st and 99th percentiles of its distribution, and treated firms which get an observation trimmed are dropped. For other treated firms, we interpolate linearly any missing values in the dependent variable and other variables used for the matching. We consider as treatment year the one in which

Figure B.8: Cost of labor (log)



(a) Treated and synthetic control separately



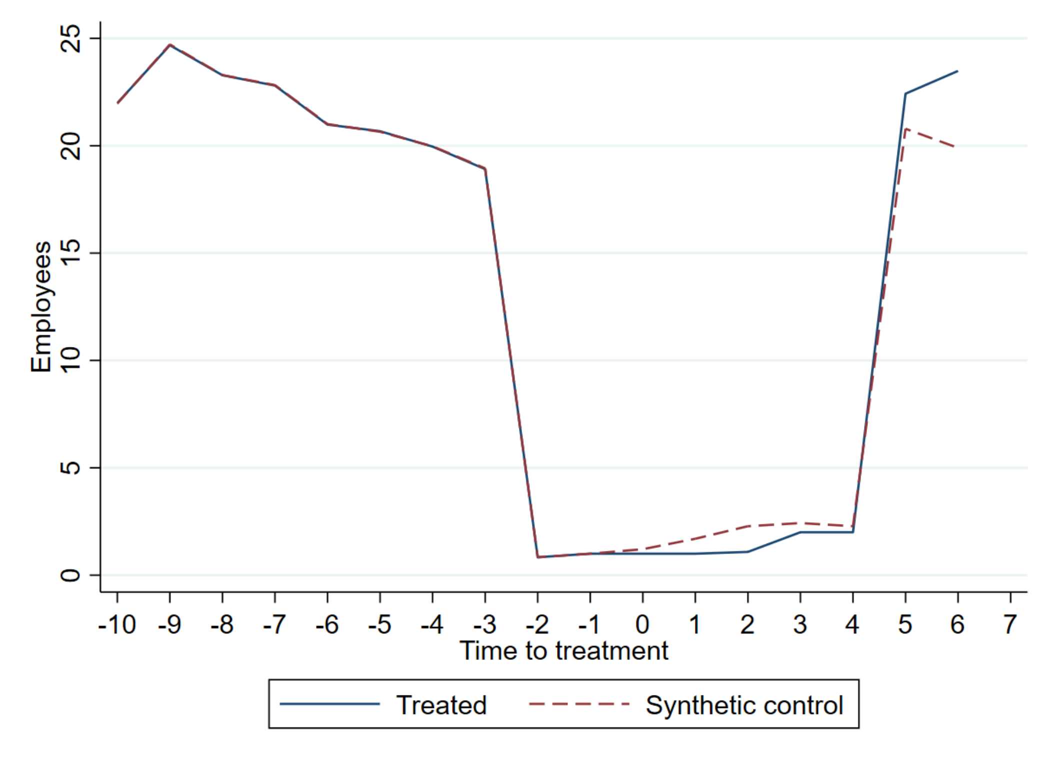
(b) Real ATT and density of placebo ATTs used for permuation

Table B.8: Cost of labor (log)

