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Small grant subsidy application effects on productivity improvement: evidence from Japanese SMEs

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Abstract This study examines the effects of a small grants subsidy on small- and medium-sized enterprises' (SMEs) productivity. Using rich Japanese firm-level data, we analyze the effects of both applying for and receiving subsidies. We employ a sharp regression discontinuity design for the receipt effects and a difference-in-differences (DID) design for the application effects. The result shows that there are no statistically significant changes in likelihood after receiving the subsidy. By contrast, applicants experienced higher productivity and sales growth than non-applicants. These positive effects are most obvious in post-entry firms whose operating years are 6–10 years in the service sector. These results are robustly confirmed using a DID model with propensity score matching, controlling for both pre-intervention levels and trends in the outcome. Our findings imply that the subsidy application process with external support fosters entrepreneurship for firms that have survived the first 5 years after start-up, leading to their growth.

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Plain English Summary Subsidy application with external support increases young SMEs' productivity more significantly than the receipt of small grants. We show that receiving a small subsidy does not have significant outcomes for SMEs; however, applying for one can increase SMEs' sales and productivity, using the Business Sustainable Subsidy in Japan as a case study. These positive application effects are heterogeneous depending on firm age and industry and are clearly observed in firms operating for 6–10 years in the service industry. Our findings imply that the subsidy application process with external support fosters entrepreneurship for firms that have survived the first 5 years after start-up, leading to firm's growth. With regard to public subsidy policies aiming at developing SMEs, a scheme with external support that helps young post-entry firms find their own business issues would be effective.

Keywords SME · Subsidy · Productivity · Industrial policy · Entrepreneurship

JEL Classification D04 · D24 · H25 · L26 · L50

1 Introduction

According to Stigler (1971), the state is a potential resource or threat to every industry in society as government intervention can either promote industry and firm growth or make them more inefficient.[1] Regarding intervention in small- and medium-sized enterprises (SMEs), if it is optimal for firms to stay small when the business environment is weak, subsidizing SMEs may be at best ineffective, but at worst, counterproductive (Beck & Demirguc-Kunt, 2006). After all, the validity and effectiveness of government intervention can vary depending on many factors, including political regime, industrial structure, and economic conditions. Nevertheless, policymakers need concrete examples (specific industries and growth stages) of the effective support programs for SMEs to efficiently enhance their performance within limited budget resources. They can refer to the accumulated evidence of SME support close to their policy goals when proposing new policies or modifying existing ones.

This study provides evidence of the effects of applying for and receiving the small grant subsidy on SMEs' performance and productivity using the case of the Business Sustainable Subsidy (BSS), an intervention of the Japanese government.[2] While the literature on the effect of receiving subsidies on SMEs is well established (e.g., Bronzini & Iachini, 2014 in Italy; Criscuolo et al., 2019 in the UK), little attention has been paid to comprehensively exploring the effects of both applying for and receiving subsidies on firm productivity across industries. Further, it is not clear whether support for SMEs at the application stage has a uniform or heterogeneous effect across firm ages and industries.

In Japan, while large businesses have experienced a gradual increase in labor productivity since 2008, SME productivity has remained rather stagnant.[3] In response, the Ministry of Economy, Trade, and Industry (METI) launched the BSS program in 2013 to support small firms in resolving productivity issues. The program's objectives include increased productivity and greater sustainable development for small firms by partially supporting their business expenses. To apply for the BSS, firms must submit a 1-year business plan for their improving sales and productivity. The application process includes advisory support from institutions collaborating with the program to augment these plans, which is a unique feature of the program.

To evaluate the comprehensive effects of the BSS, in this study, we test two types of treatment groups—receipt and application. As there is a cutoff point for the assessment score for receiving the subsidy, we employ a sharp regression discontinuity design (RDD) to estimate the receipt effects. We also conduct a difference-in-differences (DID) analysis to examine the effect of applying for the subsidy. This analysis of the grant application is extended to examine heterogeneous effects on firm productivity, depending on industry and firm age.

Our results show that the application scheme has benefits: applicants had higher performance and productivity than non-applicants. In contrast, there is no significant evidence to show an improvement in subsidy recipients' firm productivity. These results suggest that the application process itself offers benefits irrespective of whether or not the firm is granted the subsidy. However, note that the selection of applying for the BSS is still not well controlled. To address the bias resulting from the selection of applicant firms, following Ryan et al. (2019), we employ DID analysis with propensity score matching (PSM–DID) with the assumption stricter than the simple parallel trend. Thus, we show the effects rigorously by controlling any conceivable selection bias. Our results again confirm our initial finding that applying for the BSS benefits firm performance and productivity.

These results imply that the planning and external support influence the effectiveness of applying for the subsidy. SMEs often seek support from third parties because they lack efficient resources. By imparting knowledge, advisory support helps firms resolve their business troubles and promotes further growth (Robson & Bennett, 2000). Planning strategies can also help SMEs carry out tasks systematically and, thus, gain a competitive edge in the market (Hewlett, 1999; O'Regan & Ghobadian, 2002). Similarly, strategic planning with advisory support can lead to innovation

[1] In historical cases, in the USA, public support such as unemployment insurance, the legislation that enabled savings and loan associations, and mortgage support has brought about innovations in the private sector, such as in the consumer credit and housing markets (Perez, 2010). By contrast, some of the state-owned firms subsidized by the government were criticized for inefficiency and privatized (e.g., Dyck (1997) in East Germany; Mizutani (1999) in the Japan National Railway).

[2] Support for start-ups also plays an important role in the policy of subsidizing SMEs. However, given that Japan has a high firm age and few new start-ups among OECD countries (Miyakawa et al., 2022), we focus on the BSS aimed at the growth of existing firms.

[3] The Small and Medium Enterprise Agency (2020).

for small businesses (Batra et al., 2018; Pawliczek et al., 2015). Our analysis supports the positive effects of strategic planning and advisory support on productivity, making a firm more innovative.

Moreover, we note that these positive application effects are heterogeneous on firm age and industry. The lowest effect was observed for newborn firms (operating for less than 5 years), and the highest effect on productivity was observed for young firms (operating for 6–10 years). We followed these results, especially in the service and construction sectors. In contrast, for the manufacturing industry, newborn firms with less than 5 years of operation benefited more from the BSS application than those with more years of operation. This suggests that, despite the heterogeneity among sectors, fostering entrepreneurship through business plan support for young firms within their first 10 years of business is effectively increase productivity.

This study contributes to the literature in three ways. *First*, it examines the effects of a government subsidy program, i.e., the BSS, on the productivity of small firms, an understudied subject in the literature having mixed results. Cin et al. (2016) found that receiving R&D subsidies benefits the value-added productivity of manufacturing SMEs in Korea. However, Bernini and Pellegrini (2011) clarified that the state-aid policy *Law 488/1992* for the manufacturing and service sectors harms labor productivity, although their data precludes small firms owing to a lack of SME budgetary data. By contrast, small firms have the potential to achieve high growth by obtaining subsidies. Research in Japan on the relationship between subsidy and firm productivity is even scarcer. Most studies are focused on R&D outcomes (Inoue & Yamaguchi, 2017; Motohashi, 2002; Nishimura & Okamuro, 2011a, 2011b; Okubo et al., 2016). To fill a gap in the literature, we focus on the effect of the BSS on SME productivity.

Second, our measurement of the effect of "applying" for a subsidy is a novel approach. Various previous research focused on the magnitude of the effect of receiving a subsidy. Bronzini and Iachini (2014) evaluated the program of R&D subsidization in Italy. Their analysis showed that the subsidies affected the investments of SMEs but not those of large firms. Criscuolo et al. (2019) analyzed the UK Regional Selective Assistance program, a policy change that made plants located in disadvantaged areas eligible to receive public subsidies. They found large positive effects on manufacturing employment, but the treatment effects were only seen in small firms. Hottenrott and Lopes-Bento (2014) investigated the effects of public support for R&D investment on SMEs in Belgium, showing that subsidies triggered R&D expenditure, particularly in companies that collaborate internationally.

One exception is Suzuki (2019). He analyzed the effect of applying for the Support Industry Program of Japan's METI in 2009. This compound government program incorporated multiple policy measures to support the R&D of SMEs in the manufacturing sector. Although the effects of receiving the subsidy were not significant or negative, the researcher showed the positive effect of *soft support*, the advisory support for commercializing their R&D without the subsidy, on firm sales and technological improvement. We expand on Suzuki's (2019) study by employing a more rigorous PSM–DID setting, as proposed by Ryan et al. (2019), to examine the heterogeneous subsidy effects by industry.

Third, we contribute to the identification of the right timing of grant applications. Our analysis shows that, on the whole, the effect of BSS application is the smallest for newborn firms and the largest for young firms that survived the first 5 years of an unstable period after establishment. These results, observed especially in the service and construction industries, are explained by the "revolving door" mechanism[4] (Audretsch & Fritsch, 2002; Santarelli & Vivarelli, 2007). Namely, it is less efficient to support newborn *revolving door* firms with a high probability of failure. In contrast, in the manufacturing industry, firms with less than 5 years of operation benefited the most from the BSS application. Our findings indicate that the right timing of grant applications leads to productivity gains in SMEs that vary across industrial sectors, having implications for efficient selective subsidy policy for SMEs.

The rest of the paper is organized as follows. Section 2 summarizes the BSS program and the status of subsidy policies in Japan. In Section 3, the data used for analysis are presented. Section 4 explains

[4] "Revolving door" firms, as detailed in Section 7.2., are those exhibiting early failures and continuously entering and exiting the market.

the empirical strategies and presents our main results. Section 5 checks the robustness of the results. Section 6 examines the heterogeneity of application effects on industry and firm age, and Section 7 provides comprehensive implication of our findings. Section 8 concludes the paper.

2 Background

The METI of Japan established the BSS in 2013 to support SMEs in improving their productivity and sustainable development by partially funding the expenses of their business activities, such as expanding sales channels. The size of the subsidy is within two-thirds of total expenses, not exceeding 500,000 yen ($3700). To qualify for the subsidy, firms must first submit a viable business plan to one of the two organizations depending on their location: the Japan Chamber of Commerce and Industry (JCCI) and the Central Federation of Societies of Commerce and Industry (CFSCIJ). The JCCI manages city-level firms, whereas the CFSCIJ manages town- and village-level firms.[5] These organizations manage the BSS and promote small businesses through services such as advice, guidance, and loan placement. A key feature of the BSS is that the JCCI and the CFSCIJ provide consultation services to all grant applicants on matters such as business management and sales expansion.

