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The impact of public R&D subsidy on small firm productivity: evidence from Korean SMEs

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Abstract This paper explores the effects of R&D promotion policy on SME performance. We use a large panel data set on public R&D subsidies to Korean manufacturing firms. We control for counterfactual outcomes employing the DID (difference in differences) estimation procedure as well as for the endogeneity of the R&D investment and the R&D subsidy using the 2-stage Tobit/Logit DPD (dynamic panel data) procedure. We find significant evidence for positive effects of the public R&D subsidy on both the R&D expenditure and the value added productivity of Korean manufacturing SMEs. The policy thus appears to have been successful in fostering technological advancement and in promoting economic growth.

Keywords SMEs · R&D · Research subsidy · Productivity

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1 Introduction

Economic growth depends on innovation and the application of new knowledge in order to develop improved products and processes. In particular, research and development (R&D) investment is considered to be one of the most important factors for enhancing technological progress and economic growth for developed and developing countries (Romer 1990; Grossman and Helpman 1991; Aghion and Howitt 1992; Wang et al. 2007). This has provided a strong signal to policy decision makers to endorse technology-enhancing R&D policy.

Absent of government intervention, a social rate of return to R&D expenditure that exceeds the private rate due to pecuniary externalities and/or knowledge spillovers will lead to a socially suboptimal rate of investment in R&D (Leyden and Link 1991; David et al. 2000; Nelson 1959). The presence of uncertainty in the technical enterprise and lack of adequate insurance to deal with such uncertainty will further push private R&D expenditure below socially optimal levels (Arrow 1962). The central rationale for government R&D promotion policy such as subsidy for new technology development is to correct this type of market failure by boosting incentives through the reduction of the cost of R&D activities.

For more than five decades there have been extensive empirical research to assess the relationship between public R&D subsidies, private R&D investment, and firm performance. The empirical results of these studies are mixed. The question about whether the R&D subsidies are additional to company-financed R&D investment or crowd out private R&D investment is far from conclusive (Zuniga-Vicente et al. 2014). Moreover, relatively few of these studies focus on developing or newly industrialized countries (Hall and Maffioli 2008 for Argentina, Brazil, Chile and Panama; Ozcelik and Taymaz 2008 for Turkey; Lee and Cin 2010 for Korea). Studies on the effect of the R&D subsides on productivity for emerging countries are rare (Cerulli 2010). Positive effects of public R&D subsidies on private R&D investment do not necessarily mean that the subsidies enhance productivity and thus eventually contribute to economic growth, especially in the newly industrialized countries (Hall and Maffioli 2008).

This paper empirically investigates the productivity effect of R&D subsidy in dynamic panel model framework, using a large panel data set on public subsidies to Korean manufacturing small and medium sized enterprises (SMEs). We employ both the DID (difference-in-deference) methodology to mitigate sample selection bias caused by the evaluation of counterfactual outcomes (what would have happened to subsidized firms if they had not been subsidized by government). The DID estimator does not, however, eliminate the endogeneity problem that may arise when the probability of being selected by government is correlated with error terms. That is, firms receiving subsidy may have been selected by the policy-maker because they are likely to implement research projects successfully and thus the selection procedure follows a 'picking the winners' pattern. We use the two-stage Tobit/Logit-GMM procedure to control for the endogeneity bias of the private R&D investment and of the public subsidy. We find a positive and significant effect of R&D subsidies on productivity of the examined SMEs. Our finding suggests that subsidies have an indirect additional effect on private R&D investment as well as direct positive output effect.

What makes Korea an interesting case to study is the strong emphasis placed by policy decision makers on R&D assistance to SMEs to sustain economic growth having realized since the Asian financial crisis of 1997 that the Korean economy is heavily dependent on large conglomerates (*Chaebol*). It was hoped that new technological knowledge created by SMEs would be an important driver of future economic growth. The promotion of SME capabilities and knowledge intensity has, of course, nowadays become a critical policy concern around the world. From this vantage point, Korea's experience could provide useful lessons and guidelines to newly industrialized countries and to emerging economies.

The rest of the paper is organized as follows. Section 2 describes R&D policies in Korea. Section 3 summarizes the empirical literature linking R&D subsidies, R&D investment, and firm performance. Section 4 specifies the theoretical model and describes the empirical methodology to evaluate the effect of R&D subsidy on SME productivity. Section 5 describes the panel data and analyzes estimation results. Finally, Sect. 6 concludes.

2 Background of R&D subsidy policy to SMEs in Korea

The Republic of Korea has achieved impressive growth for significant lengths of time. Annual real GDP growth had averaged around 6.0 % during the period of 1986–1997. The onslaught of the Asian financial crisis of 1997 disrupted that era: average growth rate declined to 4.4 % during the next ten years (1998–2007) and, in the aftermath of the global financial crisis of 2008, declined even further to around 3.0 % during 2008–2014. Early reports attributed a good part of the Korean economic growth story to the expansion of production inputs, rather than to technological progress and higher productivity, which is inevitably subject to diminishing returns (Krugman 1994; Young 1995).

To sustain long-term economic growth, successive Korean governments recognized the need for active policy to promote science, technology and innovation. Policy pillars included the building of infrastructure, the promotion of technology acquisition from more advanced economies, and comprehensive education and R&D investment (Shin 1998).

Korean development has gone through several phases. The comparative advantage in labor-intensive industries such as garment and footwear of the 1960s was followed by the Heavy and Chemical Industries (HCI) Promotion Plan of the 1970s and 1980s. During that time the government intentionally supported big conglomerates (*chaebols)*—considered necessary for the required scale of operations in the targeted sectors—by providing policy loans at preferential lending interest rates (Kim 1997). While the institutional and legal system of supporting SMEs was introduced in the 1970s, it was nowhere comparable with the support to large firms (Park et al. 2013). C*haebols*' heavy dependence on foreign component suppliers, however, exacerbated Korea's trade deficit during the 1970s and 1980s (Kim 1997). Manufacturing SMEs offered a possible solution in the effort to break this dependence on imports of parts and components (Hodgkinson 2000). Besides, government officials considered that SMEs can have an overall beneficial role in economic growth since they could respond/adjust relatively quickly to changes in market conditions and be more innovative than large firms (Lee and Noh 1996). Since the beginning of the twenty-first century the Korean economy has been led by technology-intensive industries such as electronics and automobiles.