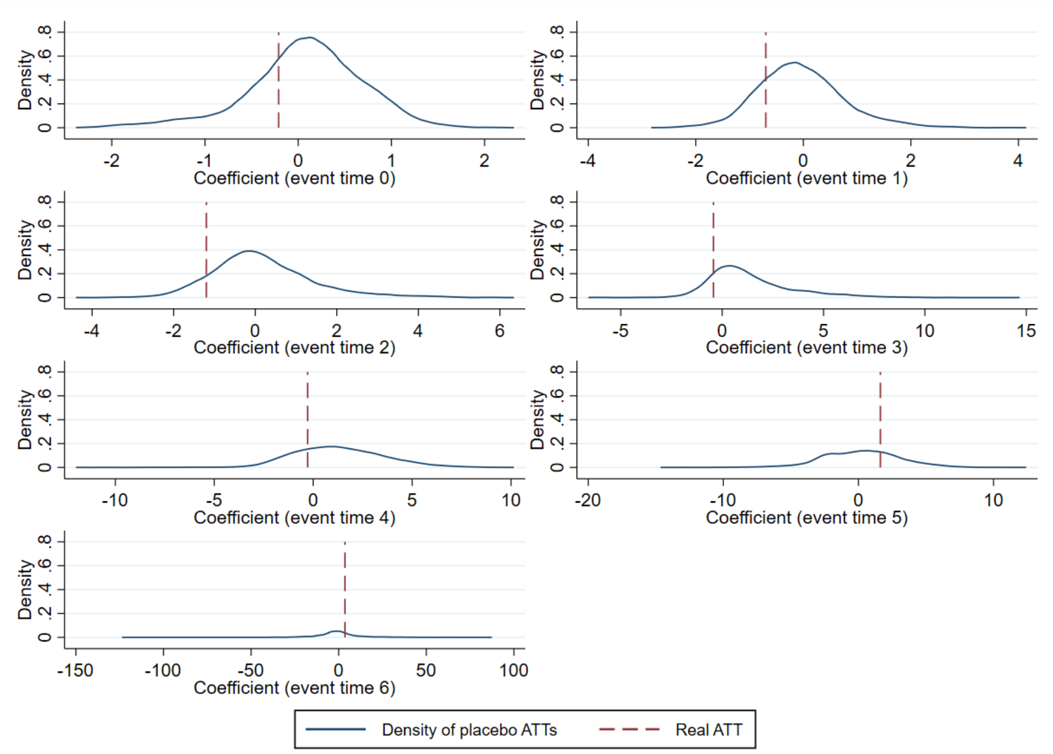
Pre-treatment					
Event time	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
β_{-19}	0.0330	0.194	3	0.0034	3
β_{-18}	0.0071	0.285	13	-0.0099	13
β_{-17}	0.0107	0.160	31	0.0165	31
β_{-16}	0.0122**	0.022	66	0.0137	66
β_{-15}	0.0178***	0	91	0.0234	91
β_{-14}	0.0109***	0.004	117	0.0288	117
β_{-13}	0.0107***	0.001	125	0.0282	125
β_{-12}	0.0142***	0	133	0.0274	133
β_{-11}	0.0096***	0	140	0.0259	140
β_{-10}	0.0098***	0	144	0.0227	144
β_{-9}	-0.0002	0.246	155	0.0092	155
β_{-8}	-0.0013	0.448	169	0.0064	169
β_{-7}	0.0060***	0.008	179	0.0153	179
β_{-6}	0.0064***	0.002	194	0.0150	194
β_{-5}	0.0084***	0.002	202	0.0197	202
β_{-4}	0.0073***	0.003	220	0.0203	220
β_{-3}	0.0008	0.126	232	0.0075	232
β_{-2}	-0.0006	0.405	251	0.0082	232
Post-treatment					
Event time	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
β_{0}	-0.0024	0.400	259	-0.0186	232
β_{1}	-0.0066	0.495	256	-0.0290	229
β_{2}	-0.0125	0.491	233	0.0141	208
β_{3}	0.0226	0.338	209	0.0414	187
β_{4}	0.1413*	0.054	157	0.0317	139
β_{5}	0.1687	0.117	89	0.1218	79
β_{6}	0.1870	0.127	50	0.1447	46
β_{7}	0.5440*	0.093	3	0.5550	2
Overall ATT					
Average	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
ϕ	0.1303*	0.064	1	0.1076	1

Note: We exclude all firms with zero or missing fixed assets or total cost of labor, or with weakly negative or missing value added. The dependent variable is trimmed at the 1st and 99th percentiles of its distribution, and treated firms which get an observation trimmed are dropped. For other treated firms, we interpolate linearly any missing values in the dependent variable and other variables used for the matching.