The BSS aims to increase productivity by encouraging SMEs to develop new products and sales channels and can be interpreted as a subsidy to promote entrepreneurship in existing firms. According to Shane (2003, p. 4), entrepreneurship is defined as "an activity that involves the discovery, evaluation, and exploitation of opportunities to introduce new goods and services, ways of organizing, markets, process, and the raw materials through organizing efforts that previously had not existed." In addition, the Center for American Entrepreneurship refers to its scope and domain: "This process is generally organized through a new organization (a start-up company), but may also occur in an established small business that undergoes a significant change in product or strategy".[6] In summary, the objectives of the BSS are realized by fostering entrepreneurship in discovering and developing new opportunities for established small firms.

The firms seeking the BSS should be small and located in Japan. Note that the definition of "small" varies by industry. In commerce and service industries, except for accommodation and entertainment businesses, a small firm has fewer than five full-time employees. In the accommodation and entertainment industries, this number is 20 or fewer, similar to other industries such as manufacturing. Thus, application criteria in terms of small firm size are different among industries. Moreover, the applicant firms must also satisfy the following eligibility criteria: *First*, they must have a concrete business plan for improving their productivity and work efficiency that leads to an increase in sales within 1 year after completing the business plan. *Second*, there should be no overlap with other government subsidy projects.[7] *Finally*, a firm seeking a subsidy from the JCCI (CFSCIJ) should be located and operating within its jurisdiction.

SMEs are offered several opportunities to apply for the subsidy within a fiscal year. For example, the METI recruited applicants in February and May 2013. If their application fails in the first attempt, they can reapply later in that year itself. This opens numerous opportunities for SMEs to update and upgrade their business plans and receive the subsidy. In 2013, 27,402 firms applied and 47.0% were successful. The receiving rate is the average of two offering periods.

3 Data

We use a large panel dataset, combining the list of all companies that applied for the BSS with the Tokyo Shoko Research (TSR) data, which contain business information pertaining to over 1.5 million Japanese firms. Both the JCCI's and the CFSCIJ's applicant lists in 2013, the starting year, include the applicant

[5] Besides jurisdiction, there are other differences between the two organizations. For example, the JCCI's operation falls under The Small and Medium Enterprise Agency, whereas the CFSCIJ operates under the Economic and Industrial Policy Bureau, although both are part of the METI.

[6] https://startupsusa.org/what-is-entrepreneurship/

[7] Firms can receive other government subsidies simultaneously as long as the purpose or use of grants is different.

Table 1 Descriptive statistics by reception/application (aggregated 2009–2016)

Variables	(1) Receive					(2) Not receive				
	Obs	Mean	Std. dev	Min	Max	Obs	Mean	Std. dev	Min	Max
TSR score	25,769	45.671	4.276	24	66	24,759	45.269	4.351	15	65
Firm age	22,933	26.959	17.722	0	113	22,531	24.851	17.800	0	99
No. of employees	25,611	5.846	4.353	1	40	24,527	5.457	4.241	1	48
CEO_male	25,774	0.926	0.262	0	1	24,764	0.908	0.289	0	1
Sales (MM yen)	22,556	114.8	133.9	0	3362.5	21,498	119.7	216.5	0	21,969.6
Sales per capita (MM yen)	22,396	22.466	23.638	0	1104.8	21,289	25.159	52.844	0	3000
	(3) Apply					(4) Not apply				
TSR score	50,528	45.474	4.318	15	66	9,064,959	45.228	5.063	0	87
Firm age	45,464	25.915	17.792	0	113	7,692,982	26.428	16.073	0	147
No. of employees	50,138	5.656	4.303	1	48	8,937,269	5.290	4.598	1	180
CEO_male	50,538	0.917	0.276	0	1	9,074,461	0.926	0.261	0	1
Sales (MM yen)	44,054	117.2	179.0	0	21,969.6	7,267,255	158.1	1498.0	0	889,656.6
Sales per capita (MM yen)	43,685	23.779	40.609	0	3000	7,142,172	29.829	425.2	0	444,141.8

firm's name and whether they received a subsidy, as well as basic attributes, such as the address, postcode, telephone number, and representative name. One shortcoming is that the CFSCIJ data lack the postcode and telephone number information; in contrast, the JCCI list stores all such basic information.

To build a panel dataset to estimate the effect of the BSS, we merged the applicant lists with serial outcome information of firms from 2009 to 2016 obtained from the TSR. As the TSR database records included large firms, we limited the sample to small firms that were eligible to apply for the BSS. We excluded firms with more than five permanent employees on average in commerce and service industries, excluding accommodation and entertainment businesses. We also excluded companies in other industries with 20 or more permanent employees on average.

The TSR includes not only basic information to merge but also serial outcome information, such as information on sales and the number of employees. Further, it includes the two-digit industry classification number, as stipulated by the Japan Standard Industrial Classification. In the merging process, we need to match the two datasets by combining multiple information points related to firm attributes, as there is no common identification number stored in both the lists and the TSR data. In the matching process, *first*, we merge each list dataset by each of application time into the TSR data using the firm name and postcode (as described earlier, there were two offering periods in 2013). *Second*, we merge the samples that were not matched previously into the TSR data using the firm name and address. *Third*, through the same process, but with the firm name and telephone number, we merged these samples. *Finally*, we merged the remaining unmatched samples using the telephone and postcode data. To create a dataset for the fiscal year 2013, we accumulated a dataset of each application period. Firms that applied twice in the fiscal year are counted as one application.[8] The final matching rate is approximately 33%.

There are several reasons that some firms have not been matched. *First*, as mentioned above, there are no common identification numbers. We had to merge the lists using somewhat ambiguous firm information on name, address, phone number, and postcode. Some observations are not matched due to orthographic variance between the TSR data and the list. *Second*, we cannot use the data of firms not registered in the TSR database. This is especially typical for sole

[8] There is no limit to how many times a firm can apply to qualify once within a year.

proprietors, which are not registered as corporations. Thus, the matched firms tend to have a larger number of employees and higher capital than non-matching firms. *Third*, data from the CFSCIJ does not often include the firm address and phone number, which limits the merge operation.

Table 1 shows the descriptive statistics of all sample firms, divided into groups "received or not" and "applied or not." These data are merged from the JCCI and the CFSCIJ. Columns (1) and (2) compare the firms that did and did not receive the subsidy. On average, the outcome variables, such as sales and sales per capita, for the subsidy recipient firms are smaller than for non-subsidy recipient ones. These trends can also be seen in the "applied or not" case in columns (3) and (4). This simple comparison between the treatment and control groups does not mean the post-treatment effects. Therefore, we empirically examine the effects of receiving and applying for the BSS with RDD and DID approaches.

Note that the applicant list used for analysis does not include firms that have withdrawn from the BSS after adoption. Thus, we could not consider the effects of withdrawing firms in the treatment group. It means that in the analysis of the application effects, withdrawing firms could be included in the control group that consists of firms that did not apply for the BSS. Therefore, our analysis does not strictly meet the requirement of the intention-to-treatment (ITT) effect.[9] Regardless, we do not think that the existence of a small number of withdrawing firms threatens the robustness of our results. According to the authority of the BSS program, only 201 firms declined to receive the subsidy, which is less than 1% of the total number of applicant firms. We are not aware of the adopted firms that withdraw, but we are aware of all the applicant firms. There is no possibility that firms originally assigned to the treatment group can be included in the control group, except for the withdrawing firms. Therefore, although our case does not completely meet the requirement of the ITT analysis, the issues raised by the withdrawing firms are minor.

[9] We define ITT analysis as the assessment of treatment group based on the group they were originally assigned to, following McCoy (2017). To estimate ITT in our context, we should include all applicants of the BSS, including the withdrawing firms in our sample, and evaluate the treatment effects between the groups to which they were originally assigned.

4 Empirical analysis

4.1 Regression discontinuity analysis for receiving the BSS

4.1.1 Framework

In this section, we examine whether the receipt of the BSS is associated with changes in firm outcomes using the dataset constructed in the previous section. The RDD can be used to isolate the treatment effect of interest from all other systematic differences between the treated and control groups. Under appropriate assumptions, a comparison between firms where the subsidy is barely received and firms where the subsidy is barely rejected will reveal the causal (local) effect of subsidization on firm performance. If a judgment cannot systematically manipulate the assessment score, observations just above and below the cutoff will be comparable in terms of all characteristics, except for obtaining the subsidy.

The BSS framework satisfies the canonical sharp regression discontinuity setup having the following three features: (i) the score is continuously distributed and has only one dimension; (ii) there is only one cutoff; and (iii) compliance with the treatment assignment is perfect. More specifically, all applicant firms receive an assessment score, and treatment is rigorously assigned to those firms whose score is above the cutoff. When the assessment score exceeds the cutoff score, the treatment firms receive the subsidy; otherwise, they do not.

As mentioned in Section 2, there were two offerings in 2013. The cutoff score that determines the subsidization is different for each application period and implementing organization, namely, the JCCI or the CFSCIJ. We estimate four equations using the data pertaining to the applicant firms in each offering from each organization.

As the productivity of subsidized firms is expected to improve within a few years, the outcome variables (Y) are management indicators—the change in sales, the number of employees, and sales per capita 1–3 years after the subsidization year. The running variable (X) is based on the assessment score. When it exceeds the cutoff score (c), the firm is assigned to the treatment group (T) and receives the subsidy.

Our dataset also contains several predetermined covariates that are used to investigate the plausibility of the RDD and illustrate the covariate-adjusted estimation methods. The covariates include the TSR score, industry group indicator, and the number of employees in the base year.[10]

Table 10 presents the descriptive statistics for the three regression discontinuity variables (Y, X, and T). While the variability of the mean value for each application is not too large for the outcome of interests (Y) and predetermined covariates, the subsidy received rate (T) varies greatly across the applicant organizations and application times. The subsidy received rate ranges from 0.882 (first offering under the CFSCIJ) to 0.235 (second offering under the JCCI). This explains why we analyze the subsidy effects separately for each organization and each application period. The overall rate of subsidy received in 2013 is 50.8%, which is calculated using the TSR-matched sample. These sample subsidy-received rates are not very different from those of the population, implying that the sample used in the analysis correctly reflects the treatment decision of the population.