Korean SMEs have traditionally spent little on R&D. They have also found it difficult to undertake risky R&D projects with external funding in the absence of well-established capital markets. As elsewhere, small firms are more reliant on internal financing which exposes them to higher default risk. These two factors—high capital costs and high default risk—in combination to shortage of human capital and capabilities, have long been expected to result in R&D under-investment by SMEs.

The Korean government has used various financial instruments to that effect such as R&D loans with low interest rates from state-controlled banks, direct R&D subsidies, and tax credit and tax-based indirect R&D subsidy (Shin and Woo 2013). The government has placed most emphasis on the expansion of corporate R&D investment through direct R&D subsidies to SMEs for the development of new technology and for boosting technology transfer across industries. The R&D subsidies to the SMEs have been allocated to several selected activities: technology development and innovation projects, new product development projects conditional on government procurement, university-industry R&D collaboration, technology transfer projects, and cooperative R&D projects. The lion's share of resources has gone to technology development and innovation and to university-industry R&D collaboration programs.

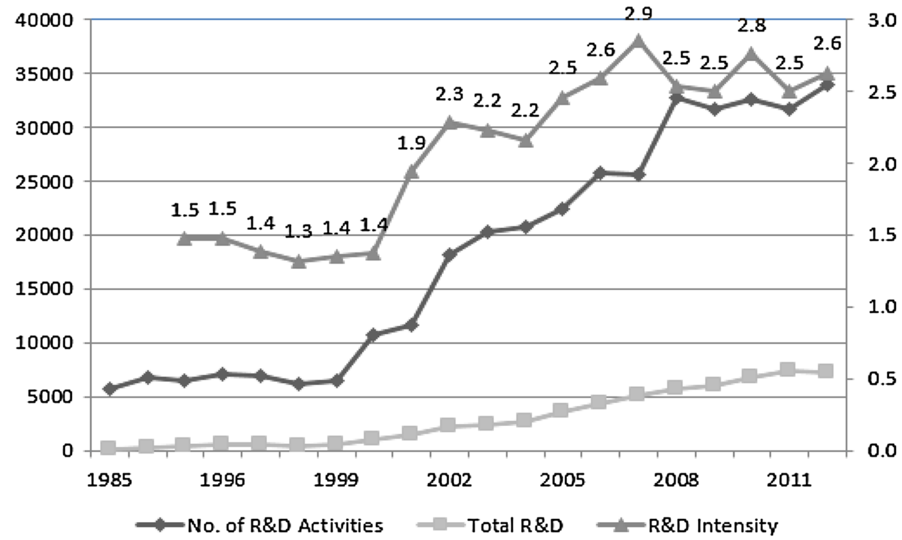
The Korean R&D subsidy policy for SMEs has evolved since the 1980s when the first large-scale government R&D program was initiated. During 1982–1986, the government prepared a legal framework targeting support for SME R&D activities. During 1987–1996, along with the foundation of the Korea Technology Credit Guarantee Fund (KOTEC), a series of R&D subsidy programs were introduced. The active government support for SME R&D activities contributed to the so-called 'venture boom' in the early 2000s: the number of SMEs involved in R&D activities increased remarkably from 6472 in 1999 to 18,101 in 2002. Similarly, SME R&D expenditure increased from 595 billion Korean won in 1999 to 2.2 trillion Korean won in 2002. Thanks to continuous support by subsequent government administrations, SME R&D expenditure, especially targeting the manufacturing sector, rose from 2.4 trillion Korean won in 2003 to 5.1 trillion Korean won in 2007. R&D intensity also increased from 1.37 percent in 2000 to 2.63 percent in 2012. The overall share of R&D expenditure by SMEs across all industries increased sharply from 11.4 % in 1995 to 25.8 % of the total in 2011.

Figure 1 shows the time trend of overall R&D expenditure and of SME R&D intensity in the manufacturing sector. The amount of R&D expenditure by SMEs was as little as 64.2 billion Korean won in 1985 at the start of public R&D promotion policy. This amount increased significantly during 1985–1996 and then again from 1999 to 2007. Both periods coincide with active public R&D promotion policy including R&D subsidy.

3 Literature review

The literature on assessing the relationship between public R&D subsidies, private R&D investment, and firm performance has been built over the past few decades. There are three main streams of research. The first stream focuses on whether public R&D spending is complementary and additional to private R&D

Fig. 1 R&D Expenditure of SMEs in Manufacturing Sectors. (Unit: Billion Korean Won, 1000 Korean Won is equivalent to about 1 US dollar, %) *Source* Korea Federation of SMEs, *Korean SME Statistics*, various issues



spending or whether it substitutes for and tends to crowd out private R&D, mainly focusing on developed countries. For instance, Scott (1984), Levin and Reiss (1984), and Leyden and Link (1991) have looked at U.S. firms, Holeman and Sleuwaegen (1988) have examined Belgian firms, and Klette and Moen (1999) Norwegian firms.

David et al. (2000) have, however, argued that most of the earlier studies are subject to potential selection bias. Since the act of applying for and receiving government funds cannot be regarded as a random process, simple OLS estimation is subject to selection bias. That is to say, firms receiving subsidy may have been selected by the policy-maker because they are perceived as more likely to implement research projects successfully and thus the selection procedure follows a ‘picking the winners’ pattern. From the firms’ perspective, only those already successful in conducting R&D projects may apply for R&D subsidies. Overlooking this self-selection mechanism can bias the empirical results and lead to unreliable policy recommendations. The selection bias can reflect the lack of information regarding the counterfactual: what would have happened absent of the government subsidy program.