Figure B.9: Number of employees



(a) Treated and synthetic control separately



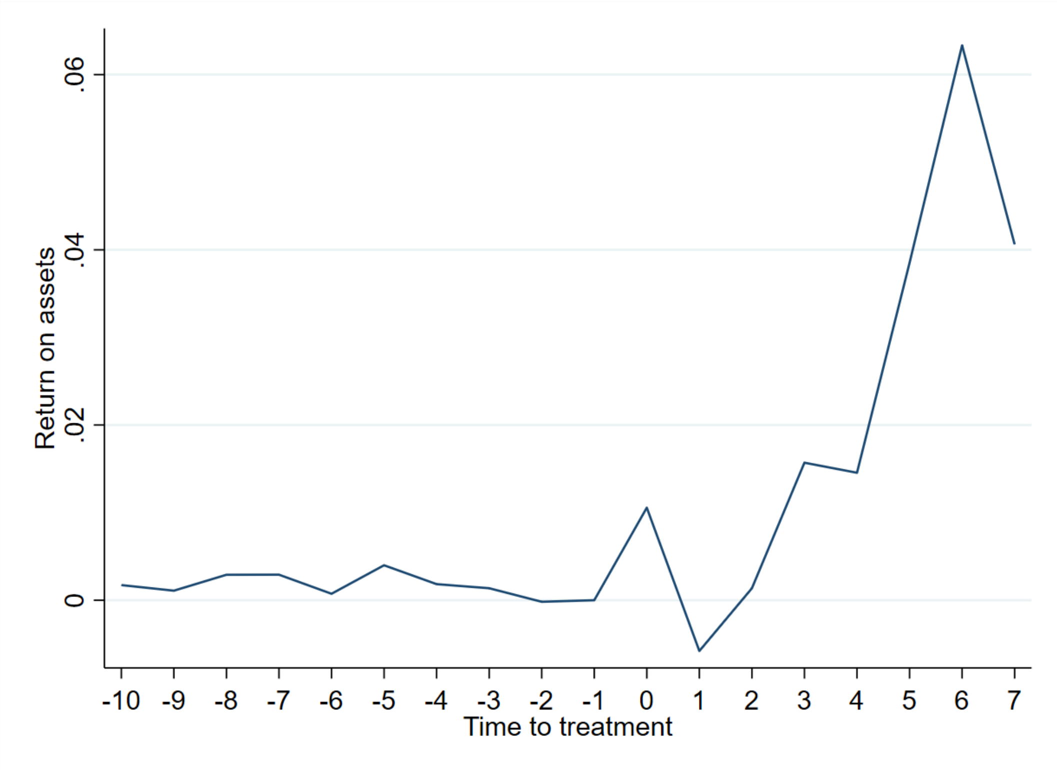
(b) Real ATT and density of placebo ATTs used for permuation