Before moving to the regression discontinuity results, we conduct two validity checks. *First*, we examine whether the density of the score variable—the assessment score—is continuous at the cutoff. The null hypothesis is that there is no density manipulation at the cutoff. Figure 1 is a graphical representation of the continuity in the density test approach, exhibiting the actual density estimate with the shaded 95% confidence intervals. As shown in the figure, all density estimates for the treated and control groups at the cutoff (the two intercepts in the figure) are quite close, and the confidence intervals (shaded areas) overlap. This result implies that there is no statistical evidence of manipulation at the cutoff.

Second, we assess the control variables used in later regressions at the cutoff. Except for their treatment status, firms just above and below the cutoff should be similar with respect to all variables that could not have been affected by the treatment (Cattaneo et al., 2019). To implement this test, we use variables measured in the year prior to the base year and check whether the predetermined covariates are continuous at the cutoff. The results are presented in Table 11. All point estimates are not significant. This means that, at the cutoff, the treated and control firms do not differ systematically in predetermined covariates.

4.1.2 *Results*

Table 2 presents the regression discontinuity results for three outcomes in the JCCI and CFSCIJ: sales growth rate, change in the number of employees, and sales growth rate per capita. As mentioned above, the cutoff that determines the subsidization is different for each application period. We, thus, analyze the effect of the subsidy separately for each. The change from the base year to the evaluation year is measured as the outcome for each application period. For example, we report the change rate of sales for 2012–2013, 2012–2014, and 2012–2015 using 2012 as the base year. We estimate a local linear regression discontinuity effect with triangular kernel weights and common mean square error-optimal bandwidth. All estimations include controls for the TSR score, industry group indicator, and the number of employees in the base year.

All results in Table 2 are statistically insignificant. We cannot confirm positive or negative significant effects for every outcome 1–3 years after the base year. The regression discontinuity results reveal that even 1–3 years after the base year, receiving a subsidy had not led to a significant improvement in firm outcomes.

4.2 Difference-in-differences analysis for applying the BSS

4.2.1 *Framework*

For exploiting the effect of applying the BSS, we conduct DID analysis of large panel data. In the DID estimation, we compare the firm outcomes due to the subsidy program before and after treatment and between the treatment and control groups. We specifically examine the case wherein all small firms that applied comprise the treatment group and those that did not comprise the control group. This allows us to examine the effect of applying for the program itself. The RDD analysis cannot be employed for the application analysis, as there are no cutoff points when applying for the program.

[10] The TSR score is the reputation index that the TSR employs to comprehensively assess each firm based on four dimensions: managerial ability, potential growth, potential stability, and transparency of information. This score is a real number ranging from 0 to 100. It is different from the assessment score of a subsidized project.

Table 2 RDD results for receiving the BSS

	A. JCCI						B. CFSCIJ					
	First offering in 2013			Second offering in 2013			First offering in 2013			Second offering in 2013		
	2013	2014	2015	2013	2014	2015	2013	2014	2015	2013	2014	2015
Outcome: change rate of sales												
RD_estimate	−0.0865	−0.0660	−0.0567	0.00274	0.0223	0.0399	−0.0095	−0.0703	−0.0981	0.0276	−0.0319	−0.0406
Std. err	(0.0746)	(0.116)	(0.144)	(0.0217)	(0.0375)	(0.0450)	(0.0320)	(0.0515)	(0.0657)	(0.0294)	(0.0376)	(0.0403)
Observations	491	480	448	2584	2490	2400	506	492	476	1981	1936	1868
Outcome: change in the number of employees												
RD_estimate	−0.313	0.519	−0.766	−0.179	0.287	0.164	−0.662	−0.212	−0.180	0.0301	−0.254	−0.248
Std. err	(0.357)	(0.681)	(0.945)	(0.223)	(0.300)	(0.335)	(0.415)	(0.308)	(0.396)	(0.147)	(0.224)	(0.275)
Observations	554	548	534	2888	2851	2825	564	560	555	2204	2183	2165
Outcome: change rate of sales per capita												
RD_estimate	−0.0407	−0.518	0.154	−0.0758	−0.124	−0.0954	−0.118	−0.0881	0.0082	−0.0708	0.107	0.295
Std. err	(0.135)	(0.631)	(0.568)	(0.115)	(0.148)	(0.186)	(0.178)	(0.209)	(0.216)	(0.0843)	(0.164)	(0.201)
Observations	491	480	448	2582	2486	2398	506	492	476	1981	1935	1867

***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively. Robust standard errors are in parentheses. The standard year is FY2012. Control variables in the estimation include TSR score, industry group indicator, and the number of employees in the base year, but these are not shown to save space

Table 3 DID results for applying for the BSS

Applied for or not	Base			Lagged		
	(1)	(2)	(3)	(4)	(5)	(6)
	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita
Panel A: JCCI						
Treatment × post dummy	−0.003	−0.043***	0.047***			
	(0.014)	(0.008)	(0.012)			
Lagged treatment × post dummy				0.013	−0.049***	0.061***
				(0.016)	(0.009)	(0.014)
Observations	7,283,156	8,945,605	7,158,603	6,773,948	8,328,619	6,691,877
R-squared	0.292	0.221	0.185	0.298	0.223	0.189
Panel B: CFSCIJ						
Treatment × post dummy	0.038***	0.008	0.039***			
	(0.014)	(0.009)	(0.012)			
Lagged treatment × post dummy				0.042***	0.004	0.046***
				(0.016)	(0.010)	(0.013)
Observations	7,278,401	8,939,783	7,153,946	6,769,894	8,323,652	6,687,877
R-squared	0.292	0.221	0.185	0.298	0.223	0.189
Panel C: all						
Treatment × post dummy	0.015	−0.021***	0.044***			
	(0.010)	(0.006)	(0.009)			
Lagged treatment × post dummy				0.026**	−0.026***	0.054***
				(0.011)	(0.007)	(0.010)
Observations	7,302,802	8,967,752	7,178,115	6,792,252	8,349,310	6,710,113
R-squared	0.292	0.221	0.185	0.297	0.223	0.189

***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively. All explained variables are logarithmic. Robust standard errors are in parentheses. The post dummy of the base model is a variable that takes 1 for 2014–2016, after 1 year from application in 2013. Treatment dummy, post dummy, lagged post dummy, CEO male dummy, TSR score, industry fixed effects, and year effects are also included in this estimation but not shown to save space

For specification, the base estimation equation is as follows:

$$Y_{it} = \alpha + \delta\left(\text{Treat}_i \times d_t\right) + \gamma\text{Treat}_i + \theta d_t + \lambda_t + \tau_s + \boldsymbol{X}'_{it}\beta + \varepsilon_{it},$$

where i and t denote firm and year, respectively. The time t ranges from 2009 to 2016. Treat_i is a dummy variable that equals one for the treatment group; d_t is a dummy variable that equals one when time is the post-treatment period from 2014 to 2016; λ_t is a year dummy variable; τ_s is an industry fixed effect; $\boldsymbol{X}'_{it}$ represents the transposed matrix of control variables; and ε_{it} is a disturbance term. We induce the treatment effects by estimating the coefficient δ in this equation. In terms of the post-period dummy variable d_t, as the effects can be delayed further, we define the post-period as 1 year after receiving or applying for the subsidy. This criterion is in accordance with the BSS program where firms are expected to improve sales performance until the end of the following year when the subsidy is received.

Under the assumption that the treatment effects will continue for a while, we also regress the one lagged post-period model:

$$Y_{it} = \alpha + \delta\left(\text{Treat}_i \times d_{t-1}\right) + \gamma\text{Treat}_i + \theta d_{t-1} + \lambda_t + \tau_s + \mathbf{X}'_{it}\beta + \varepsilon_{it}.$$

The control variables we use in $\boldsymbol{X}'_{it}$ are a CEO male dummy variable and the TSR score. We measure outcomes Y_{it} from three viewpoints: sales, the number of employees, and sales per capita. Sales per capita are interpreted as the firm's labor productivity. All the variables are logarithmic.

In terms of the sample set, contrary to the RDD analysis, we merge each stage in a particular year to keep a sufficient sample size for accurate estimation. Moreover, as discussed above, firms apply to different institutions—the JCCI or the CFSCIJ—depending on their location. We analyze the data for each institution separately and then aggregate these into two datasets. In the analysis of each institution, since the control group includes whole non-applicant small firms in the TSR, for example, firms that applied for the BSS through the CFSCIJ are included as the control group in the JCCI dataset. Thus, to avoid the treated samples being included in the control group in the analysis of another institution, we exclude the sample firms that applied for the BSS through the CFSCIJ from the JCCI dataset and vice versa.

Like the RDD analysis, we validate the DID method before moving to main results. The DID analysis requires that we satisfy parallel trends and show that values before the treated periods form the same tendency between the treatment and control groups. We, thus, estimate the following model:

$$Y_{it} = \alpha + \delta\left(\text{Treat}_i \times d_t\right) + \gamma \text{Treat}_i + \theta d_t + \lambda_t \times \text{Treat}_i + \lambda_t + \tau_s + \boldsymbol{X}'_{it}\beta + \varepsilon_{it,}$$

where $\lambda_t \times \text{Treat}_i$, the additional term in the basic DID model, refers to the interaction term of the treatment and year dummies, where the standard is the year when firms applied for or received the BSS. We can assume parallel trends hold if the interaction dummies before the treatment year are not statistically significant in comparison with the standard.

In the estimation of adding the interaction term between the treatment and year dummies, there are some significant coefficients for the interaction dummies before the treatment year (results available upon request). These results imply that the parallel trend with respect to grant applications is only partially met. We employ PSM–DID approach to deal with the violation of the parallel trend assumption in Section 5.

4.2.2 Results

Table 3 shows the estimates of the subsidy when the treatment group includes firms that applied the subsidy. The upper part of columns (1)–(3), panel A, shows the base estimates of each outcome of the JCCI. Columns (4)–(6) refer to the case of the lagged interaction terms.