Even considering the selection and the counterfactual outcome problems, many studies still find a statistically significant positive effect of R&D subsidies on private R&D investment. Using a DID estimator to estimate the effect of receiving a R&D subsidy, Lach (2002) finds positive but insignificant effect on private R&D investment. Estimating a dynamic panel data model, he finds that Israeli OCS (the Office of Scientist) subsidies do not crowd out company-financed R&D. For France, Duguet (2004) finds that on average public funds add to private funds; no evidence of significant crowding-out was reported. Gonzalez et al. (2005) evaluate R&D funding programs for about 2000 Spanish firms. They also find that private R&D investment is stimulated by public subsidies. Gonzalez and Pazo (2008) confirm the effect of R&D subsidies on Spanish firms considering firm size and technological levels of the industrial sectors. Their empirical results show no evidence of crowding-out, either full or partial, between public and private R&D spending, and that small and low-tech firms would have not engaged in R&D activities had they not received the government subsidy. By applying parametric and nonparametric selection model, Hussinger (2008) finds that public funding increases private R&D investment in Germany. Using propensity score matching techniques to avoid the counterfactual outcome problem, Czarnitzki and Lopes-Bento (2013) find that the R&D subsidies for Flemish firms are not subject to full crowding-out and that the policy effects are stable.

Some studies do, however, find evidence of crowding-out effects of R&D subsidies. Using a 3SLS approach, Wallsten (2000) employs a data set of U.S. firms involved in the Small Business

Innovation Research program and finds that the R&D grants crowd out firm-financed R&D spending. Gorg and Strobl (2007) examine the crowding-out effect based on government subsidies to Irish plants and find that the government subsidy crowds out company-financed R&D investment.

On the other hand, Busom (2000) finds partial crowding-out effects for 30 % of R&D participants: while overall public R&D subsidies stimulate private R&D effort, 30 % of R&D participants experience crowding-out effect of the R&D subsidies. Czarnitzki et al. (2007) comparatively analyze Finnish and German subsidies and find different impacts between them. In Germany subsidies do not affect significantly either R&D nor patenting, while in Finland both effects are positive.

Thus, empirical results on crowding-out are mixed and far from conclusive. Surveying the literature, Cerulli (2010) and Zuniga-Vicente et al. (2014) point out that the results of the reviewed articles vary depending on types of data set, the aggregation level of data, estimation method, industrial structure and national differences.

The second stream of research focuses on the link between innovation input (typically proxied by R&D investment), innovation output (typically proxied by patents), and productivity while considering endogeneity and selection bias of R&D investment. Representative references here include Hall and Mairesse (1995), Crepon et al. (1998), Janz et al. (2004), and Griffith et al. (2006). The underlying crucial assumption of these studies is that innovation inputs determine innovation outputs, and that innovation output in turn affects productivity. Firms will invest in R&D only if the net returns on this investment are positive. Janz et al. (2004) estimate a variant of the CDM model (Crepon et al. 1998) on pooled firm level data for Sweden and Germany. The estimates rely on innovative firms only, but, rather than using just R&D expenditure, the authors use all innovation related expenditures as inputs in the knowledge production function. Griffith et al. (2006) apply another variant of the CDM model to 3-year data (1998–2000) for France, Germany, Spain and the UK. They estimate the model on all firms in the manufacturing sector, as they believe that firms reporting zero R&D may still have positive knowledge outputs. The underlying assumption here is that the relationship between innovation inputs and innovation outputs is the same for firms that report positive R&D and firms that report no R&D. The model is estimated separately for each country.

The third stream of research empirically examines the relationship between R&D subsidy and firm performance. Many studies find positive results for R&D intensity or patent activity. Almus and Czarnitzki (2003) find that Eastern German firms which received public subsidies increased their innovation activities by about 4 % points while Czarnitzki and Licht (2006) find a positive impact of public R&D funding on R&D intensity and patent fillings in Germany. Evaluating public technology development funds in Argentina, Brazil, Chile and Panama, Hall and Maffioli (2008) find no crowding-out effect but find not much statistically significant impact on patent applications nor on new product sales and little positive effect on productivity. Alecke et al. (2012) find that SMEs in East Germany, especially micro firms, increased both R&D intensity and the probability of patent applications as a result of subsidies.

Although numerous countries have introduced R&D support programs aimed at increasing private R&D effort, studies about how government R&D subsidies affect company productivity are relatively hard to find. Previous studies on crowding-out effects deal mainly with firm R&D additionality without analyzing other types of additionality such as productivity and profitability (Cerulli 2010, p. 422). To the best of our knowledge, no studies prior to the one reported herein have addressed the impact of public R&D subsidies on the performance of Korean SMEs by using actual subsidy data provided by the Korean government.

4 Model specification and estimation method

We start from the typical Cobb–Douglas production function that has been frequently used in the R&D investment literature.[1] The production function is given as $Q = AK^{\beta_1}L^{\beta_2}$, and total factor productivity (A) is assumed to depend on private R&D investment (R&D), R&D subsidy (D) realized in the R&D

[1] See for example Griliches (1986, 1995), Basant and Fikkert (1996), and Guellec and Van Pottelsberghe De La Potterie (2001), Tsang et al. (2008).

investment, education and job training expenses for employees (Edu), and firm age (Age):

$$A = C(\mathrm{R\&D})^{\gamma_1+\gamma_2 D}(\mathrm{Edu})^{\beta_3}(\mathrm{Age})^{\beta_4}$$

where C is a constant term and D is a zero–one indicator for positive R&D subsidy.

Dividing both sides of the production function by labor (L) and taking logarithms we get the following labor productivity model:

$$\ln(Q/L)_{i,t} = \beta_0 + \gamma_1 \ln(\mathrm{R\&D}/L)_{i,t} + \gamma_2 D_{i,t} \times \ln(\mathrm{R\&D}/L)_{i,t} + \beta_1 \ln(K/L)_{i,t} + \alpha \ln L_{i,t} + \beta_3 \ln(\mathrm{Edu}/L)_{i,t} + \beta_4 \ln(\mathrm{Age})_i \quad (i = 1, 2, \ldots, N \text{ and } t = 1, 2, \ldots, T) \tag{1}$$

where
$\beta_0 = ln(C)$, and $\alpha = \gamma_1 + \gamma_2 + \beta_1 + \beta_2 + \beta_3 - 1$.