Table B.9: Number of employees

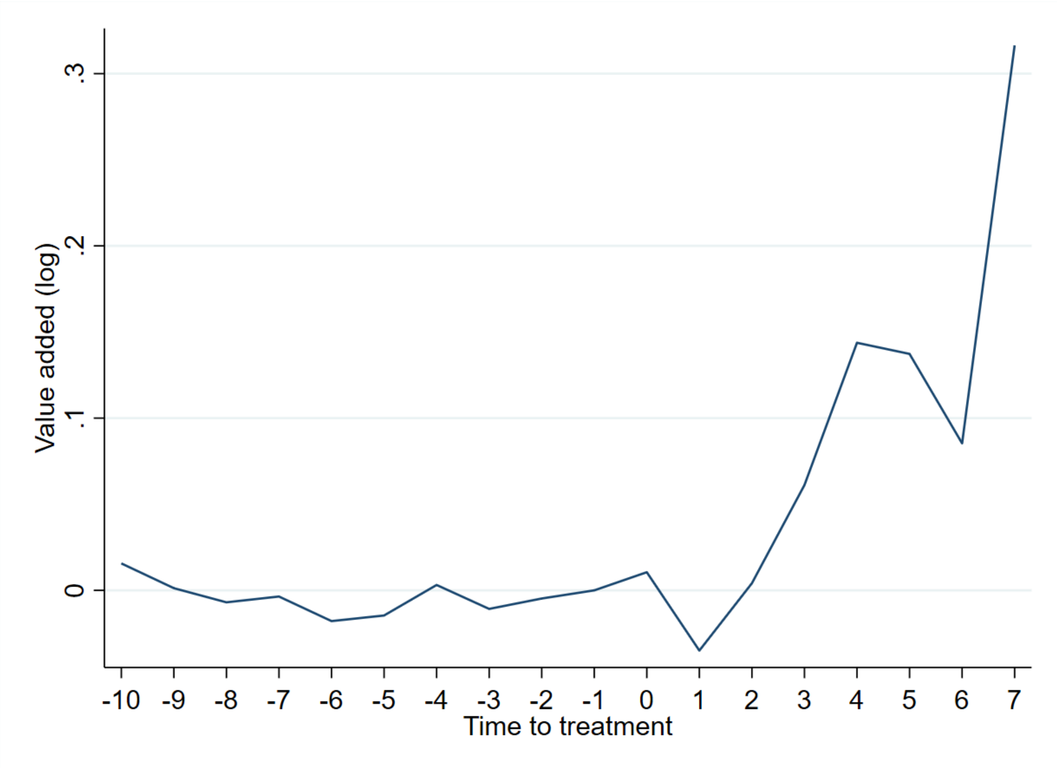
Event time	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
Pre-treatment					
β_{-13}	-1.1568**	0.026	4	-0.9660	4
β_{-12}	0.0008	0.477	14	-0.0879	14
β_{-11}	-0.0086	0.486	44	0.1933	44
β_{-10}	0.0460	0.235	92	0.0534	92
β_{-9}	-0.0031	0.397	125	0.1852	125
β_{-8}	-0.0075	0.223	170	0.1482	170
β_{-7}	-0.0185	0.150	184	0.0932	184
β_{-6}	-0.0016	0.295	200	0.1312	200
β_{-5}	0.0532	0.114	207	0.2707	207
β_{-4}	0.0199	0.478	223	0.2063	223
β_{-3}	-0.0126	0.110	236	0.0720	236
β_{-2}	0	0.328	254	0.0350	236
Post-treatment					
Event time	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
β_0	-0.2100	0.272	260	-0.2665	236
β_1	-0.6967	0.202	245	0.0741	222
β_2	-1.1966	0.111	221	0.8784	200
β_3	-0.4266	0.154	167	1.5750	149
β_4	-0.2780	0.258	93	2.8678	85
β_5	1.6240	0.310	54	0.9919	50
β_6	3.6174	0.275	3	39.4276	2
Overall ATT					
Average	SDiD (1)			Backdating (2)	
	Coefficient	P-value	Obs	Coefficient	Obs
ϕ	0.3474	0.492	1	6.5069	1

Note: We exclude all firms with zero or missing fixed assets or total cost of labor, or with weakly negative or missing value added. The dependent variable is trimmed at the 1st and 99th percentiles of its distribution, and treated firms which get an observation trimmed are dropped. For other treated firms, we interpolate linearly any missing values in the dependent variable and other variables used for the matching.