First, in contrast to the reception cases in the last section where we found no significant effects, the results show significant key coefficients. In the JCCI case (panel A), employment growth has a significant negative relationship with treatment, whereas sales per capita are positive and significant at the 1% level. For the CFSCIJ (panel B), the results are slightly different, the interaction variable is statistically significant and positive with respect to both sales and sales per capita in both the base and lagged models. However, it is insignificant for the number of employees.

For the merged datasets (panel C), we derive the significant relationship between the treatment variable and the outcomes; for the number of employees and sales per capita, the coefficients are statistically significant at the 1% level and consistent with the JCCI case. Specifically, the coefficient of sales per capita, namely, labor productivity, is significantly positive at 0.044 for the base model. In the lagged model, the coefficient of sales becomes positively significant at the 5% level, and the estimate of labor productivity is larger than the base model at 0.054.

Next, to examine the heterogeneity of the subsidy application effects by industry, we divide the sample into three industries: construction, manufacturing, and service industries.[11] Table 4 presents the estimation results. For the construction industry (panel A), both the basic and the lagged estimation models show that the treatment is positively correlated with productivity. The manufacturing industry described in panel B shows limited effects. Positively significant correlations are only shown in the productivity in the lagged model but at the 10% significance level. By contrast, applying for the BSS affects firm productivity significantly in the service industry (panel C). Treatment has significant positive effects on productivity in both the base and lagged models. It negatively affects employee growth in lagged model but consistently affects sales growth positively in both models. These findings imply that the positive effects of the BSS application on productivity stem mainly from the construction and service industries.

[11] Service industry consists of infrastructure, telecommunications, logistics, wholesales, finance, real estate, academic, accommodation, entertainment, education, medical, compound services, other services, and public. The proportions of construction, manufacturing, and services are 35.0%, 11.4%, and 52.5%, respectively, covering 98.9% of the industry.

Table 4 DID results for application as treatment group by industry

Applied for or not	Base			Lagged		
	(1)	(2)	(3)	(4)	(5)	(6)
	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita
Panel A: construction						
Treatment × post dummy	0.029	−0.014	0.042**			
	(0.020)	(0.014)	(0.017)			
Lagged treatment × post dummy				0.041*	−0.012	0.049**
				(0.024)	(0.015)	(0.020)
Observations	2,537,897	3,123,874	2,521,126	2,404,457	2,950,564	2,392,972
R-squared	0.203	0.152	0.085	0.210	0.157	0.090
Panel B: manufacturing						
Treatment × post dummy	0.015	−0.004	0.021			
	(0.019)	(0.014)	(0.016)			
Lagged treatment × post dummy				0.019	−0.009	0.032*
				(0.022)	(0.016)	(0.018)
Observations	827,713	1,008,273	823,455	778,597	949,631	776,152
R-squared	0.315	0.222	0.140	0.319	0.220	0.145
Panel C: service						
Treatment × post dummy	0.057***	−0.006	0.074***			
	(0.013)	(0.008)	(0.012)			
Lagged treatment × post dummy				0.066***	−0.015*	0.081***
				(0.015)	(0.009)	(0.014)
Observations	3,849,486	4,728,804	3,747,392	3,502,576	4,319,371	3,435,461
R-squared	0.327	0.235	0.232	0.336	0.237	0.238

***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively. All explained variables are logarithmic. Robust standard errors are in parentheses. The post dummy of the base model is a variable that takes 1 for 2014–2016, after 1 year from application in 2013. Treatment dummy variables, post dummy variables, CEO male dummy, TSR score, industry fixed effects, and year effects are also included in this estimations, but not shown to save space

This section showed that applying for the BSS consistently affects firms' labor productivity positively, whereas receiving the subsidy has no such effects. Thus, applying to the BSS program may be more valuable than receiving the subsidy. We will discuss the interpretation of these results in Section 6 after checking the robustness of the above results in the next section.

5 Robustness checks

5.1 No effects of receiving the BSS

We estimate the effects of receiving subsidies as treatment effects by the DID model to check the robustness of the results derived from the RDD analysis. Firms that applied for but did not receive the BSS are assigned to the control group. Table 5 presents the DID results. We note that all coefficients are insignificant, which implies that receiving the subsidy is unlikely to be correlated with the firm's outcomes.

We observe insignificant effects for the lagged variable as well. That is, the effectiveness of receiving the subsidy is unclear even under the assumption that the effects appear after some time. The same tendency is found in the results of the CFSCIJ columns in panel B and those of the combined JCCI and CFSCIJ datasets in panel C. Both base and lagged estimates show insignificant coefficients in almost all outcomes. An exception is employee growth in panel C, which is significant at only 10% level. However, it

Table 5 DID results for receiving the BSS

Received or not	Base			Lagged		
	(1)	(2)	(3)	(4)	(5)	(6)
	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita
Panel A: JCCI						
Treatment × post dummy	−0.021	0.000	−0.028			
	(0.028)	(0.018)	(0.025)			
Lagged treatment × post dummy				−0.003	0.005	−0.024
				(0.033)	(0.020)	(0.029)
Observations	24,394	27,961	24,162	22,351	25,650	22,229
R-squared	0.286	0.234	0.137	0.278	0.228	0.137
Panel B: CFSCIJ						
Treatment × post dummy	0.018	−0.007	0.015			
	(0.031)	(0.022)	(0.027)			
Lagged treatment × post dummy				0.006	−0.014	0.004
				(0.035)	(0.025)	(0.030)
Observations	19,639	22,139	19,505	18,297	20,683	18,229
R-squared	0.227	0.178	0.135	0.222	0.176	0.138
Panel C: all						
Treatment × post dummy	0.023	0.021*	−0.004			
	(0.019)	(0.012)	(0.016)			
Lagged treatment × post dummy				0.020	0.022	−0.009
				(0.021)	(0.013)	(0.019)
Observations	44,040	50,108	43,674	40,655	46,341	40,465
R-squared	0.254	0.204	0.128	0.246	0.199	0.129

***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively. All explained variables are logarithmic. Robust standard errors are in parentheses. The post dummy of the base model is a variable that takes 1 for 2014–2016, after 1 year from receipt in 2013. Treatment dummy, post dummy, lagged post dummy, CEO male dummy, TSR score, industry fixed effects, and year effects are also included in this estimation but not shown to save space

does not change our claim that the BSS reception has no effects on productivity.

To consistently compare the results with the RDD case, we also estimate the same specification using the sample from the RDD analysis. The results reveal that all coefficients of the treatment effect are also insignificant, even when DID analysis is restricted to the sample used in the RDD analysis (results available upon request). There is still no proof that receiving the subsidy increases firm productivity.

5.2 Effects of application without receivers

To confirm the robustness of application effects, we estimate the same application model with DID, excluding firms that succeeded in receiving the subsidy. This allows us to analyze the application effect on firm performance by excluding the receiver effects. In other words, if the same effects shown in the last section are sustained for firms that applied but failed to obtain financial support, we can confirm the positive effects of the application on productivity.

Table 6 shows the analysis results. While the significant coefficients disappear in some columns, most of the results are consistent with the original DID estimations. Particularly, the analysis of the JCCI and combined datasets yield a strongly significant coefficient and the same plus/minus sign as the original calculation. Thus, unsuccessful applicants also benefit from the BSS program.

Table 6 DID results for application without receivers

Applied for or not	Base			Lagged		
	(1)	(2)	(3)	(4)	(5)	(6)
	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita
Panel A: JCCI						
Treatment × post dummy	0.006	−0.043***	0.059***			
	(0.017)	(0.010)	(0.015)			
Lagged treatment × post dummy				0.016	−0.050***	0.070***
				(0.019)	(0.011)	(0.017)
Observations	7,275,888	8,937,256	7,151,390	6,767,214	8,320,883	6,685,173
R-squared	0.292	0.221	0.185	0.298	0.223	0.189
Panel B: CFSCIJ						
Treatment × post dummy	0.032	0.011	0.032			
	(0.032)	(0.021)	(0.026)			
Lagged treatment × post dummy				0.050	0.013	0.051*
				(0.036)	(0.023)	(0.029)
Observations	7,263,129	8,922,547	7,138,776	6,755,655	8,307,542	6,673,687
R-squared	0.292	0.221	0.185	0.298	0.223	0.190
Panel C: all						
Treatment × post dummy	0.012	−0.032***	0.054***			
	(0.015)	(0.009)	(0.013)			
Lagged treatment × post dummy				0.023	−0.037***	0.066***
				(0.017)	(0.010)	(0.015)
Observations	7,280,255	8,942,159	7,155,725	6,771,272	8,325,456	6,689,212
R-squared	0.292	0.221	0.185	0.298	0.223	0.189

***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively. All explained variables are logarithmic. Robust standard errors are in parentheses. The post dummy of the base model is a variable that takes 1 for 2014–2016, after 1 year from application in 2013. Treatment dummy, post dummy, lagged post dummy, CEO male dummy, TSR score, industry fixed effects, and year effects are also included in this estimation but not shown to save space

5.3 DID with propensity score matching

We confirm the robustness of application effects and further discuss causality. Although applying for the subsidy program has positive effects on performance, it may be that firms with higher performance tend to apply more, suggesting heterogeneity between applicants and non-applicants. That the application decision is endogenous for firms means that firms' key characteristics, such as business discipline, affect their productivity after the subsidy program. The literature also argues that, in the manufacturing industry, firms with a large size, higher human capital, and past R&D experiences apply for national and regional R&D subsidy programs more (Blanes & Busom, 2004). Thus, firm status can affect the decision to apply for the subsidy.

Furthermore, in Section 4.2.1, we checked the existence of parallel trends based on the insignificance of the interaction terms between year and treatment prior to the treatment period to validate the DID estimation. However, not every interaction term was insignificant, and we doubt that the parallel trend assumption is satisfied.

To respond to the selection problem and the violation of parallel trend assumption, we conduct PSM–DID to choose a pair of samples with similar intervention possibilities. Ryan et al. (2019) compared the PSM–DID approach with other alternative methods for cases in which the parallel trend assumption was violated. Employing a Monte Carlo simulation experiment, their findings suggest that PSM–DID is more effective than the other two estimators, single- and multi-group interrupted time-series analyses.