Of course, only a segment of the total SME population would receive the government R&D subsidy in a particular period t. Let $D_{i,t}$ be a zero–one indicator that equals unity if firm i received the subsidy at time t and zero otherwise.

Adding a cross-product term of private R&D investment and public subsidy to reflect the fact that the subsidy can affect labor productivity indirectly by raising private R&D investment, and considering the dynamic nature of productivity as well as time and industry effects in Eq. (1), the estimated model can be rewritten in the following dynamic panel data (DPD) framework:

$$\ln(Q/L)_{i,t} = \beta_0 + \alpha \ln L_{i,t} + \gamma_1 \ln(\mathrm{R\&D}/L)_{i,t} + \gamma_2 D_{i,t} \times \ln(\mathrm{R\&D}/L)_{i,t} + \beta_1 \ln(K/L)_{i,t} + \beta_3 \ln(\mathrm{Edu}/L)_{i,t} + \beta_4 \ln(\mathrm{Age})_i + \theta \ln(Q/L)_{i,t-1} + \sum_k \delta_k \mathrm{Industry}_k + \sum_j \tau_j \mathrm{Year}_j + \varepsilon_{i,t} \tag{2}$$

where θ is an adjustment parameter in the dynamic productivity model, Industry is a dummy variable for the SMEs belonging to a specific industry to control for factors specific to industries that may explain variation in firm performance across industries—for instance technological opportunity and stage of the technology life cycle—and Year is a dummy variable for a specific year to reflect unobserved time variation factors.

In the DPD model, if $\gamma_1 > 0$ and statistically significant, then private R&D investment can affect positively labor productivity. When $\gamma_2 > 0$, an R&D subsidy that raises private R&D investment can enhance labor productivity indirectly. Otherwise, it would crowd-out private R&D investment given a positive and statistically significant γ_1.

If $D_{i,t-1} = 0$ and all explanatory variables were exogenous, then both the first differencing estimator and the DID estimator should be equivalent (see Appendix 1) and the traditional panel analysis could be applied. It is not unusual, however, that the R&D subsidy dummy variable $D_{i,t}$ is correlated to the temporary error term $\varepsilon_{i,t}$. This issue is closely related to the bias in the OLS estimation of γ_2 which is attributed to the endogenous selection of firms, referring to either the firm's own decision to apply for the subsidy or to the selection process by the government. DID fails to control for idiosyncratic factors affecting simultaneously the level of R&D investment and the probability of receiving a subsidy which is in turn affected by determinants of the decision to apply for the subsidy. In order to control for both simultaneity and selection bias of the government subsidy for technology development, we employ both the DID methodology and the 2-stage Tobit/Logit-GMM procedure.

The DID estimator equals the difference in the mean R&D change between the previous period ($t - 1$) and the current period t among the subsidized and not subsidized firms conditional on not having received a subsidy at the period ($t - 1$). The fixed effect and the DID estimators do not only share the same asymptotic distribution but they are also computationally identical under some assumptions.

Equation (2) shows that current productivity is influenced by lagged productivity as well as by the current explanatory variables. When the model includes the lagged dependent variable, for small T but large N, the fixed effect (FE) and the random effect (RE) GLS estimators can be biased and inconsistent because the lagged dependent variable is correlated with the disturbance term (Arellano 2003).[2] Thus, without any endogeneity and counterfactual problems, traditional panel data estimation

[2] See Baltagi (2013, p. 155) for further details.

methods such as FE and RE estimation cannot produce unbiased results any more.

One method to mitigate the problem is to employ the Anderson and Hsiao (1981) procedure which is to wipe out the individual effects and estimate the first-differencing model using lags of the dependent variable as instruments. As an extension of the Anderson and Hsiao estimator, Arellano and Bond (1991) proposed a generalized method of moment (GMM) procedure. Further, Arellano and Bover (1995) and Blundell and Bond (1998) propose an alternative estimation method of the dynamic panel model (system GMM) by using additional non-linear moment restrictions not exploited by the GMM estimator. Blundell and Bond (2000) argue that using the system GMM estimator can overcome many problems with the standard GMM estimator for dynamic panel models. In this paper, we use the system GMM method to estimate the dynamic labor productivity model given by Eq. (2), considering the endogeneity of private R&D investment and government R&D subsidy.

5 Data and estimation results

5.1 Data

The panel data to estimate the model is constructed by merging the Annual Report of the Financial Statement of the Korean manufacturing firms and public subsidy data. We collect firm financial data from the NICE (National Information and Credit Evaluation). The financial data set includes individual accounting items from the balance sheet as well as the profit and loss statement of listed and unlisted companies over the period 2000–2007. The advantage of these data is the extensive coverage of private companies for a variety of firm sizes for all industries. The data on government R&D subsidy were provided by the Small and Medium Business Administration (SMBA). The sample period for the subsidy data set also covers fiscal years 2000–2007.

Table 1 shows the operating definition for the variables used in the paper. As a dependent variable of labor productivity we use value-added productivity, or value-added (VA) per employee.[3] Since quantity produced is not available and many firms produce multiple products, we use the firm's VA as a proxy for firm production (Tsang et al. 2008). Firm total sales are frequently used as a proxy for production but they are over-estimated because intermediate material costs are not excluded. Since firms intermediate material costs are not exactly known, we calculate the VA following the definition of the Korean central bank as shown in the Table.

The R&D subsidy refers to direct financial support (grant) through some government program and excludes loans and tax benefits to SMEs. The subsidy is not required for amortization. The Korean SMBA chooses the firms and the amount of subsidy they will receive based on an evaluation of the SME's performance and the validity of the public R&D subsidy program.

Incomplete observations for the variables are excluded from the regression analysis. If there are missing values in the list of dependent, independent, and control variables of a firm in a particular year, the observation related to the firm in that year is automatically excluded. We also deflate all nominal variables such as the value added, fixed assets, private R&D spending by Korean industrial wholesale price indices.