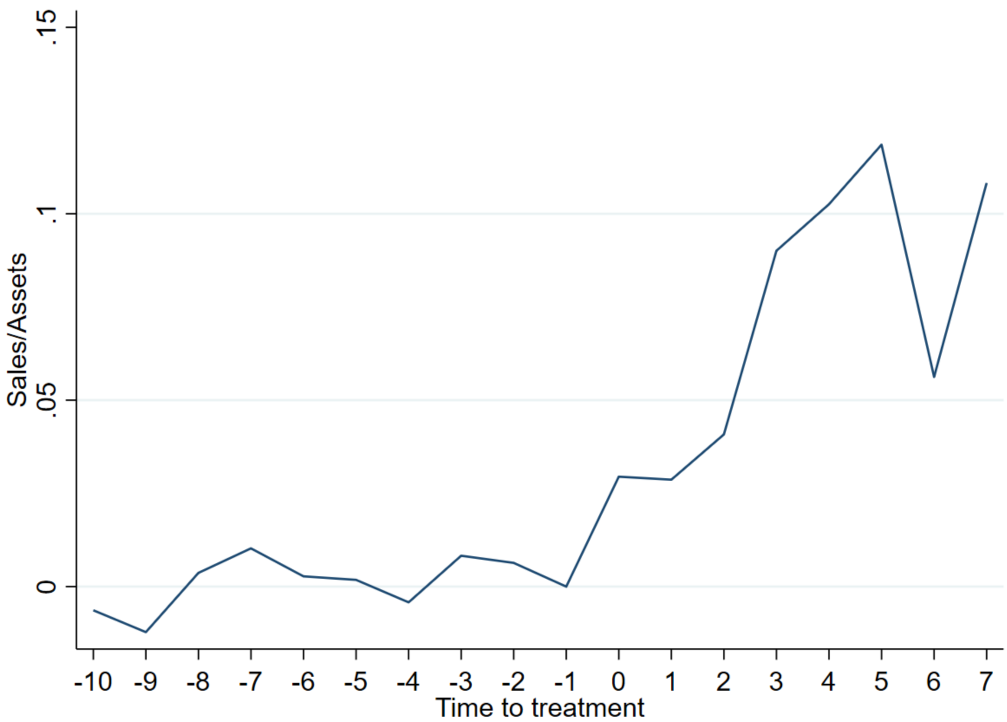
Figure B.10: Backdating



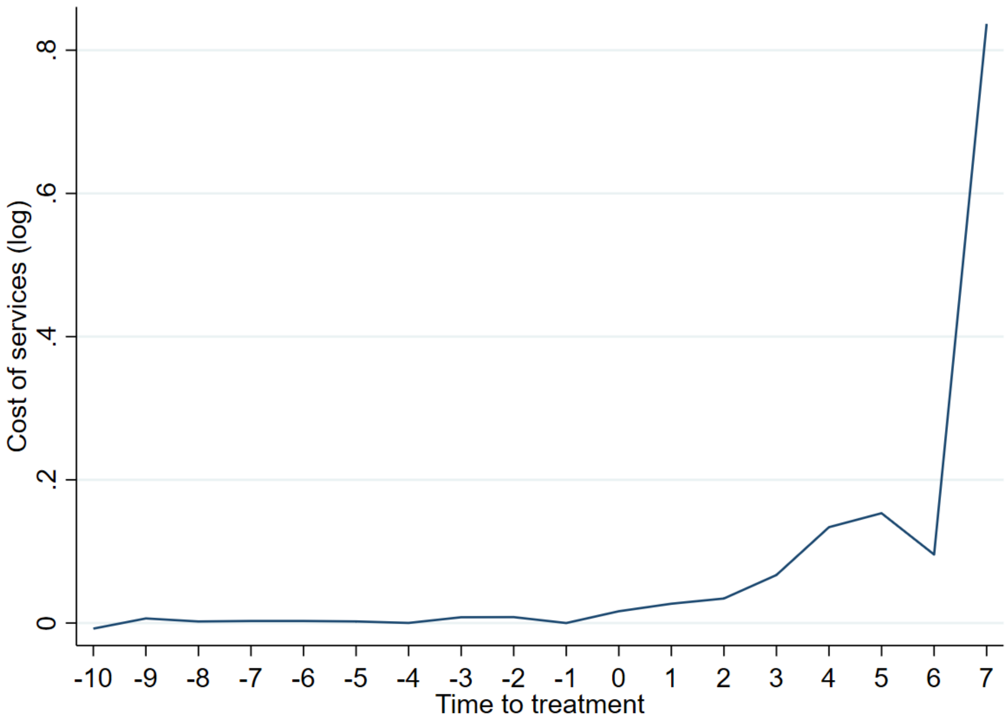