For the matching process, we follow Ryan et al. (2019) and Suzuki (2019). *First*, we exactly match industries (using the two-digit Japan Standard Industrial Classification number) by classifying the sample by each industry. *Second*, we calculate the propensity score by probit estimation in the sample of each industry. Here, it is assumed that firms that have similar *levels* of outcomes in the pre-intervention periods in the same industries are more likely to have similar characteristics. Therefore, we match the levels of outcome in the pre-treatment periods (*t-1*, *t-2*, *t-3*, and *t-4*). This is a stronger assumption than the simple parallel trends, as we control the outcome level for multiple periods. To avoid matching to a control group with missing values, we exclude the sample in the control group that contains missing values for the outcome of at least once from 2013 to 2016. We match each pre-treatment outcome level separately according to the dependent variable to be analyzed. For example, when we analyze sales growth, we match the sample using the pre-intervention level of only sales growth up to the fourth lag. This way, we create a sample with the matched sales growth level. We repeat the same matching using employee growth and productivity to create a corresponding matched sample. The PSM method is a one-to-one matching with replacement, common support, and calipers of 0.01. *Finally*, we append the subsample of industries to one full sample and implement the semi-parametric DID estimation by using only the matched sample. The outcomes are the same as those in Section 4.2: sales growth, the number of employees, and sales per capita as labor productivity. The control variables are also the same as those in Section 4.2.

Panel A of Table 7 summarizes the results of PSM–DID analysis for all industries. Columns (1)–(3) are the base model estimation with control variables.[12] Columns (4)–(6) represent the results of the lagged model. We use the sample of merged data in all cases. The estimations reveal significantly positive coefficients of labor productivity, although the magnitude and significance levels of the labor productivity coefficients are decreasing. The positive effects of the application remain in the lagged model. These results confirm that applying to the BSS enhances firm productivity, and its impact remains for a while. However, the less magnitude and the lower significance levels of the labor productivity coefficients explain that some effects in the basic DID model were caused by selection problems between the treatment and control groups.

Like the basic DID analysis, we look at the heterogeneity by industry for the PSM–DID analysis. Panels B to D show the results. We find no significant treatment effects on productivity in any estimation models of each industry including lagged cases. These effects are not consistent with the above panel A result.

How should we interpret these seemingly inconsistent results? We propose that the application effects may have heterogeneity *within* each industry, and their positive and negative effects are canceled out. Audretsch and Fritsch (2002) report heterogeneity in growth patterns across regions, using Germany as a case study. However, unlike Germany in the 1990s after the integration of East and West Germany, the regional differences in growth patterns in Japan today do not appear to be very large. Rather, Inui et al. (2015) argues that productivity gaps within the industry have persisted since the 2000s in Japan. As a factor for this intra-industry heterogeneity, we focus on firm age and consider whether the effect of applying for the BSS differs across firm age groups within the same industry in the next section.

6 Heterogeneous application effects by firm age

The above results support the positive application effects of the BSS on productivity. However, the subsample analysis of industries does not provide significant effects. To explore seemingly contradictory results, we further consider the heterogeneity of effects by firm age group within industries. The revised PSM–DID model, including the interaction terms between application effects and firm age, then becomes.

$$
\begin{aligned}
Y_{it} = {} & \alpha + \sum \varphi_k \left(\mathrm{Treat}_i \times d_t \times \mathrm{Firm\_age}_{\mathrm{itk}}\right) + \delta\left(\mathrm{Treat}_i \times d_t\right) \\
& + \sum \eta_k \left(\mathrm{Treat}_i \times \mathrm{Firm\_age}_{\mathrm{itk}}\right) + \sum \nu_k \left(d_t \times \mathrm{Firm\_age}_{\mathrm{itk}}\right) \\
& + \gamma \mathrm{Treat}_i + \theta d_t + \sum \rho_k \mathrm{Firm\_age}_{\mathrm{itk}} + \lambda_t + \tau_s + X'_{it}\beta + \varepsilon_{it},
\end{aligned}
$$

[12] CEO male dummy and TSR score, industry fixed effects, and year effects are controlled.

Table 7 PSM–DID results for application as the treatment group

Applied for or not	Base			Lagged		
	(1)	(2)	(3)	(4)	(5)	(6)
	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita
Panel A: all						
Treatment × post dummy	0.039**	0.040***	0.023*			
	(0.016)	(0.015)	(0.013)			
Lagged treatment × post dummy				0.037**	0.037**	0.026*
				(0.019)	(0.017)	(0.016)
Observations	62,212	46,411	62,082	61,675	45,993	61,565
R-squared	0.249	0.193	0.147	0.247	0.193	0.147
Panel B: construction						
Treatment × post dummy	0.060**	0.055*	0.030			
	(0.031)	(0.029)	(0.025)			
Lagged treatment × post dummy				0.054	0.070**	0.029
				(0.035)	(0.032)	(0.029)
Observations	14,448	10,636	14,441	14,269	10,487	14,267
R-squared	0.174	0.142	0.056	0.174	0.142	0.058
Panel C: manufacturing						
Treatment × post dummy	0.038	0.038	0.025			
	(0.030)	(0.030)	(0.028)			
Lagged treatment × post dummy				0.040	0.030	0.026
				(0.035)	(0.034)	(0.032)
Observations	14,357	11,124	14,281	14,180	10,971	14,092
R-squared	0.211	0.121	0.106	0.210	0.121	0.107
Panel D: service						
Treatment × post dummy	0.033	0.036	0.020			
	(0.023)	(0.022)	(0.019)			
Lagged treatment × post dummy				0.033	0.029	0.025
				(0.027)	(0.025)	(0.023)
Observations	32,773	24,079	32,728	32,321	23,720	32,296
R-squared	0.280	0.148	0.172	0.280	0.147	0.172

***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively. All explained variables are logarithmic. Robust standard errors are in parentheses. The post dummy of the base model is a variable that takes 1 for 2014–2016, after 1 year from application in 2013. Treatment dummy, post dummy, lagged post dummy, CEO male dummy, TSR score, industry fixed effects, and year effects are included in the estimation, but only key variables are shown to save space

where $\mathrm{Firm\_age}_{itk}$ is a category dummy variable dividing the firm age into five levels: under 5 years old, 6–10 years old, 11–15 years old, 16–20 years old, and over 21 years old, indicating years in operation. The reference group is firms with less than 5 years in operation. The parameter φ_k refers to the relative application effects of each firm age category k based on firms whose operating years are under 5 years.

Table 8 displays estimates of the interaction term between treatment and post dummy and the interaction of three variables: treatment dummy, post dummy, and firm age category to conserve space.

Table 8 PSM-DID results for applying for the BSS by firm age and industry

Applied for or not	All			Construction			Manufacturing			Service		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita
Treatment × post dummy	−0.417***	−0.122	−0.423***	−0.400**	−0.483***	−0.435*	−1.273***	−0.568***	0.634***	−0.066	−0.136	−0.549***
	(0.150)	(0.122)	(0.158)	(0.187)	(0.129)	(0.244)	(0.241)	(0.107)	(0.164)	(0.231)	(0.150)	(0.135)
Treatment × post × 6–10_firm_years	0.631***	0.085	0.541***	0.563**	0.548***	0.560**	1.759***	0.462***	−0.436*	0.240	0.131	0.661***
	(0.164)	(0.140)	(0.175)	(0.219)	(0.181)	(0.270)	(0.275)	(0.175)	(0.229)	(0.249)	(0.175)	(0.174)
Treatment × post × 11–15_firm_years	0.452***	0.139	0.483***	0.288	0.536***	0.287	1.114***	0.347*	−0.475**	0.190	0.194	0.645***
	(0.162)	(0.137)	(0.169)	(0.209)	(0.187)	(0.263)	(0.277)	(0.186)	(0.217)	(0.249)	(0.168)	(0.161)
Treatment × post × 16–20_firm_years	0.359**	0.171	0.410**	0.459**	0.530***	0.451*	1.329***	0.600***	−0.721***	−0.089	0.171	0.557***
	(0.157)	(0.135)	(0.164)	(0.204)	(0.158)	(0.253)	(0.263)	(0.170)	(0.212)	(0.242)	(0.171)	(0.150)
Treatment × post × ≧ 21_firm_years	0.438***	0.129	0.438***	0.454**	0.481***	0.464*	1.295***	0.612***	−0.608***	0.074	0.132	0.550***
	(0.151)	(0.124)	(0.158)	(0.190)	(0.133)	(0.246)	(0.244)	(0.112)	(0.167)	(0.233)	(0.152)	(0.137)
Observations	56,454	43,294	55,288	12,894	9,814	12,457	13,549	10,656	13,357	29,477	22,289	28,926
R-squared	0.251	0.209	0.145	0.196	0.174	0.078	0.210	0.158	0.101	0.273	0.152	0.162

***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively. All explained variables are logarithmic. Robust standard errors are in parentheses. The post dummy is a variable that takes 1 from the standard year onwards. The reference of firm age is under 5 operating years. Treatment dummy, post dummy, other interaction variables, CEO male dummy, TSR score, industry fixed effects, and year effects are also included in this estimation but not shown to save space

Columns (1)–(3) are the estimations of all industries.[13] Examining the results of sales per capita, i.e., labor productivity, all interaction coefficients are significantly positive at over 5% level. This means that, compared to firms that had been in business for less than 5 years, productivity increased significantly with the application of the BSS for firms in other firm age categories. Additionally, the coefficient values become smaller from the 6th year onward with an increase in the number of firm age categories. These findings reveal that the effect of applying the BSS on productivity peaks as firms' operating years reach 6–10 years.

Audretsch and Fritsch (2002) argue that a single regime does not account for growth as diverse growth regimes exist across time and space. Since the BSS has different application criteria for each industry as described above, we set industry as a "space" and explore the heterogeneity of the effects of BSS application in time and industry. Columns (4)–(12) report the heterogeneous effects among three kinds of industries: construction, manufacturing, and service. For construction and service industries, we found a similar tendency as in the case of overall samples; most productivity coefficients are statistically significant and positive, and the values of coefficient drop as the age category rises, except for the 11–15 and 16–20 years in the construction industry. In contrast, for the manufacturing industry, the productivity coefficients show the opposite negative signs. These significant negative results mean that newborn firms with less than 5 years of operation benefit from the BSS application relative to the other categories with more years of operation. Furthermore, the gap between the effects of the base group, firms that have been in business for less than 5 years, and those of firms that have been in business for 16–20 years is the largest.