Table 2 shows the number of firms receiving and not receiving this financial assistance (grant) over the period 2000–2007. Among industries, the machinery and equipment industry received the largest subsidies in terms of the number of firms. It was followed by the TV and communication industry and the heavy chemicals and chemical product industry.

In Table 3, the total annual number of companies with and without R&D subsidy is presented. The table shows that the number of firms receiving the R&D subsidy has increased over the years during the examined time period.

Table 4 presents descriptive statistics. The number of firms (observations) receiving the subsidy 2 years in a row is 4981 over the sample period.[4]

Table 5 presenting the correlation between variables used in the paper shows that all correlation coefficients except for two are statistically significant at 5 % level.

[3] We use the definition from The Bank of Korea (i.e. the central bank in Korea) for value-added (VA). See OECD (2001) for further discussion about various productivity measures.

[4] Since we used unbalanced data across the variables, the numbers of observations for variables used here are different depending on the number of missing observations.

Table 1 Definition of variables used

Variables	Definition/description
VA	Value added = (operating surplus + labor costs + interest expenses + taxes & dues + depreciation & amortization)
Ln(Q/L)	Dependent variable: Value-added productivity = Ln(VA/L)
Ln(K/L)	Capital Intensity = Ln(Fixed asset of the firm per employee)
Ln(L)	Ln(Number of employees)
Ln(Edu/L)	Ln(Education and job training expenses per employee)
Sales	Firm total sales
R&D	R&D expenses = ordinary development expenses + ordinary research and development expenses + amortization of research and development expenses + changes of research and development expenses
Ln(R&D/L)	Ln(R&D/L)
R&D Subsidy	Government financial support for new technology development and technology transfer
D	$D = 1$ if the firm received government R&D subsidy; Otherwise, $D = 0$.
Ln(Age)	Firm age; Ln(2008-founding year)
Industry	A dummy variable; take the value 1 if the SME belongs to k industry and 0 otherwise,
Year	A dummy variable for a specific year

5.2 Estimation method and results

In order to examine the effect of public R&D subsidy on firm performance, we estimate the labor productivity model by several different methods for the DID samples during the period 2001–2007. We estimate the static labor productivity model by simple pooled-OLS estimation and by traditional panel estimation methods such as random effects (RE) and fixed effects (FE).[5]

As explained earlier, however, the results estimated by simple OLS and traditional panel procedures could be biased due to unknown heterogeneity and potential endogeneity for private R&D investment and R&D subsidy.[6] While private R&D investment can positively affect labor productivity, better performing SMEs can also invest more in R&D. This bi-directional causality can cause endogeneity bias. Moreover, the R&D subsidy can also positively affect labor productivity indirectly through an additional effect on the private R&D investment. Conversely, and very importantly, the better performing SMEs may have higher chance to receive public R&D support. To remind, the Korean SMBA chooses the SMEs to be supported and determines the level of support on the basis of an appraisal of company performance and the perceived relevance of the specific R&D subsidy program to the specific company.

To control for the potential endogeneity of private R&D investment and public R&D subsidy, we use a two-stage RE estimation method. In the first step, we regress private R&D investment on instrument variables (such as lagged total sales in logs) in the panel model and on the R&D subsidy in the Logit framework, respectively. In the second step, we re-estimate the static labor productivity model, including the expected values of private R&D investment E (ln(R&D)) and of the R&D subsidy $E(D)$ instead of the current period of the R&D investment and subsidy.

The empirical results are presented in the first two columns of Table 6 and can be summarized as follows. First, all estimated coefficients for the private R&D investment are significant at the 1 % level, implying that expansion of private R&D investment should play an important role on enhancing productivity. Second, for employment, all the estimated coefficients except one are negatively

[5] See Appendix 3 for the pooled OLS and panel estimation results.

[6] In Appendix 3, the Breusch-Pagan LM test statistics indicates that the null hypothesis of no heterogeneity effects can be rejected at the 1 % level for all cases. This implies that the simple pooled-OLS estimation should lead to biased results.

Table 2 R&D subsidy recipients by industry

ISIC	Industry name	No. of firms w/o subsidy	No. of firms w/subsidy	Total no. of firms
15	Manufacture of food products and beverages	2472	30	2502
16	Manufacture of tobacco products	27		27
17	Manufacture of textiles	1870	34	1904
18	Manufacture of wearing apparel; dressing and dyeing of fur	1358	2	1360
19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear	456	4	460
20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	258	0	258
21	Manufacture of paper and paper products	989	3	992
22	Publishing, printing and reproduction of recorded media	1401	4	1405
23	Manufacture of coke, refined petroleum products and nuclear fuel	219	9	228
24	Manufacture of chemicals and chemical products	4410	201	4611
25	Manufacture of rubber and plastics products	2469	92	2561
26	Manufacture of other non- non-metallic mineral products	2183	40	2223
27	Manufacture of basic metals	3054	60	3114
28	Manufacture of fabricated metal products, except machinery and equipment	2740	69	2809
29	Manufacture of machinery and equipment n.e.c.	5616	369	5985
30	Manufacture of office, accounting and computing machinery	635	40	675
31	Manufacture of electrical machinery and apparatus n.e.c.	2121	133	2254
32	Manufacture of radio, television and communication equipment and apparatus	5379	296	5675
33	Manufacture of medical, precision and optical instruments, watches and clocks	1336	153	1489
34	Manufacture of motor vehicles, trailers and semi	4080	154	4234
35	Manufacture of other transport equipment	993	39	1032
36	Manufacture of furniture; manufacturing n.e.c.	869	24	893
37	Recycling	229	1	230
Total		45,164	1757	46,921

ISIC International Standard Industrial Classification of All Economic Activities by UN Revision 3.1

Table 3 R&D subsidy recipients by year

Year	No. of firms w/o subsidy	No. of firms w/subsidy	Total no. of firms
2000	4464	146	4610
2001	4796	179	4975
2002	5093	178	5271
2003	5433	215	5648
2004	5754	244	5998
2005	6206	236	6442
2006	6760	268	7028
2007	6658	291	6949
Total	45,164	1757	46,921

significant, suggesting that corporate performance is negatively associated with firm size even within the SME population. Third, in the 2-stage RE, the estimated coefficients for capital intensity are not significant any longer and the estimated coefficients for the cross-product term are negatively significant.