(a) Retun on assets



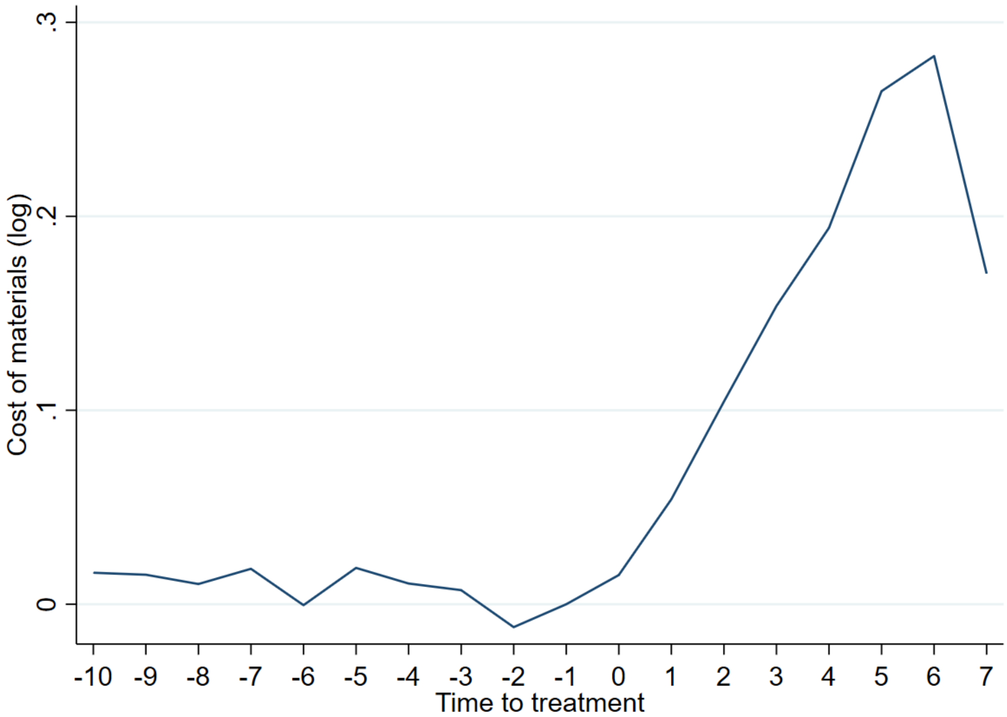
(b) Value added (log)