To check the robustness of the PSM–DID results with industrial heterogeneity on firm age, we conducted a placebo analysis. We change the standard year of the post dummy variable to pre-treatment periods and limit the sample before the treatment year. Specifically, we estimate the same PSM–DID specification with an interaction term of firm age but using restricted panel data up to 2013 and setting each year from 2009 to 2013 as a placebo standard year of the post-treatment dummy variable. We assume no significant coefficients on both the interaction term between the treatment and placebo post dummy and the interaction terms of treatment, firm age, and the placebo post dummy if there is no selection problem.

Table 9 provides the placebo analysis results. Panel A refers to the overall sample. There are no significant coefficients on both $\mathrm{Treat}_i \times d_t$ dummy variables and $\mathrm{Treat}_i \times d_t \times \mathrm{Firm\_age}_{itk}$ dummy variables in every standard year case. Panels B to D describe the results of placebo tests in each industry. While some $\mathrm{Treat}_i \times d_t$ dummy variables for the number of employees in the construction sector show significant coefficients, all coefficients for sales per capita are insignificant in any industry. We, thus, confirm that applying for the BSS in 2013 led to productivity improvement and its heterogeneous impacts on firm age without suffering from selection bias.

With robustness, we ultimately show that the BSS application's effects on productivity improvement depend on the industry and the number of years of operation. In the service and construction industries, the lowest application effect was observed for newborn firms operating for less than 5 years, and the highest effect on productivity was observed for young firms operating for 6–10 years. The manufacturing industry exhibited the opposite pattern. Furthermore, we confirmed that the lack of significant application effects in each industry in Table 7, which did not distinguish firm age, is attributed to the heterogeneity of the application effects by firm age group within each industry, offsetting the positive and negative effects.

7 Implications

7.1 Effectiveness of business planning support during the application process

Consider the mechanisms underlying the BSS's positive application effect and lack of a significant receiving effect. The mechanisms can be interpreted as that SMEs can improve their productivity through the process of applying to the BSS rather than the result of receiving direct financial support.

[13] As per previous DID analyses, we also estimate the lagged model of the equation, and the results are noted in Table 12. Overall, the results show a similar tendency as Table 8.

Table 9 Results of placebo PSM–DID

Applied for or not	Standard year: 2010			Standard year: 2011			Standard year: 2012			Standard year: 2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita
Panel A: all												
Treatment × post	0.087	−0.161	0.086	0.112	−0.121	0.054	0.228	−0.109	0.039	0.295	−0.200	−0.094
	(0.102)	(0.112)	(0.103)	(0.105)	(0.104)	(0.114)	(0.144)	(0.117)	(0.148)	(0.273)	(0.143)	(0.204)
Treatment × post × 6–10_firm_years	−0.158	0.100	−0.065	−0.123	0.125	−0.006	−0.190	0.094	0.048	−0.232	0.205	0.150
	(0.139)	(0.151)	(0.139)	(0.130)	(0.131)	(0.136)	(0.162)	(0.141)	(0.166)	(0.288)	(0.171)	(0.226)
Treatment × post × 11–15_firm_years	−0.119	−0.019	−0.112	−0.162	−0.052	−0.112	−0.292*	−0.032	−0.112	−0.359	0.052	0.094
	(0.126)	(0.149)	(0.127)	(0.122)	(0.129)	(0.130)	(0.159)	(0.138)	(0.162)	(0.288)	(0.166)	(0.224)
Treatment × post × 16–20_firm_years	−0.092	0.214	−0.067	−0.160	0.101	0.015	−0.275*	0.126	0.014	−0.332	0.303*	0.137
	(0.119)	(0.134)	(0.116)	(0.117)	(0.123)	(0.123)	(0.154)	(0.135)	(0.156)	(0.282)	(0.168)	(0.216)
Treatment × post × ≧ 21_firm_years	−0.099	0.145	−0.088	−0.105	0.119	−0.051	−0.216	0.102	−0.030	−0.281	0.186	0.111
	(0.106)	(0.116)	(0.106)	(0.107)	(0.106)	(0.115)	(0.145)	(0.119)	(0.149)	(0.274)	(0.145)	(0.206)
Observations	36,310	27,151	35,591	36,310	27,151	35,591	36,310	27,151	35,591	36,310	27,151	35,591
R-squared	0.248	0.211	0.142	0.248	0.211	0.142	0.248	0.211	0.142	0.248	0.211	0.142
Panel B: construction												
Treatment × post	−0.064	−0.274	0.074	0.034	−0.370**	0.100	0.074	−0.355*	0.128	−0.022	−0.474*	0.068
	(0.148)	(0.234)	(0.171)	(0.150)	(0.187)	(0.161)	(0.191)	(0.205)	(0.188)	(0.269)	(0.286)	(0.277)
Treatment × post × 6–10_firm_years	−0.044	0.036	−0.005	−0.158	0.209	−0.080	−0.132	0.104	−0.065	0.098	0.269	0.149
	(0.198)	(0.341)	(0.228)	(0.186)	(0.255)	(0.204)	(0.223)	(0.257)	(0.227)	(0.307)	(0.329)	(0.319)
Treatment × post × 11–15_firm_years	0.185	0.100	−0.211	0.052	0.302	−0.202	0.003	0.351	−0.153	0.075	0.426	−0.161
	(0.191)	(0.300)	(0.203)	(0.180)	(0.241)	(0.186)	(0.217)	(0.260)	(0.211)	(0.299)	(0.362)	(0.301)
Treatment × post × 16–20_firm_years	0.176	0.330	0.049	−0.006	0.285	0.020	−0.033	0.328	−0.053	0.077	0.488	0.063
	(0.180)	(0.276)	(0.193)	(0.174)	(0.220)	(0.178)	(0.213)	(0.231)	(0.203)	(0.293)	(0.312)	(0.292)
Treatment × post × ≧ 21_firm_years	0.056	0.205	−0.136	−0.022	0.310	−0.139	−0.053	0.306	−0.143	0.038	0.437	−0.085
	(0.161)	(0.240)	(0.179)	(0.157)	(0.192)	(0.166)	(0.197)	(0.209)	(0.192)	(0.274)	(0.290)	(0.280)
Observations	8297	6108	8022	8297	6108	8022	8297	6108	8022	8297	6108	8022
R-squared	0.194	0.171	0.076	0.195	0.171	0.077	0.194	0.170	0.076	0.194	0.170	0.076

Table 9 (continued)

Applied for or not	Standard year: 2010			Standard year: 2011			Standard year: 2012			Standard year: 2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita
Panel C: manufacturing												
Treatment × post	0.099	0.103	0.100	0.170	0.037	0.286	0.272	−0.172	0.386	0.285	−0.120	0.625
	(0.202)	(0.187)	(0.266)	(0.195)	(0.185)	(0.240)	(0.238)	(0.155)	(0.297)	(0.362)	(0.222)	(0.397)
Treatment × post × 6–10_firm_years	−0.130	−0.096	−0.030	−0.121	0.124	−0.228	−0.122	0.274	−0.258	−0.058	0.194	−0.567
	(0.282)	(0.270)	(0.314)	(0.255)	(0.247)	(0.281)	(0.287)	(0.234)	(0.336)	(0.410)	(0.310)	(0.448)
Treatment × post × 11–15_firm_years	−0.179	−0.483	−0.047	−0.277	−0.483*	−0.294	−0.470*	−0.222	−0.526	−0.496	−0.280	−0.659
	(0.259)	(0.298)	(0.352)	(0.238)	(0.260)	(0.299)	(0.279)	(0.224)	(0.337)	(0.411)	(0.283)	(0.440)
Treatment × post × 16–20_firm_years	−0.083	0.078	−0.186	−0.158	0.172	−0.298	−0.208	0.353	−0.361	−0.244	0.373	−0.694
	(0.236)	(0.246)	(0.299)	(0.223)	(0.237)	(0.275)	(0.266)	(0.224)	(0.339)	(0.395)	(0.302)	(0.454)
Treatment × post × ≧ 21_firm_years	−0.148	−0.093	−0.092	−0.183	−0.002	−0.267	−0.272	0.197	−0.366	−0.266	0.118	−0.580
	(0.208)	(0.194)	(0.270)	(0.199)	(0.190)	(0.242)	(0.241)	(0.161)	(0.299)	(0.365)	(0.227)	(0.399)
Observations	8715	6684	8587	8715	6684	8587	8715	6684	8587	8715	6684	8587
R-squared	0.208	0.166	0.090	0.208	0.167	0.090	0.209	0.167	0.090	0.208	0.166	0.090
Panel D: service												
Treatment × post	0.137	−0.210	0.110	0.105	−0.090	0.028	0.239	−0.067	−0.030	0.409	−0.202	−0.240
	(0.148)	(0.158)	(0.142)	(0.152)	(0.151)	(0.171)	(0.215)	(0.185)	(0.235)	(0.455)	(0.180)	(0.331)
Treatment × post × 6–10_firm_years	−0.242	0.130	−0.129	−0.106	0.063	0.045	−0.208	0.066	0.139	−0.412	0.233	0.252
	(0.204)	(0.208)	(0.199)	(0.189)	(0.185)	(0.204)	(0.240)	(0.211)	(0.259)	(0.472)	(0.217)	(0.356)
Treatment × post × 11–15_firm_years	−0.227	0.113	−0.103	−0.201	−0.034	−0.099	−0.334	−0.035	−0.063	−0.484	0.091	0.268
	(0.182)	(0.203)	(0.174)	(0.178)	(0.181)	(0.193)	(0.239)	(0.208)	(0.256)	(0.477)	(0.211)	(0.360)
Treatment × post × 16–20_firm_years	−0.208	0.255	−0.102	−0.217	0.044	0.044	−0.366	0.069	0.087	−0.523	0.331	0.265
	(0.174)	(0.188)	(0.162)	(0.171)	(0.180)	(0.184)	(0.229)	(0.214)	(0.246)	(0.466)	(0.231)	(0.344)
Treatment × post × ≧ 21_firm_years	−0.134	0.213	−0.099	−0.092	0.102	−0.024	−0.226	0.072	0.035	−0.401	0.202	0.250
	(0.153)	(0.163)	(0.146)	(0.156)	(0.155)	(0.173)	(0.217)	(0.188)	(0.237)	(0.456)	(0.184)	(0.332)
Observations	18,965	14,029	18,642	18,965	14,029	18,642	18,965	14,029	18,642	18,965	14,029	18,642
R-squared	0.273	0.158	0.160	0.273	0.158	0.160	0.273	0.158	0.160	0.273	0.158	0.160

***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively. All explained variables are logarithmic. Robust standard errors are in parentheses. The post dummy is a variable that takes 1 from the standard year onwards. The reference of firm age is under 5 operating years. Treatment dummy, post dummy, other interaction variables, CEO male dummy, TSR score, industry fixed effects, and year effects are also included in this estimation but not shown to save space

Regarding the positive effects of the BSS application, we believe that strategic planning support embedded in the subsidy application process plays an important role. Such strategic planning enables businesses to complete tasks in a systematic manner, giving them a competitive advantage[14] (Hewlett, 1999; O'Regan & Ghobadian, 2002). A growing body of empirical evidence suggests that planning is more prevalent in better-performing firms[15] (AlQershi, 2021; Gibson & Cassar, 2005).