Table 4 Descriptive statistics for full sample and DID Sample (million Won)

	Full sample			DID sample		
	No. of obs	Mean	SD	No. of obs	Mean	SD
Ln(VA/*L*)	44,014	17.24	0.81	39,084	17.24	0.80
Ln(*K*/*L*)	44,014	18.46	1.14	39,084	18.43	1.13
Ln(*L*)	44,014	4.35	1.19	39,084	4.10	0.93
Ln(R&D/*L*)	44,014	4.30	9.20	39,084	3.96	9.08
D	46,921	0.04	0.19	41,940	0.03	0.17
Ln(Edu/*L*)	44,014	8.14	5.91	39,084	7.82	5.98
Ln(Age)	46,921	2.72	0.63	41,940	2.68	0.60

The DID sample is created by excluding the firms which received the government subsidies in the period ($t - 1$): That is, if $D_{i,t-1} = 1$, then the firm is excluded

Table 5 Correlation matrix for variables in DID sample

	Ln(VA/*L*)	Ln(*K*/*L*)	Ln(*L*)	Ln(R&D/*L*)	Ln(Subsidy)	Ln(Edu/*L*)
Ln(*K*/*L*)	0.3030**					
Ln(*L*)	−0.1735**	−0.0796**				
Ln(R&D/*L*)	0.1164**	−0.0246**	0.1836**			
Ln(Subsidy)	−0.0031	−0.0097**	−0.0157**	0.0583**		
Ln(Edu/*L*)	0.1540**	0.0501**	0.2891**	0.2355**	0.0207**	
Ln(Age)	−0.0099**	0.0725**	0.1765**	0.0088	−0.0234**	0.0274**

** 5 % significance levels

Table 6 Effects of R&D subsidies on labor productivity using DID sample: 2-Stage Model

Variables	2 Stage-RE	2 Stage-RE	Tobit-RE	Tobit-RE
Ln(*K*/*L*)	0.207*	0.009	0.065***	0.116***
	(0.123)	(0.113)	(0.003)	(0.006)
Ln(*L*)	−0.279	−0.404***	−0.294***	−0.410***
	(0.170)	(0.142)	(0.007)	(0.009)
E(Ln(R&D/*L*))	0.177**	0.318***	0.188***	0.148***
	(0.084)	(0.095)	(0.011)	(0.014)
E(Ln(R&D/*L*)) × *E*(*D*)	−4.493**	−7.214***	0.065***	0.048***
	(2.133)	(2.139)	(0.005)	(0.006)
Ln(Age)		−0.350	−0.035***	
		(0.240)	(0.006)	
Ln(Edu/*L*)	0.028	0.043**	0.011***	0.021***
	(0.017)	(0.020)	(0.001)	(0.001)
$\text{Ln(VA/}L)_{t-1}$			0.531***	0.171***
			(0.005)	(0.006)
Year dummy	Yes	Yes	Yes	Yes
Industry dummy	No	Yes	Yes	No
Hausman specification test			−0.169***	−0.131***
Overall R^2	0.001	0.001	0.517	0.367
No. of observations	30,078	30,078	30,078	30,078

The DID sample is created by excluding the firms which received the government subsidies in the period (t − 1)

RE Random effect models, *FE* fixed effect models

***, **, * indicates 1, 5 and 10 % significance levels, respectively

However, these results should be biased too because of ignoring the nature of the censored distribution of the R&D investment. To alleviate such a distribution problem with the R&D investment, we employ the Tobit-RE estimation procedure: in the first step, we regress the private R&D investment on the same instrument variable in the Tobit model instead of the RE model framework; in the second step we use the same RE estimation procedure even though we include the lagged dependent variable. The results of the censored distribution are shown in the last two columns of Table 6.

The estimated coefficients for private R&D investment and the cross-product term are positively significant at the 1 % level, implying that government subsidies can raise labor productivity indirectly through the promotion of R&D investment. The Hausman test rejects the exogeneity hypothesis for the R&D investment variable, which validates the 2-stage estimation method (see Wooldridge 2010 for detailed Hausman testing procedure).

However, these results can be also biased because of the potential endogeneity of the lagged dependent variable. When the model includes the lagged dependent variable, the random effect (RE) GLS estimator is biased because the firm-specific effect η_i is correlated with the disturbance term ε_{it} (Arellano 2003). Thus, even if we consider endogeneity and counter-factual outcome problems, traditional panel data estimation such as FE and RE estimation cannot produce unbiased results any longer due to the lagged dependent variable.

To mitigate this problem, we employ the GMM estimation suggested by Arellano and Bond (1991) and system GMM suggested by Arellano and Bover (1995) and Blundell and Bond (1998, 2000). The first two columns in Table 7 below present the estimated results for the DPD model of labor productivity by simple GMM and system GMM estimation methods without any of the endogeneity and distribution problems. The overall estimated results are similar to those in the Tobit-RE of Table 6. In Table 7 all the estimated coefficients for the lagged dependent variable (speed adjustment parameter) are statistically significant and less than one implying that labor productivity follows a converging dynamic process. On the other hand, estimated coefficients for cross-product term between current R&D investment and government subsidy (ln(R&D) × D) are not significant. This might be caused from ignoring the endogeneity of private R&D investment and government subsidy in the DPD model.