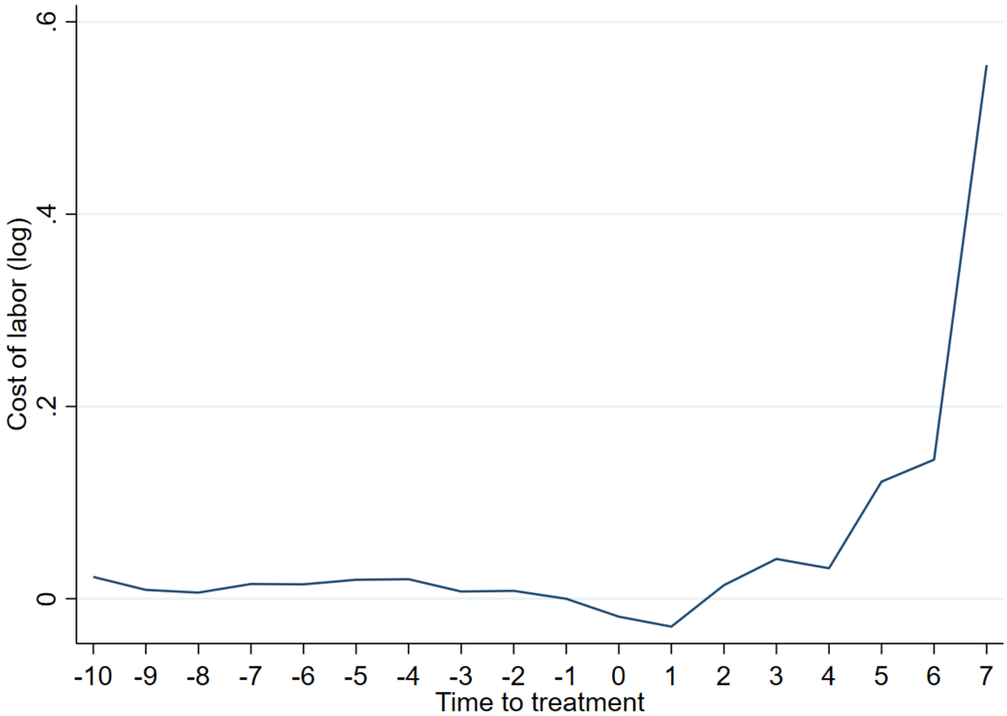
(c) Sales/Assets



(d) Cost of services (log)



(e) Cost of materials (log)



(f) Cost of labor (log)

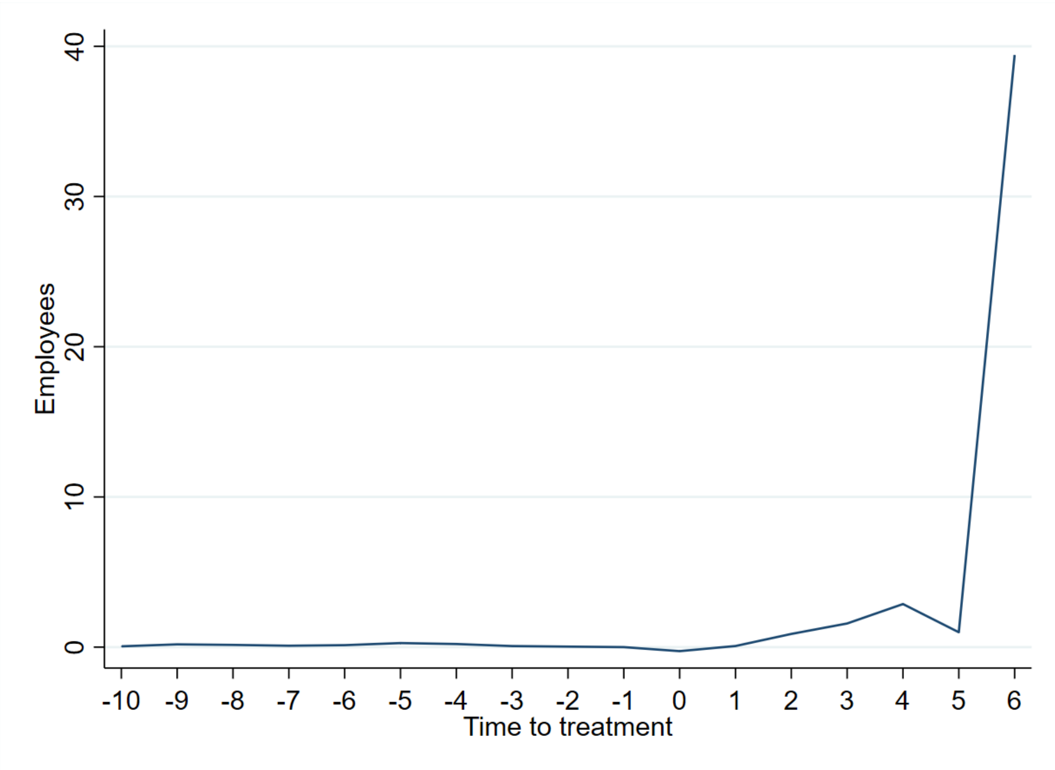


Figure B.10: Number of employees

Appendix C

Assume the following Cobb-Douglas production function:

$$Y_i = e^{\omega_i} K_i^{\alpha} L_i^{\beta} \tag{C.1}$$

where Y_i is value added, K_i is capital, L_i is labor, α and β are the respective inputs' output elasticity coefficients, and e^{ω_i} is an Hick-neutral productivity term (TFP) for firm i. Taking logarithms, we get:

$$y_i = \omega_i + \alpha k_i + \beta l_i \tag{C.2}$$

where lowercase letters represent logarithmic values and ω_i is observed by the firm but not the econometrician and has to be estimated. Running a simple OLS would lead us to incur in both endogeneity and selection problems because firms' input choices and entry decisions depend on their level of productivity ω_i. Using state-of-the-art control function methodologies[17], we would be able to solve such problems. However, with the data available, we would be able to aggregate firms at best at the two-digit industry level, leading to equal estimates of the coefficients α and β for all firms operating in the same sector. In this way, given that we match treated firms with companies in the donor pool which operate in the same 2-digit industry, this would lead us to compare a rescaled version of the difference between value added and inputs' contributions rather than true differences in productivity. Think, for example, of two firms, A and B, which operate in the same 2-digit industry. Their TFPs would be estimated as:

$$\hat{\omega}_A = y_A - \hat{\alpha} k_A - \hat{\beta} l_A - \hat{\epsilon}_A \tag{C.3}$$

$$\hat{\omega}_B = y_B - \hat{\alpha} k_B - \hat{\beta} l_B - \hat{\epsilon}_B \tag{C.4}$$

where ϵ_A and ϵ_B are the error terms and inputs' elasticity coefficients α and β are the same for firm A and B. We would then be assuming that all treated firms have the exact same technology with respect to those in the donor pool, making our results depend on a very strong assumption.

[17]See, for example, Olley and Pakes (1996), Levinsohn and Petrin (2003), or Ackerberg et al. (2015).

Summary

This study focuses on investigating the economic returns and potential barriers to innovation faced by small and medium-sized innovative enterprises, specifically examining the impact of the Italian public program *Brevetti+* on the performance of treated firms. The program aimed to provide financial support to SMEs for acquiring specialized services to improve existing patents.

To address the challenge of estimating the causal effect of the policy on firms' performance, we adopt a Synthetic Difference-in-Differences (SDiD) methodology with staggered treatment and aggregate the estimated coefficients using a measure of the synthetic controls' goodness of fit. This approach allows for a comparison between treated firms and a weighted average of eligible companies that closely resemble them in terms of industry, geographical area, and relevant variables. It allows us to account for concerns related to selection bias in patenting and treatment, establish parallel pre-trends in the dependent variables, and mitigate possible issues related to heterogeneity bias.

Our results reveal that firms receiving financial assistance under the *Brevetti+* program initially perform below comparable innovative companies after filing their latest patent. However, this trend is reversed once they receive the grants, as they manage to enhance their long-run performance in terms of return on assets, value added, and sales/assets ratio. Specifically, we observe a noticeable gap of 0.65%, 24.59%, and 13.68%, respectively, between the treated firms and their synthetic controls.

We also explore the mechanisms through which the additional funds may have assisted SMEs in developing their patents. We find that, in the short term, there is an increase only in service expenses, as the funds were specifically allocated for such purposes. However, in the long run, all three cost components—services, materials, and labor—experience significant increases. These increases can be attributed to improved input quality resulting from technological change and increased productivity following technology adoption.

Our findings underscore the challenges faced by SMEs in acquiring the complementary assets necessary for implementing new technology. The provision of financial aid for the acquisition of specialized services has proven effective, enabling Italian SMEs to significantly improve their performance after participating in the *Brevetti+* program. This policy tool holds promise for firms that have already patented, as it helps them fully exploit their new technologies. The study emphasizes the relevance of such initiatives for policymakers, as it highlights the potential benefits of targeted funding in enhancing innovation outcomes for SMEs.

In conclusion, we provide evidence of the positive impact of the *Brevetti+* program on the performance of small and medium-sized innovative enterprises in Italy. Our findings suggest that financial support and access to specialized services play a crucial role in enabling SMEs to fully capitalize on their innovative efforts. The study's results contribute to a better understanding of the challenges faced by SMEs in the innovation process and highlight the importance of tailored policies to support their growth and competitiveness in the marketplace.