Even though many SMEs recognize the importance of strategic planning, they frequently lack adequate internal resources and desperately need third-party guidance. Such business advice from a third party provides an opportunity to foster or rediscover entrepreneurship that leads to growth. Firms having high growth need external advice to expand their business further, whereas those with low growth require more assistance to survive. For any firm, objective management advice from a third party is often a catalyst for fostering and rediscovering an entrepreneurial spirit that leads to future growth.

Robson and Bennett (2000), for example, confirm the interrelationship between increased advice use and SME growth. According to Okamuro (2007), greater access to external resources increases the likelihood of cooperative R&D success for Japanese SMEs. Focacci and Kirov (2021) investigate how external intervention by the government and local governments benefited firms in the automotive sectors in the UK and the ICT sectors in Bulgaria. Robson and Bennett (2000), Berry et al. (2006), Uhlaner et al. (2013), and Bruhn et al. (2018) show that external advice on business strategy, staff recruitment, taxation, and financial management has a positive impact on total factor productivity, employment, and turnover.

Taken together, subsidies that incorporate both strategic planning and external advice into the application process, such as the BSS, can help SMEs increase their productivity. In particular, the effect on external advice may be more pronounced in the service industry, which is less dependent on equipment and more likely to immediately reflect outside advice in its management.

By contrast, we find no significant differences in productivity between SMEs that received and did not receive small subsidies. McKenzie (2017) organizes a business plan competition in Nigeria and emphasizes the importance of substantial prizes. In his experimental study, winners have increased innovation by purchasing more capital and hiring more labor. The amount up to 500,000 yen ($3700) for the BSS might not be enough to purchase expensive equipment or hire additional workers. A recent Croatian study shows that the grant amount's share of firm profits must be high for the grants to be effective (Srhoj et al., 2021a). As a result, the BSS subsidy amount may have been insufficient to relieve SMEs' credit constraints and purchase innovation inputs. Another reason could be that the business plan scores from judges do not significantly predict sales and profits (McKenzie & Sansone, 2019). If predicting firm growth is hard, no significant differences are likely to be observed in outcomes between the subsidized treatment group and the non-subsidized control group.

7.2 Selective effects for nascent and young firms

Another important finding of this study is that the effect of BSS application is the smallest on newborn firms and the largest on young firms that survived the unstable period immediately after establishment. Our firm age analysis found that the BSS application is the most beneficial for firms operating for 6–10 years, whose business gets on the right track. In contrast, new entrant firms were not able to grow, even though they had external advice and made a business plan when they applied for the BSS.

These evidences are explained using Audretsch and Fritsch (2002) and Santarelli and Vivarelli's (2007) *revolving door* mechanism. *Revolving door* firms are those who are causing suboptimality and early failures, and continuously entering and exiting the market. They should be distinguished from real entrepreneurs bringing about innovation and economic growth. Management advice to newborn

[14] Strategic planning is formalized planning refined by decision-making strategies for the organization's present and future prospects (Abbar and Echcharqy, 2016). Lyles et al. (1994) identified the benefits of strategic planning: improving the quality of the strategic decision-making process, receiving more effective attention, and obtaining complete knowledge of the firm's strategic management issues.

[15] The contents of planning are also important. Abbar and Echcharqy (2016) decomposed the nature of strategic planning and found that decentralization and strategic control from the external environment contributed to sales growth.

revolving door firms is likely to be ineffective owing to a lack of innovative motivation and realization of their own management issues in these firms. Conversely, firms operating for 6–10 years are in the most balanced stage, where they become viable and identify management issues for the next growth phase. It implies that subsidy applications had the greatest effect on the productivity of the young firms having high potential. Our findings are also consistent with the previous research that argues that the youth of firms is related to the larger effects of the subsidy (Bronzini & Iachini, 2014; Howell, 2017; Santoleri et al., 2020; Srhoj et al., 2021b).

However, the empirical evidence suggested that the *revolving door* mechanism was found in the service and construction sectors, while the opposite pattern was observed in the manufacturing industry: manufacturing firms with less than 5 years of operation benefited more from the BSS application than those with more years of operation.

There are two possible reasons for the positive application effects for new entrants only in the manufacturing sector. The *first* is the possibility that fewer firms make early mistakes in the manufacturing industry. Entry mistakes should be less frequent in sectors characterized by higher sunk costs (Audretsch et al., 1999; Santarelli & Vivarelli, 2007). In the manufacturing industry, which is representative of such sectors, it is assumed that the proportion of *revolving door* firms among new start-ups is smaller and that the proportion of entrepreneurs with higher motivation and growth potential is higher. Furthermore, previous work experience in technical and commercial functions within the same industry plays an important role in increasing the likelihood of survival of new firms (Santarelli & Vivarelli, 2007). Comparing CEO age in firms that have been in business for less than 5 years between the manufacturing industry and the other two industries by *t* test, we found that the age in the manufacturing industry is statistically significant and older than in the other two industries. Therefore, it seems that in the manufacturing industry, new entrants led by experienced entrepreneurs had a lower likelihood of early mistakes and became more productive by taking advantage of the advisory support built into the BSS application process.

The *second* reason is the difference in access to other operating funds. One example is the Subsidy for Manufacturing, Commerce, and Services to Promote Improvement of Productivity (called the *Monodukuri* subsidy), which was launched in 2013 before the BSS, with a maximum subsidy amount of 10 million yen (approximately US$8000). This subsidy was initially intended for the manufacturing industry and is still used mainly by manufacturing firms. If new entrants in the manufacturing industry, where intensive capital investment is particularly important in their early stages, are also willing to obtain other sources of financing, such as *Monodukuri* subsidies, the effects of applying for and receiving the BSS may be overestimated.[16]

8 Conclusions

This study showed that receiving a small subsidy does not have significant outcomes, but applying for one can increase SMEs' sales and productivity. These positive application effects are heterogeneous on firm age and industry and are most pronounced in firms operating for 6–10 years in the service industry.

Our findings suggest three things. *First*, receiving subsidies in small amounts may be ineffective for small firms. The maximum amount of the BSS is about 500,000 yen (US$3700), which may not be enough to invest in more productive areas, such as human resource reinforcement and massive equipment. *Second*, small-scale subsidy policies could improve productivity by embedding an application process that encourages firms to formulate business plans through external advice. *Third*, these application effects are not significant among newborn firm groups whose likelihood of survival is low but are the most pronounced for young firms that have survived the first 5 years after start-up.

The effectiveness of business planning and external advice for SMEs has been found in many countries other than Japan. However, when implemented through grant projects or competitions, business plan preparation support is provided only for firms that pass the screening process (Wren & Storey, (2002) in the UK; Klinger and Schündeln (2011) in the Central USA). There are few nationwide grant projects that

[16] Unfortunately, we could not check the extent of underestimation since we did not have information linking the *Monodukuri* subsidy to the BSS.

mandate firms to prepare business plans as application requirements, such as the BSS in Japan. The BSS offers applicants support from associated local institutions (the JCCI and the CFSCIJ) for free. These institutions have over 2000 local chapters all over Japan and would be familiar with the problems faced by SMEs in the region. They can provide practical support, such as pointing out managerial and financing issues that the firms might not have been aware. The effectiveness of counseling in line with the regional situation is also shown by Dalton et al. (2021). Our finding of the positive effects of the assistance provided by the JCCI and the CFSCIJ, which are well versed in local business practices of preparing business plans at the application stage, is consistent with that of Dalton et al. (2021). If other countries plan to execute subsidy projects like the BSS, the effectiveness will depend on whether a local organization such as the JCCI and the CFSCIJ can provide valuable advice to SMEs with low additional costs.

For policymakers to efficiently promote the high competitiveness of SMEs, first, the subsidy should be designed to support SMEs in finding their managerial problems by themselves. In the case of the BSS, although the organization has not been able to provide enough money to alleviate capital constraints, external advisory support has been incorporated into the grant application process, urging SMEs to address their managerial issues voluntarily. Our analysis suggests that, for small-scale subsidy policies, a mechanism that incorporates channels for external advice and encourages SMEs to address their issues voluntarily will improve their productivity. Furthermore, in the next execution stage, the practical enforcement of a post-entry subsidy program should be selective based on empirical studies. Our findings suggest that an application assistance program for SMEs is more effective for the steadily growing post-entries rather than too young entrepreneur firms. This is consistent with Santarelli and Vivarelli (2007) arguing that post-entry subsidies would benefit young firms that have already proved themselves in coping with market selection. It is important to concentrate on subsidizing post-entry entrepreneur firms with greater growth potential for efficient policy operations.

Despite these important findings, our study has certain limitations. *First*, because of the lack of common identification numbers, the matching rate of the list with the TSR data is at most approximately 40%. This leads to concerns that the treatment and control groups have not been properly classified, as unmatched applicant firms may be included in the non-applicant group. *Second*, we do not directly identify the effects of advisory support and planning as a mechanism of productivity improvement in our estimations. We interpret the estimation results based on the characteristics of the BSS and previous studies. *Third*, we have only focused on the outcomes of participants in the subsidy program, without accounting for spillover effects on other non-participating firms. We admit that participation in the BSS program may also affect business partners and local business areas positively. The lack of business network data precluded this factor from the analysis. Further analysis that rigorously solves these limitations is needed to provide a more nuanced understanding of the effect of subsidy programs on SMEs.