Table 7 R&D subsidy effect on labor productivity using the DID sample: DPD Model

Variables	GMM	System GMM	Tobit-GMM	Tobit-system GMM
Ln(K/L)	0.177***	0.406***	0.181***	0.381***
	(0.008)	(0.017)	(0.008)	(0.017)
Ln(L)	−0.476***	−0.218***	−0.471***	−0.233***
	(0.011)	(0.022)	(0.011)	(0.022)
Ln(R&D/L)	0.011***	0.005**		
	(0.002)	(0.002)		
Ln(R&D/L) × D	0.007	0.003		
	(0.008)	(0.008)		
Ln(Edu/L)	0.019***	0.021***	0.021***	0.017***
	(0.001)	(0.002)	(0.001)	(0.002)
Ln(VA/L)$_{t-1}$	0.326***	0.610***	0.348***	0.640***
	(0.011)	(0.019)	(0.011)	(0.018)
E(Ln(R&D/L))			0.115***	0.072**
			(0.016)	(0.031)
E(Ln(R&D/L)) × E(D)			0.030***	0.028***
			(0.004)	(0.007)
Year dummy	Yes	Yes	Yes	Yes
Industry dummy	No	No	No	No
Wald chi	4952.7***	416,893***	4981.1***	202,798***
Hausman specification test			−0.115***	−0.055**
No. of observations	22,616	30,078	30,078	30,078

The DID sample is created by excluding the firms which received the government subsidies in the period (t − 1)

RE Random effect models, *FE* fixed effect models

***, **, * indicates 1, 5 and 10 % significance levels, respectively

To control for the endogeneity, we employ the 2-stage Tobit/Logit-GMM and Tobit/Logit-system GMM. More accurately, we use Tobit estimation for private R&D investment and Logit estimation for public subsidy in the first stage but GMM or system GMM estimation for labor productivity in the second stage.

In Table 7, the Tobit-GMM and Tobit-system GMM estimation results for the DPD productivity model are similar to those of the simple GMM and system GMM estimation without considering any endogeneity. Labor productivity is positively associated with capital intensity whereas it is negatively affected by the number of workers (proxy for firm size). Now the estimated coefficients for the predicted R&D investment are significant ($E(\ln(\text{R\&D}/L))$ and those for the predicted cross-product term ($E(\text{R\&D}/L) \times E(D)$) turn out to be positively significant at 1 % level.

The results suggest that government subsidy raises labor productivity indirectly through stimulating private R&D investment, thus providing support to the additionality argument. The result implies that sharing the cost and the underlying risk of R&D investment with the government could stimulate R&D expenditures of Korean SMEs.

6 Concluding remarks

R&D projects entail significant costs. Firms with large revenue streams can allocate sufficient internal resources to R&D activities whereas SMEs cannot. In addition, imperfect capital markets will make external finance available to only a small subset of startups and other SMEs, a phenomenon well understood (David et al. 2000; Guellec and Van Pottelsberghe De La Potterie 2001). The resulting market failure invites government intervention. Such intervention can take many different forms—R&D subsidies, R&D tax breaks, loan guarantees, etc. (Ben-Ari and Vonortas 2007)—depending on the perceived cause of the market failure the policy is trying to correct such as imperfect capital markets, technological uncertainty, market risk, and asymmetric information between investors and small companies. Some of those instruments are more neutral than others. For instance, R&D tax breaks do not involve selection of companies that will be assisted, contrary to R&D subsidies which does. While economists have long debated which type of intervention is preferable and are frequently reluctant to prescribe direct subsidies (picking winners), others perceive that the lack of information and information asymmetry between stakeholders creates very serious problems for policy makers, investors, and researchers alike (Tversky and Kahneman 1974; Slovic et al. 1980). R&D subsidies to SMEs then can have the additional benefit of providing a quality signal to private investors helping them improve the subjective judgments and heuristics they use for investments in R&D (Fischhoff et al. 1980; Finucane et al. 2000).

While the debate on whether public R&D subsidies improve firm performance has been going on in developed countries for a long time, there is very limited hard evidence in newly industrialized economies, especially concerning SMEs. This paper has empirically addressed this topic using a unique panel data set on Korean manufacturing SMEs and government R&D subsidies. In doing so, we have employed a battery of econometric techniques to control for the selection and simultaneity biases of the government subsidy for new technology development.

Our results point in one clear direction: the public subsidy stimulated private R&D investment and boosted labor productivity in manufacturing SMEs. Several possible explanations for this positive effect have been offered in the literature including cost sharing, risk sharing, and the inducement of external investment through the provision of qualitative information to investors to facilitate decision making.

These findings provide support to the Korean R&D promotion policy for SMEs through subsidy. It is our conjecture that by stimulating corporate R&D investment and enhancing productivity the government policy measures have also contributed to fostering entrepreneurial activity in knowledge-intensive manufacturing fields. The next step would be to empirically show if and how this might have happened.

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Appendix 1

In this appendix we show the equivalence in estimating policy parameter γ_2 between the first difference estimator and the standard panel estimator used in this paper.

Let $D_{i,t}$ be a zero–one indicator that equals unity if firm i received the subsidy at time t and zero otherwise. Adding a cross-product term of private R&D investment and public subsidy to reflect the fact that the subsidy can affect labor productivity indirectly by promoting private R&D investment, and re-expressing Eq. (1) gives us the following dynamic labor productivity model:

$$q_{i,t} = \beta_0 + \gamma_1 R_{i,t} + \gamma_2 (D_{i,t} \times R_{i,t}) + X'_{i,t}\beta + \eta_i + \varepsilon_{i,t} \tag{3}$$

where labor productivity $q = \ln(Q/L)$, R&D investment per employee $R = \ln(\text{R\&D}/L)$, γ_2 reflects the indirect subsidy effect on productivity, X is a vector of explanatory variables such as capital intensity $\ln(K/L)$, number of employees $\ln(L)$, education and job training expenses per employee $\ln(\text{Edu}/L)$ and Age $\ln(\text{Age})$, η_i denotes a time-invariant effect unique to firm i, and $\varepsilon_{i,t}$ is a time varying error distributed independently across firms and independently of all η_i.

Estimation of model (1.1) as a special case of the error component model has been discussed in the literature. When η_i is a random component with a distribution independent of the observed right-hand side variables, then conventional generalized least squares produces a consistent and efficient estimator.

However, if the firm specific effect, η_i is correlated with $\varepsilon_{i,t}$ then OLS estimation of the policy parameter γ_2 in Eq. (3) could produce simultaneity bias. A popular way of getting consistent estimators involves first differencing Eq. (1) (main section) over time:

$$\Delta q_{i,t} = \gamma_1 \Delta R_{i,t} + \gamma_2 (\Delta D_{i,t} \times \Delta R_{i,t}) + \Delta X'_{i,t}\beta + \Delta\varepsilon_{i,t} \tag{4}$$

The first differencing eliminates the unobservable time-invariant firm-specific effects which can cause endogeneity of $R_{i,t}$ or $D_{i,t}$ in Eq. (1). Suppose, for simplicity, that the sample consists of only two periods: period $(t-1)$ which is before the firm receives the subsidy for technology development and period t. Let the group S represent the firms which are subsidized and the group N represent the firms which are not subsidized. As Lach (2002) suggests, if Eq. (3) is applied to the firms without a subsidy at $(t-1)$, $D_{i,t-1} = 0$, then $\Delta D_{i,t} = D_{i,t}$ and thus we get:

$$\Delta q_{i,t} = \gamma_1 \Delta R_{i,t} + \gamma_2 (D_{i,t} \times \Delta R_{i,t}) + \Delta X'_{i,t}\beta + \Delta\varepsilon_{i,t} \tag{5}$$

From (5), it follows that:

$$\begin{aligned} E(\Delta q^s_{i,t} - \Delta q^N_{i,t}) &= E(\Delta q^s_{i,t} | \Delta X, \Delta R, D_{i,t} = 1, D_{i,t-1} = 0) \\ &\quad + E(\Delta q^N_{i,t} | \Delta X, \Delta R, D_{i,t} = 0, D_{i,t-1} = 0) \\ &= \gamma + E(\Delta\varepsilon^s_{i,t} | \Delta X, \Delta R, D_{i,t} = 1, D_{i,t-1} = 0) \\ &\quad - E(\Delta\varepsilon^N_{i,t} | \Delta X, \Delta R, D_{i,t} = 0, D_{i,t-1} = 0) \end{aligned}$$

Under the assumption that $\varepsilon_{i,t}$ is mean independent of the subsidy dummy variable $D_{i,t}$ at time t, the expected difference conditional on ΔX and $D_{i,t-1} = 0$ between the growth rate of subsidized ($\Delta q^S_{i,t}$) and non-subsidized firms ($\Delta q^N_{i,t}$) can be identified as policy parameter γ_2:

$$\begin{aligned} &E(\Delta\varepsilon^s_{i,t} | \Delta X, \Delta R, D_{i,t} = 1, D_{i,t-1} = 0) \\ &\quad = E(\Delta\varepsilon^N_{i,t} | \Delta X, \Delta R, D_{i,t} = 0, D_{i,t-1} = 0) \\ &\qquad E(D_{i,t} \times \varepsilon_{i,t}) = 0, \forall t) \end{aligned} \tag{6}$$

If $D_{i,t-1} = 0$, and $E(X_{i,t}\, \varepsilon_{i,t}) = 0$ (Lach 2002), then both the first differencing estimator and the DID estimator are equivalent, meaning that the traditional panel analysis can be applied.

Appendix 2

See Table 8.

Table 8 R&D subsidy by firm size

ISIC	100 < workers < 300		50 < workers ≤100		10 < workers ≤50		workers ≤10	
	No. of firms w/subsidy	Total no. of firms	No. of firms w/subsidy	Total no. of firms	No. of firms w/subsidy	Total no. of firms	No. of firms w/subsidy	Total no. of firms
15	3	669	5	594	9	565	1	212
16	0	0	0	6	0	8	0	5
17	12	632	13	528	4	423	0	163
18	1	393	0	308	0	363	0	152
19	2	140	1	93	1	120	0	44
20	0	51	0	52	0	97	0	39
21	1	281	0	225	1	275	1	85
22	1	410	1	252	1	394	0	146
23	1	56	3	78	1	54	0	10
24	39	1272	41	1092	54	1177	8	339
25	19	706	18	738	28	675	8	255
26	5	436	11	548	6	756	0	217
27	13	643	12	849	15	1003	4	378
28	13	579	11	690	15	991	2	318
29	54	1183	80	1533	100	2184	21	641
30	7	160	8	178	11	207	3	73
31	34	629	41	643	15	562	3	200
32	55	1431	62	1347	59	1650	24	631
33	35	356	36	372	35	494	4	127
34	42	1364	29	1059	29	909	11	401
35	9	189	10	261	10	336	2	134
36	5	254	6	221	3	253	4	84
37	1	62	0	64	0	81	0	23
Total	352	11,896	388	11,731	397	13,577	96	4677

ISIC International Standard Industrial Classification of All Economic Activities by UN Revision 3.1

Appendix 3

See Table 9.

Table 9 R&D subsidy Effect on labor productivity using DID sample: RE & FE Model

Variables	Pooled OLS	RE	RE	FE	FE
Ln(*K*/*L*)	0.151***	0.159***	0.145***	0.167***	0.151***
	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
Ln(*L*)	−0.216***	−0.245***	−0.285***	−0.264***	−0.300***
	(0.004)	(0.007)	(0.007)	(0.006)	(0.006)
Ln(R&D/*L*)	0.012***	0.015***	0.013***	0.016***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(R&D/*L*) × *D*	−0.003	−0.000	−0.001	0.000	0.000
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)

Table 9 continued

Variables	Pooled OLS	RE	RE	FE	FE
Ln(Age)	0.032***	0.070***	0.075***		
	(0.007)	(0.012)	(0.012)		
Ln(Edu/L)			0.024***		0.023***
			(0.001)		(0.001)
Year dummy	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	NA	NA
R^2	0.0169	0.168	0.198	0.163	0.192
H_0: No hetero		18,454.0***	18,260.1***	7.23***	5.52***
F	250.041			694.451	752.198
No. of observations	39,084	39,084	39,084	39,084	39,084

The DID sample is created by excluding the firms which received the government subsidies in the period ($t - 1$).

RE Random Effect Models, *FE* Fixed Effect Models.

***, **, * indicates 1, 5 and 10 % significance levels, respectively

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