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Author contribution Kohei Takahashi (corresponding author): conceptualization; methodology; software; validation; formal analysis; investigation; data curation; writing — original draft; writing — review and editing; and visualization. Yuki Hashimoto: conceptualization; methodology; formal analysis; investigation; resources; data curation; writing — review and editing; supervision; and project administration.

Declarations

Conflict of interest The authors declare no competing interests.

Appendix

Table 10

Table 11

Table 12

Figure 1

Table 10 Descriptive statistics for regression discontinuity variables

Variables	First offering in 2013			Second offering in 2013		
	Obs	Mean	Std. dev	Obs	Mean	Std. dev
A. JCCI						
Percent change in sales (2012–2013)	503	0.011	0.22	2618	0.015	0.195
Percent change in sales (2012–2014)	492	−0.005	0.337	2523	0.014	0.306
Percent change in sales (2012–2015)	459	0.009	0.436	2431	0.025	0.37
No. of change in employee (2012–2013)	554	0.002	1.258	2889	0.026	2.38
No. of change in employee (2012–2014)	548	0.206	2.108	2852	0.02	2.963
No. of change in employee (2012–2015)	534	0.069	2.575	2826	−0.029	2.954
Percent change in sales per emp (2012–2013)	491	−0.02	0.827	2582	−0.026	0.996
Percent change in sales per emp (2012–2014)	480	−0.114	1.32	2486	−0.106	1.275
Percent change in sales per emp (2012–2014)	448	−0.068	1.469	2398	−0.113	1.508
Assessment score	814	143.746	28.834	4221	140.934	29.044
Subsidy received dummy	814	0.533	0.499	4221	0.235	0.424
B. CFSCIJ						
Percent change in sales (2012–2013)	514	0.013	0.193	2004	0.02	0.193
Percent change in sales (2012–2014)	500	0.012	0.27	1960	0.027	0.272
Percent change in sales (2012–2015)	484	0.007	0.336	1892	0.025	0.335
No. of change in employee (2012–2013)	564	0.018	1.664	2205	−0.05	1.352
No. of change in employee (2012–2014)	560	0.046	1.569	2184	0.034	1.914
No. of change in employee (2012–2015)	555	0.11	2.156	2166	0.096	2.291
Percent change in sales per emp (2012–2013)	506	−0.057	0.925	1982	−0.011	0.915
Percent change in sales per emp (2012–2014)	492	−0.1	1.133	1936	−0.073	1.198
Percent change in sales per emp (2012–2014)	476	−0.157	1.309	1868	−0.131	1.453
Assessment score	763	150.301	37.308	2928	153.346	24.007
Subsidy received dummy	763	0.882	0.323	2928	0.74	0.438

Table 11 Continuity-based analysis for predetermined covariates

	First offering in 2013			Second offering in 2013		
	TSR score (2012)	No. of emp (2012)	Sales (2012)	TSR score (2012)	No. of emp (2012)	Sales (2012)
A. JCCI						
RD_estimate	0.0583	−0.918	−0.348	−0.00594	0.215	0.0586
Std. err	(0.846)	(1.585)	(0.273)	(0.510)	(0.917)	(0.127)
Observations	573	560	523	2970	2929	2729
B. CFSCIJ						
RD_estimate	−0.554	−0.829	0.210	−0.292	−0.503	−0.0177
Std. err	(1.128)	(1.396)	(0.270)	(0.579)	(0.619)	(0.123)
Observations	576	568	533	2254	2228	2078

***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively. Robust standard errors are in parentheses

Table 12 PSM–DID results with interaction variables of lagged treatment, post, and firm age

Applied for or not	All			Construction			Manufacturing			Service		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita	Sales	Employees	Sales per capita
Lagged treatment × post dummy	−0.505***	−0.048	−0.451**	−0.496***	-	−0.504*	−1.128***	−0.618***	0.678***	−0.050	0.065	−0.506***
	(0.172)	(0.149)	(0.206)	(0.191)	-	(0.295)	(0.305)	(0.117)	(0.181)	(0.278)	(0.141)	(0.172)
Lagged treatment × post × 6–10_firm_years	0.747***	0.018	0.616***	0.680***	-	0.643*	1.628***	0.574***	−0.550**	0.270	−0.079	0.702***
	(0.190)	(0.170)	(0.229)	(0.238)	-	(0.328)	(0.343)	(0.202)	(0.265)	(0.298)	(0.179)	(0.226)
Lagged treatment × post × 11–15_firm_years	0.540***	0.051	0.509**	0.352	-	0.345	0.954***	0.367*	−0.470*	0.183	−0.023	0.574***
	(0.188)	(0.164)	(0.219)	(0.224)	-	(0.319)	(0.346)	(0.215)	(0.250)	(0.300)	(0.167)	(0.201)
Lagged treatment × post × 16–20_firm_years	0.442**	0.081	0.437**	0.526**	-	0.483	1.241***	0.531***	−0.678***	−0.121	−0.038	0.521***
	(0.181)	(0.162)	(0.213)	(0.214)	-	(0.306)	(0.328)	(0.191)	(0.240)	(0.290)	(0.167)	(0.188)
Lagged treatment × post × ≧ 21_firm_years	0.531***	0.056	0.473**	0.561***	-	0.549*	1.156***	0.660***	−0.658***	0.061	−0.071	0.517***
	(0.173)	(0.150)	(0.207)	(0.196)	-	(0.297)	(0.308)	(0.123)	(0.184)	(0.233)	(0.152)	(0.137)
Observations	55,970	42,910	54,831	12,741	-	12,312	13,380	10,508	13,175	29,056	21,953	28,527
R-squared	0.249	0.208	0.145	0.196	-	0.078	0.207	0.157	0.102	0.272	0.151	0.162

***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively. All explained variables are logarithmic. Robust standard errors are in parentheses. The post dummy is a variable that takes 1 for 2015–2016 after 2 years from application in 2013. The reference of firm age is under 5 operating years. The estimation results of (5) is dropped because we could not run the regression due to lack of enough observation that are operating within five years in construction industry. Treatment dummy, post dummy, other interaction variables, CEO male dummy, TSR score, industry fixed effects, and year effects are also included in this estimation but not shown to save space

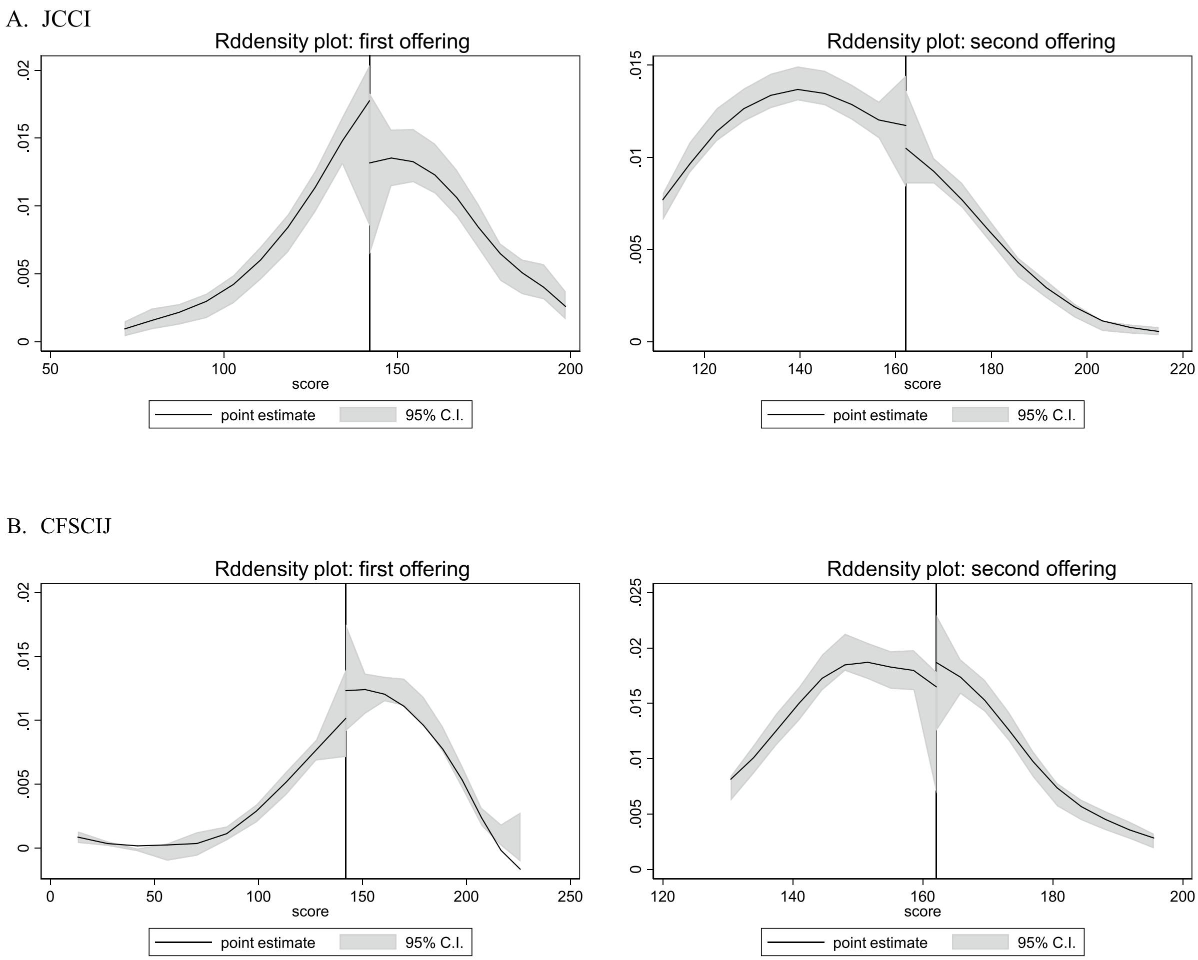

Fig. 1 Density function

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